Predictable Reversals, Cross-Stock Effects, and the Limits of Arbitrage

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Abstract

This paper presents a multi-asset model of stock returns in a market where some investors place inelastic orders that are uncorrelated with fundamentals. Risk-averse rational arbitrageurs accommodate trading imbalances but require compensation. The compensation manifests itself as predictable return reversals. Our model predicts that whenever underlying fundamentals are correlated, trading imbalances also create cross-stock (temporary) price pressure. We test implications of the model and show pervasive price pressure at daily, weekly, and monthly frequencies. A zero-cost portfolio based on sorting trading imbalances into deciles earns a risk-adjusted average return of 79 bp *per week*. Contemporaneous cross-stock trading imbalances have a price impact that is four times larger for same-industry versus different-industry pairs of stocks. We end by linking limited risk bearing capacity in the market to approximately 54% of the observed co-movement in stock returns.

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1 Introduction

Do trading imbalances by one group of investors cause prices to deviate from fundamental values? Do price deviations exist even if trades are uncorrelated with underlying fundamentals? If so, what are the magnitudes of these deviations and how long does it take prices to mean-revert back to fundamental values? Finally, does a trading imbalance in one stock cause prices of other stocks to also deviate away from their fundamental values?

To answer the questions above, we contribute to the limits to arbitrage literature along two main dimensions. Our first contribution is to provide a multi-asset model that produces specific testable implications. The model contains a finite number of risk-averse, fully-rational investors who require compensation for accommodating trading imbalances (even if the imbalances are uncorrelated with asset fundamentals). This compensation manifests itself as a predictable return reversal. When stocks have correlated fundamentals, trading imbalances create cross-stock (temporary) price pressure. The cross-stock effect is increasing in the magnitude of fundamental correlation. Stocks with highly volatile trading imbalances have higher return volatility after controlling for the variance of fundamentals. A further implication is that the limited risk-bearing capacity causes excess co-movement of stocks returns relative to underlying fundamentals.

The second contribution of this paper is to test the implications of our model with a dataset that is well-suited for testing the empirical implications of limits-to-arbitrage models. Such models typically assume that rational risk-averse arbitrageurs are able to see (condition on) the order flow they are absorbing. The arbitrageurs know whether the flow is correlated with asset fundamentals. Our data allows us to identify a large pool of daily trading imbalances across hundreds of stocks, over an eight year period. This identification is achieved without requiring a trade classification algorithm. Most importantly, the data is publicly available to all investors. And, the source of underlying trades is a specific set of investors that are unlikely to be trading on the basis of inside information. We describe the data fully in Section 3 and provide evidence that trades are not linked to underlying fundamentals.

Our analysis provides a clear picture of the economic magnitude of the price pressure and predictable reversals by means of a sorting methodology. Each week we sort stocks into deciles based on trading imbalances and form a zero-cost portfolio. Initial price distortions (as measured by the zero-cost portfolio) are 237 basis points (bp). This is clearly far beyond transaction cost boundaries. The portfolio exhibits a predictable average return of 72 bp

over the week following formation and 188 bp over the five weeks following formation. The zero-cost portfolio returns cannot be explained by exposure to known sources of systematic risk and its "alpha" is 79 bp per week on average. While the zero-cost portfolio exhibits high alpha, we show that portfolio returns are bounded by reasonable after-cost Sharpe ratios, lending support to the interpretation that risk-averse arbitrageurs do not fully diversify the exposure created by the absorption of the trading imbalances.

Finally, our paper helps rationalize the high co-movement of stock returns observed in emerging markets. Aggregate risk-bearing capacity is likely to be low in such countries and probably due to a reduced number of arbitrageurs. In our data, correlated fundamentals explains only 46% of stock return co-movement, while limited risk-bearing capacity is responsible the remaining 54%. Before introducing our model, we compare and contrast our paper to recent theoretical and empirical studies.

1.1   Related Theoretical Studies

Our theoretical model can be thought of as a multi-asset extension of Grossman and Miller (1988) and Holden and Subrahmanyam (2002) that has been stripped down to focus exclusively on how markets absorb trading imbalances. These models have a limited number of risk-averse arbitrageurs with long horizons. Trading imbalances are positively correlated with contemporaneous price changes. The same imbalances are negatively correlated with future price changes. Predictability in stock returns arise from a reduction of the risk premium required for absorbing trading shocks as more information about the stock becomes available over time. Our multi-asset approach generates the aforementioned price pressure and reversion. The major differences are the new cross-stock predictions we provide.[1]

A second strand of models in the limits to arbitrage literature assumes that risk-averse arbitrageurs behave myopically. These models include DeLong et al. (1990b); Campbell, Grossman and Wang (1993); Barberis and Shleifer (2003); and Greenwood (2005b). Return predictability in this framework is generated by the myopia in conjunction with an assumption that trading shocks are not persistent. Myopia may be a reasonable assumption for long horizons studies due to agency considerations as in Shleifer and Vishny (1997). But such assumptions may not be appropriate for testing models with high-frequency data (such as

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[1]Chordia and Subrahmanyam (2004) present a single-asset model similar to the ones just discussed. In their model, the sign of stock return predictability depends on model parameters due to a second effect. Order imbalances are (endogenously) positively correlated over time while information continues to become available over time.

we have).[2] Assumptions about non-persistence do not fit our data as we cannot reject the hypothesis that trading imbalances are fully persistent.

Greenwood (2005a) develops a model with myopic risk-averse investors in which stock returns follow a predictable pattern after a permanent, uninformed trading shock. The model assumes arbitrageurs do not consider the possibility of this shock occurring (i.e., expectations are not fully rational). Such an assumption is reasonable in situations such as the one-time index re-balancing studied in his paper. But the same assumption is not appropriate for our paper as we study repeated interactions between liquidity demanders and liquidity providers.

1.2 Related Empirical Studies

Much of the empirical literature surrounding the limits to arbitrage focuses on large rare events such as additions and deletions from stock indexes—see Harris and Gurel (1986), Shleifer (1986), Wurgler and Zhuravskaya (2002), and Greenwood (2005a) for some examples. Recently, papers have turned to identifying liquidity shocks by studying order imbalances rather than index additions. Chordia and Subrahmanyam (2004) and Chordia, Roll and Subrahmanyam (2005) use the Lee and Ready (1991) algorithm to identify high-frequency order imbalances across many stocks and over long time periods.[3] The former paper shows that daily order imbalance is positively correlated with contemporaneous returns for 99% of NYSE stocks. The authors also find that order imbalances are positively correlated with one day ahead returns for about 25% of stocks. These results could be due to the fact that underlying orders may carry information about fundamentals.

We also show pervasive price pressure across the stocks in our market. Our results differ from the aforementioned papers when it comes to the predictable reversals. An important difference is that our data are available to all investors each trading day. In our paper, the source of trading imbalances is a specific set of traders that are unlikely to be trading on the basis of inside information. In fact, we show empirically that our trading imbalances do not lead to permanent changes in prices. The empirical results in our paper are also related to Hasbrouck and Seppi (2001). We extend their work by testing implications of a specific economic model. One difference is that our model points to lagged trading imbalances (own-stock and cross-stock) as being an important determinant of stock returns.

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[2]We thank Brad DeLong for pointing this out to us.

[3]Lee et. al (2004) also study order imbalances, but use other algorithms to classify trades.

The paper now proceeds as follows. Section 2 presents our model and its testable implications. Section 3 describes the data used in this study. Section 4 provides the main results of the paper regarding trading imbalances and predictable reversals. Section 5 tests additional cross-sectional implications of the model. It is in this section that we use our trading imbalance data to explain the observed co-movement of stock returns (stock price synchronicity.) Section 6 shows the results in this paper are robust to numerous alternatives, while the final sections concludes.

2 Model

Our basic model has two risky assets labeled j and k. Each asset is in unit supply and a there is a riskless asset in elastic supply. We normalize the interest rate to zero and the price of the riskless asset to one.

The model has three dates. Agents trade at date 1 and date 2. The risky assets each pay a liquidating dividend at date 3. For stock j this dividend is equal to $S_1^j + S_2^j + \Phi_3^j$. At date 1, part of the stock j's final dividend (S_1^j) is revealed to the rational traders. At date 2, another part of stock j's final dividend (S_2^j) is similarly revealed to the rational traders. The final part of the dividend (Φ_3^j) is revealed at the time of liquidation. Stock k has an analogous revelation process and dividend structure.

For asset j, the parts of the dividends are: $S_1^j \sim N(0, V_s)$; $S_2^j \sim N(0, V_s)$; and $\Phi_3^j \sim N(0, V_\phi)$. For asset k, $S_1^k \sim N(0, V_s)$; $S_2^k \sim N(0, V_s)$; and $\Phi_3^k \sim N(0, V_\phi)$. The dividends and their revealed parts are correlated across assets, but are not serially correlated over time:

$$\left. \begin{array}{c} Corr\left(S_1^j, S_1^k\right) \\ Corr\left(S_2^j, S_2^k\right) \\ Corr\left(\Phi_3^j, \Phi_3^k\right) \end{array} \right| = \rho_\phi$$

$$Corr\left(S_1^j, S_2^j\right) = Corr\left(S_1^j, \Phi_3^j\right) = Corr\left(S_2^j, \Phi_3^j\right) = 0$$
$$Corr\left(S_1^k, S_2^k\right) = Corr\left(S_1^k, \Phi_3^k\right) = Corr\left(S_2^k, \Phi_3^k\right) = 0$$

There are two groups of agents. The first group is referred to as liquidity or noise traders. They place inelastic orders (demands) for the risky asset at date $t \in \{1, 2\}$. These orders are uncorrelated with fundamentals (i.e., uncorrelated with S_t^j, S_t^k, Φ^j, and Φ^k). The incremental demand for asset j at each period of time is denoted by: $Z_t^j \sim N(0, V_z)$ for $t \in \{1, 2\}$. In

other words, the demand shock at date 1 is fully persistent and the total demand at date 2 is $Z_1^j + Z_2^j$ for asset j. Similar incremental demand shocks exist for asset k as well. We assume that the demand shocks are contemporaneously cross-sectionally correlated, but serially uncorrelated:

$$\left. \begin{array}{c} Corr\left(Z_1^j, Z_1^k\right) \\ Corr\left(Z_2^j, Z_2^k\right) \end{array} \right| = \rho_z$$

$$Corr\left(Z_1^j, Z_2^j\right) = Corr\left(Z_1^j, Z_2^k\right) = Corr\left(Z_1^k, Z_2^k\right) = 0$$

The second group of agents are risk averse investors. We refer to this group as the maximizing agents, rational investors, or arbitrageurs. These investors maximize date 3 wealth and have CARA utility with a λ risk aversion coefficient.[4]

They observe $\left\{S_1^j, S_1^k\right\}$ at date 1 and $\left\{S_2^j, S_2^k\right\}$ at date 2. We denote the demands for risky assets by the group of risk averse agents by X_t^j and X_t^k for $t \in \{1, 2\}$.

2.1 Equilibrium Prices and Returns

Let the prices of the risky assets be P_t^j and P_t^k for $t \in \{1, 2, 3\}$. We solve for equilibrium prices by backward induction (please see Appendix 1 for details). Below, we give expressions for the prices and return of asset j only.[5] Similar expressions exist for asset k as well:

$$\begin{array}{rcl} P_3^j & = & S_1^j + S_2^j + \Phi_3^j \\ P_2^j & = & S_1^j + S_2^j + \lambda V_\phi(Z_1^j + Z_2^j) + \rho_\phi \lambda V_\phi(Z_1^k + Z_2^k) - \lambda\left(1 + \rho_\phi\right) V_\phi \\ P_1^j & = & S_1^j + \lambda(V_\phi + V_s)Z_1^j + \rho_\phi \lambda(V_\phi + V_s)Z_1^k - \lambda(1 + \rho_\phi)(V_\phi + V_s) \end{array} \tag{1}$$

The return to stock j from period 1 to 2 is given by:

$$P_2^j - P_1^j = S_2^j + \lambda V_\phi Z_2^j + \rho_\phi \lambda V_\phi Z_2^k - \lambda V_s Z_1^j - \rho_\phi \lambda V_s Z_1^k + \lambda\left(1 + \rho_\phi\right) V_s \tag{2}$$

Equation (2) contains the main results of the model. We refer almost exclusively to this equation when formulating testable hypotheses and throughout our empirical section. The first three terms of the equation represent the surprise part of stock j's return. The surprise

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[4]One can think of λ as $\frac{\overline{\lambda}}{A}$, where $\overline{\lambda}$ is the absolute risk aversion coefficient of each arbitrageur and A is the total number of arbitrageurs. The risk-bearing capacity of the market is unlimited if either $\overline{\lambda}$ goes to zero or A goes to infinity.

[5]Note that the rational investors know the trading imbalances (Z's) by conditioning on prices.

is determined by three random variables: i) News about fundamentals of stock j; ii) Trading imbalances to stock j; *and* iii) Trading imbalances to stock k. The third term drops out if the two assets have uncorrelated fundamentals (i.e., if $\rho_\phi = 0$). The last three terms represent the risk premium earned by the holder of Stock j. Terms four and five represent a conditional risk premium that arbitrageurs earn for absorbing last period's trading imbalances. If the noise traders sold stock j last period, Z_1^j is negative, and the arbitrageurs earn an extra, positive return. The last term is the unconditional risk premium associated with stock j. Note that the unconditional risk premium does not depend on V_z.

Equation (2) highlights the fact that regressions containing returns and own imbalances are technically mis-specified. Such regressions omit the cross-stock imbalances. This point is important since many papers focus on a single-asset and own-imbalance effects. Finally, we envision the length of time between date 2 and date 3 to be much larger than the length of time between date 1 and date 2 (so that $V_\phi \gg V_s$).[6] Date 3 is far enough into the future so that the horizon of rational investors coincides with the final resolution of uncertainty about the risky assets' payoffs.

2.2   Testable Implications of the Model

Own-Stock Implications: Our model predicts the existence of contemporaneous price pressure. The risk averse agents require compensation for absorbing the trading imbalances of the uninformed investors. The financial econometrician observes a positive correlation between stock j's returns today and stock j's trading imbalances today:

$$Cov\left[P_2^j - P_1^j, Z_2^j\right] = \lambda V_\phi V_z \left(1 + \rho_\phi \rho_z\right) > 0 \tag{3}$$

Even though the trading imbalances are fully persistent from date 1 to date 2, our model predicts the price pressure from the imbalance at date 1 is only temporary. As more information about the risky asset becomes available, it becomes less risky for the rational arbitrageurs to absorb a given trading imbalance. The predictable reversal in returns after an initial trading imbalance can be seen in the following equation:

$$Cov\left[P_2^j - P_1^j, Z_1^j\right] = -\lambda V_s V_z \left(1 + \rho_\phi \rho_z\right) < 0 \tag{4}$$

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[6]This is done for notational simplicity. The same qualitative results would obtain if there were many time periods of the same length.

Cross-Stock Implications: Our model predicts that trading imbalances to stock k affect the returns of stock j if the two stocks have correlated dividends (fundamentals). The intuition behind this result comes from thinking about the rational arbitrageurs' hedging possibilities. Suppose the noise traders decide to sell stock k. Risk averse and competitive arbitrageurs agree to accommodate the imbalance, but require compensation. The price of stock k is bid down. However, if fundamentals are correlated, arbitrageurs may partially offset the risk of absorbing shares of k by selling some of stock j. This mechanism transfers part of the trading imbalance from stock k to stock j. When fundamentals are positively correlated, a negative trading imbalance to stock k creates a negative price pressure in stock j.

Actual Markets and Multiple Assets: In Section 4 we test our model with stock market data. Actual markets have more than two stocks so we expand the basic model from two to N risky assets, under the simplifying assumption that all stocks share the same pairwise correlation of fundamentals (ρ_ϕ). The multi-asset extension of our model extends Equation (2) from above to:

$$P_2^j - P_1^j \;=\; S_2^j + \lambda V_\phi Z_2^j + \rho_\phi \lambda V_\phi \sum_{k \neq j} Z_2^k - \lambda V_s Z_1^j - \rho_\phi \lambda V_s \sum_{k \neq j} Z_1^k + const.$$

The equation directly above implies that we want to regress returns on current and lagged trading imbalances. As Section 3 describes, we have a balanced panel with 131 companies and 443 weeks of data. Estimation of the equation directly above requires 262 right hand side variables which is not desirable. Notice that if $\rho_Z = 0$ then $\sum_{k \neq j} Z_t^k \to 0$ for $N \to \infty$ by the Law of Large Numbers. Assuming $\rho_Z \neq 0$ the cross imbalances do not tend to cancel each other out as we consider more and more stocks. If there is a factor structure to the cross imbalances (the Z_2^k's) then we can reduce the number of right hand side variables.

In the next section, we show that $\rho_z > 0$ on average and there is a single, dominant factor to the trading imbalances. Stocks load evenly on this factor which allows us to substitute the following expression $(N-1)Z_t^{EW^*} \approx \sum_{k \neq j} Z_t^k$. Here, $Z_t^{EW^*}$ denotes the time t equal-weighted average imbalance across all stocks in the market *except* stock j.

$$P_2^j - P_1^j \;=\; S_2^j + \lambda V_\phi Z_2^j + \rho_\phi \lambda V_\phi (N-1) Z_2^{EW^*} - \lambda V_s Z_1^j - \rho_\phi \lambda V_s (N-1) Z_1^{EW^*} + const.$$

In reduced form, the above equation becomes our main estimation and is shown below. We can use this reduced form estimation equation to test the impact on returns of own-stock imbalances and cross-stock imbalances:

$$r_t^j \;=\; \pi_0 + \pi_{11} Z_t^j + \pi_{12}(N-1)Z_t^{EW^*} + \pi_{21} Z_{t-1}^j + \pi_{22}(N-1)Z_{t-1}^{EW^*} + \varepsilon_t^j \qquad (5)$$

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3 Data

We obtain data with the help of national securities firm in Taiwan and from a data provider called the Taiwan Economic Journal (TEJ). All price and trading data are from the Taiwan Stock Exchange (TSE). The date are available on a daily basis from January 1, 1994 to August 29, 2002, accounting for 2,360 trading days or 443 calendar weeks. The data cover all 647 listed companies in Taiwan. In order to account for occasional trading suspensions of a few stocks, we consider both the complete dataset as well as a sub-sample of the 131 stocks. The sub-sample has price and trading data available throughout the entire sample period and thus provides a balanced panel.[7]

Price and Return Data: We obtain share prices, returns, and number of shares outstanding for each listed stock at a daily frequency. Data are available from the TEJ. Daily and weekly returns are adjusted for capital changes.

Trading Data: We obtain the net number of shares bought or sold by margins traders on a daily basis for 608 stocks.[8] The number of shares are reported to the TSE by brokerage firms. The aggregate number of shares bought or sold (net) 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 use the net number of shares bought (sold) for stock j as the empirical analog to Z_t^j from our model. In order to compare quantities across firms, we typically normalize by the number of shares outstanding.

$$Z_t^j \equiv \frac{\textit{Net Shares Bought(Sold)}_t^j}{\textit{Total Shares Outstanding}_t^j}$$

To control for outliers in regressions, we winsorize the above measure at the 0.50% and 99.50% levels for the daily and weekly data. The change is irrelevant with non-parametric sorting tests. The aggregate holdings of stock j on date t is the sum of all past net trading. We have the holdings each day and week for each stock in our sample: $H_t^j \equiv \sum_{\tau=-\infty}^{t} Z_\tau^j$.

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[7]Results remain qualitatively similar when using both the full sample and sub-sample and Section 6.9 provides specific robustness tests. Appendix 2 provides additional description about the sub-sample selection procedure.

[8]There are 39 stocks that have no margin trading.

3.1 An (Ex-Ante) Empirical Analog of Z_t^j

There are many reasons why our net trading data are an appropriate empirical analog of Z_t^j. First, it is estimated that 99.3% of our margin trading data come from individuals rather than from institutions.[9] Several papers in the literature advance the idea that individuals trade for reasons unrelated with stock fundamentals—see Barber and Odean (2000). Using data from 1994 to 1999, Barber et. al. (2005) present compelling evidence that individuals in Taiwan trade too much and on average lose money in their trading. Annual turnover is 300% to 600%, and reduces returns by 3.5% per year. The authors point out that it is unlikely that private information, re-balancing or hedging needs of individuals can account for such numbers.

We build a representative portfolio based on the weekly long margin holdings data (H_t^j). This portfolio under-performs the market by 10.67 bp per week, adding up to a loss of over 5% per annum.[10] The turnover of the representative portfolio is approximately 250% per year. Most importantly, Barber et. al. (2005) have micro-structure data from Taiwan and classify all trades as either "aggressive" or "passive". Barber graciously calculated some summary statistics for net margin trading in the market. He reports that approximately 90% of the individual trades underlying our daily data can be classified. Of these, approximately 80% can be classified as "aggressive". These statistics show that the trades are demanding liquidity (not supplying it).

The rational investors of our model know the trading imbalance. Such assumption is quite common in limits-to-arbitrage models. Our margin trading data is disclosed to investors, rather than being proprietary to the TSE. Investors can see the full margin trading imbalance each day.

Finally, our statistical results would have low power if margin trading was responsible for just a tiny fraction of the Taiwanese stock market. Fortunately this is not the case. Our margin trading data account for a large fraction of the trading volume in the TSE. Within

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[9]It is important to note that this is not a paper about the average performance of *all* individual investors. Instead, this examines a well-defined subset of investors for whom we can identify trading imbalances. It happens that the subset is populated 99.3% by individuals which, in part, gives us confidence that the data maps rather cleanly into Z_t^j. The full set of reasons for believing this is a clean mapping are listed in this subsection, Section 4.7, and Appendix 3.

[10]The under-performance has a -2.08 T-statistic. On the one hand, the fact the T-statistic is not too big is good otherwise one might worry trades are motivated by (bad) information. On the other hand, Section 4.1 of this paper shows the price impact "paid" by the margins traders can be substantial. It is this price impact which undoubtedly contributes to the under-performance.

the sub-sample of 131 companies, margin trading accounts for an average of 42.36% of a given stock's turnover. Appendix 3 provides further additional tests that lend *ex-ante* support to the use of margin trading imbalances as the empirical analog of Z_t^j in our model. We show that net margin trades are uncorrelated with changes in the six month money market rates, commercial paper rates, loans at domestic banks, and the change in the premium on the Taiwan (equity) fund. Of course, we test the predictions of the model explicitly in Sections 4, 5, and 6. Confirmation of the model's predictions can be thought of as *ex-post* support for using the margins trading data as an empirical analog of Z_t^j. We revisit the issue of ex-post evaluation in Section 4.7 after first carrying out the tests.

3.2 Overview Statistics

Table 1, Panel A shows cross-sectional measures of Z_t^j, $\left|\Delta Z_t^j\right|$, and $H_t^j = \sum Z_t^j$. We see that the net trading is, on average, near zero. But, net trading is clearly volatile as $\left|\Delta Z_t^j\right|$ is 0.0013 per day on average and 0.0039 per week on average. On average, investors in our sample hold 0.0725 of shares outstanding, with a 0.0360 to 0.1049 intra-quartile range. There is not much difference between cross-sectional measures if we consider the full sample of 608 firms or if we consider the sub-sample of 131 firms.

Table 1, Panel B shows the time-series means and standard deviations of an equally-weighted trading measure (across stocks.) The standard deviation of net trading is analogous to V_z from our model. 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 sub-sample of 131 companies, sample averages are equal across panels.

Table 1, Panel C shows a break-down of the firms in our sample by industry. In Sections 5.1 and 5.2 we use industry classification as a proxy for correlated fundamentals. Taiwan has seen a large growth in its electronic industry, many of which are first listed late in our sample period. The balanced sub-sample of 131 firms represents over 40% of total market capitalization at the end of 1998.

Table 2 shows results that provide further justification for using our net trading data as the empirical analog to Z_t^j from our model. The model assumes trading imbalances $\left\{Z_1^j, Z_2^j\right\}$ are fully persistent. To test this assumption, we perform a unit root test of the null hypothesis that the level of holdings, $H_t^j = \sum Z_\tau^j$, follows a random walk. Using daily data and our balanced panel, Panel A shows we can only reject the null for 3 of the 131 stocks (at the

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5%-level). Using weekly data, we can only reject the null for 7 of the 131 stocks (at the 5%-level). Clearly these rejection rates are what one would expect by pure chance.

In Section 2.2 we discuss the testable implications of our model in an actual stock market with many assets. One requirement for cross-stock trading imbalances to matter is that ρ_z is different from zero (i.e., trading imbalances are contemporaneously cross-sectionally correlated.) We test this in Table 2, Panel B. The average pairwise correlation is 0.0612 using daily data and 0.1209 using weekly data. Our sub-sample has 131 stocks which gives 8,515 pairs. Of the 8,515 pairs, only 291 pairs (or 3.42%) have negatively correlated trading imbalances at a daily frequency and only 343 pairs (or 4.03%) have negatively correlated trading imbalances at a weekly frequency. The average pairwise correlation is significantly different from zero at all conventional levels.

In Table 2, Panel C we show the results of a principal component analysis. We report the fraction of explained contemporaneous correlation of trading imbalances (Z_t^j). The first principal component is clearly dominant and additional principal components are economically negligible (especially at the weekly frequency). This finding supports our use of $Z_t^{EW^*}$ in Equation 5—our main regression equation. In other words, trading imbalances do not offset each other even when the number of stocks gets large.[11] We test for statistical significance using the asymptotic approximation outlined in Hasbrouck and Seppi (2001). At a daily frequency, the first eigenvalue is 9.5181 (and the first principal component explains 7.27% of observed correlation where $0.0727 = 9.5181 \div 131$.) We can approximate the standard error with $\sqrt{2(9.5181)^2/2359} = 0.28$ which corresponds to a 34.34 Z-statistic. At a weekly frequency, the first eigenvalue is 17.6487 (and the first principal component explains 13.47% of correlation where $0.1347 = 17.6487 \div 131$.) We can approximate the standard error with $\sqrt{2(17.6487)^2/443} = 1.19$ which corresponds to a 14.88 Z-statistic.

4 Trading Imbalances and Predictable Reversals

We use our main regression equation developed in Section 2.2 and shown in Equation (5) to test the implications of our model. Although we use a single regression framework we present results in four sub-sections below: 4.1) Own-stock contemporaneous effects; 4.2) Own-stock reversals; 4.3) Cross-stock contemporaneous effects; and 4.4) Cross-stock reversals. We consider both daily and weekly frequencies. For most of this section, we consider $N =$

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[11]Results not reported, but available upon request, show that stocks load evenly on the first principal component.

131 stocks in our sub-sample. Results using the full sample of 608 stocks are checked in Section 6.9. All T-statistics reported in the four sub-sections below are based on standard errors that allow for heteroscedasticity and clustering of contemporaneous observations (i.e., across stocks, at the same point in time.)

4.1 Own-Stock, Contemporaneous Price Impact

We test if signed trading imbalances of stock j are positively correlated with contemporaneous returns of stock j. This test is a direct implication of our model and can be seen in Equation (2) and Equation (3). The simplest test involves a pooled regression of returns $\left(r_t^j\right)$ on a constant and own trading imbalances $\left(Z_t^j\right)$. In Table 3, Regression 1 we see the own trading imbalances have a coefficient (π_{11}) of 2.7014 with a 44.65 T-statistic when using daily data. In Regression 4, the own trading imbalances have a coefficient of 2.6843 with a 17.83 T-statistic when using weekly data. As predicted, we find a strong positive relationship between a stock's own trading imbalances and it's contemporaneous returns.[12]

We estimate the correctly specified form of Equation (5) in Regression 3 (daily) and Regression 6 (weekly). The own-stock coefficients (π_{11}) are now 2.0017 with a 54.39 T-statistic (daily) and 1.5493 with a 20.33 T-statistic (weekly). The adjusted-R^2 of our regression is 0.1730 at a daily frequency and over 0.2128 at a weekly frequency. To initially quantify the economic magnitude of these results, we note that a one standard deviation increase to this week's Z_t^j leads to a 91 bp increase in this week's stock price. We explore the economic magnitude more fully in Section 4.5 below.

4.2 Own-Stock, Predictable Reversals

We test if trading imbalances of stock j are negatively correlated with future returns of stock j. This test follows directly from our model and can be seen in Equation (4). Again, the simplest test involves a pooled regression of current returns $\left(r_t^j\right)$ on a constant and lagged own trading imbalances $\left(Z_{t-1}^j\right)$. In Table 3, Regression 2 we see stock j's own-stock lagged trading imbalance has a coefficient (π_{21}) of -0.4684 with a -8.65 T-statistic when using daily

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[12]As robustness checks, we re-calculate all standard errors in Table 3 allowing for clustering by stocks. We also re-estimate all coefficients and standard errors based on firm-fixed effects and clustering of contemporaneous observations. Finally Table 3, Regressions 1, 2, 4, and 5 are re-estimated using Fama-McBeth methodology. In all cases, results are not materially different from those shown in Table 3.

data. In Regression 4, the own-stock lagged trading imbalance has a coefficient of -0.4250 with a -3.13 T-statistic when using weekly data. These own-stock results give the first indication of predictable reversals and a clear pattern emerges. Positive changes in Z_t^j are followed by negative returns next period. Negative changes in Z_t^j are followed by positive returns.

We estimate the correctly specified form of Equation (5) in Regression 3 (daily) and Regression 6 (weekly). The own-stock lagged coefficients (π_{21}) are now -0.7972 with a -26.65 T-statistic (daily) and -0.4709 with a -7.82 T-statistic (weekly). Notice that the magnitudes of the coefficients on own-stock lagged imbalances are about 65% less than the magnitudes of the coefficients on own-stock contemporaneous imbalances (0.7972 vs. 2.0017 at a daily frequency and 0.4709 vs. 1.5493 at a weekly frequency). To better understand the economic magnitude of the predictable reversals we use a non-parametric sorting methodology in Section 4.5 below.

4.3   Cross-Stock, Contemporaneous Price Impacts

We test if trading imbalances in stock k impact the returns of stock j as predicted by our model. We use the full form of Equation (5) to estimate both own-stock and cross-stock price impacts, but concentrate on the contemporaneous cross-stock term (π_{12}).

The results in Table 3, Regression 3 (daily) and Regression 6 (weekly) provide strong support for our model. At a daily frequency, the estimated contemporaneous cross-stock parameter (π_{12}) is 0.1542 with a 21.54 T-statistic. At a weekly frequency, the estimated contemporaneous cross-stock parameter (π_{12}) is 0.1152 with a 16.08 T-statistic. Thus, a positive imbalances in stock k (where $k \neq j$) increases stock j's returns while a negative imbalances in k decreases stock j's returns. To initially quantify the economic magnitude of these results, we note that a one standard deviation imbalance to $(N-1)Z_t^{EW^*}$ leads to a 283 bp price movement in stock j using weekly data. This value is over three-times larger than the 91 bp own-stock impact reported in Section 4.1 above.

4.4   Cross-Stock, Predictable Reversals

Our model predicts that cross-stock effects also play a role in the predictable pattern of return reversals. Trading in stock k today impacts the returns of stock j today which

partially adds to stock j's mean-reversion in the future. Table 3 Regression 3 (daily) and Regression 6 (weekly) show that cross-stock effects lead to predictable reversals. The lagged cross-stock parameter (π_{22}) is -0.0562 with a -7.84 T-statistic at a daily frequency. The lagged cross-stock parameter (π_{22}) is -0.0536 with a -7.88 T-statistic at a weekly frequency. Again, the magnitude of the lagged cross-stock parameters are much smaller than the magnitude of the contemporaneous cross-stock parameters (0.0562 < 0.1542 daily; 0.0536 < 0.1152 weekly). We now turn to a sorting procedure to quantify the economic magnitude of the return predictability.

4.5 Sort Results and Predictable Return Reversals

In order to quantify the economic magnitude of price distortions and mean-reversion, we perform a simple sorting procedure based on trading imbalances. The sort procedure also controls for outliers in Z_t^j. Sorting is a non-parametric procedure that allows us to detect non-linear price pressure. Finally, the sort procedure allows us to account for cross-stock effects without having to specify them in a regression framework.

Each period we rank stocks based on Z_t^j. Stocks are then put into one of ten portfolios based on ranking. The lowest decile is called "Portfolio 1" and Z_t^j of stocks in this portfolio usually have a negative sign, though not necessarily. Likewise, the highest decile is called "Portfolio 10" and Z_t^j of stocks in this portfolio usually have a positive sign, though also not necessarily. Our procedure is similar to the typical sorting methodology used in momentum studies.

In Table 4, we measure the equal-weighted return to each of the ten portfolios (deciles) over the following period for the sub-sample of 131 stocks. We report returns over the next day and over the next week. Stocks with low Z_t^j this period have high returns next period; stocks with high Z_t^j this period have low returns next period. For example, stocks in the lowest weekly decile go up 39 bp on average over the following week. Stocks in the highest weekly decile go down 33 bp over the following week.

Table 4 also reports the results for a hypothetical zero-cost portfolio that goes long low Z_t^j stocks and short high Z_t^j stocks. On average, the zero-cost portfolio returns—labeled "Difference 1-10" or r^{1-10}—are 42 bp per day and 72 bp per week. T-statistics are based on Newey-West standard errors and indicate a high level of significance at both frequencies. Our full sample has 443 weeks of holdings data and 442 weeks of trading data (changes to

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holdings). The sorting procedure uses one week which leaves 441 weeks of returns as shown in the table.

While Table 4 only shows next-period returns, we track the zero-cost portfolio returns over the next ten periods. Figure 1 shows the cumulative returns to the zero-cost portfolio (inverted) for the sub-sample of 131 firms. We invert in order to aid intuition. Think of the graph as follows: at time zero, uninformed traders heavily buy (sell) certain stocks. The prices shoot up (down) a combined total of 129 bp that day or 237 bp that week. Prices then start to mean-revert back to pre-existing levels. On the first day following portfolio formation, prices fall (rise) 42 bp. At a weekly frequency, prices fall (rise) 72 bp during the first week following portfolio formation. The 42 bp and 72 bp are exactly the returns to the zero-cost portfolio shown in Table 4. 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.[13]

4.6 Risk-Adjusted Sort Returns

We examine the relationship of the zero-cost portfolio with known and potential risk factors. In Table 5, we regress the excess weekly returns of the zero-cost portfolio on a constant and the market excess return. Regression 1 shows the alpha (α) of the regression is 73 bp which is very similar to the 72 bp reported in Table 4. The market beta is low and not significantly different from zero.

In Table 5 we also include Fama-French size (SMB) and book-to-market (HML) factors as well as a Carhart momentum factor (MOM).[14] The table shows that regression coefficients relating to possible factors are insignificant, except for beta on the momentum factor. We

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[13]Figure 1 makes it easy to see how little evidence there is of private information being incorporated (on average) into stock prices. As opposed to models of insider information such as Kyle (1985), prices mean-revert almost completely back to pre-existing levels. The 237 bp price impact in week zero comes from both contemporaneous own-stock effects and contemporaneous cross-stock effect. Since trading imbalances are not perfectly correlated, the economic magnitudes discussed in Section 4.1 and Section 4.3 cannot simply be added together. The one standard deviation imbalance mentioned in these earlier sections is not the same as being included in the zero-cost portfolio.

[14]Appendix 5 provides a a description of factor construction. We note, however, that Chen and Zhang (1998) look at Taiwanese stock returns between 1976 and 1993 and conclude that neither size-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 sub-samples. Therefore, the evidence that SMB, HML and MOM are proxies for sources of systematic risk is weak in Taiwan.

conclude that any serial correlation that exists in the market does not affect the risk-adjusted alpha of the zero-cost portfolio. As can be seen in Table 5, Regression 5 the alpha is 79 bp. Thus, the fully risk-adjusted value is actually greater than the non risk-adjusted alpha of 72 bp as shown in Table 4. Additional tests, discussed in Section 6.3 and Section 6.4, show that the mean reversion is not the product of momentum, feedback trading, or volume-based strategies. In Section 5.4 and Section 6.5, we show that returns cover transaction costs after an initial one-week holding period.

4.7 An (Ex-Post) Empirical Analog of Z_t^j

Section 2 models stock returns when liquidity suppliers have limited risk bearing capacity. They accommodate order flow that is uncorrelated with stock fundamentals. The liquidity suppliers in our model know that such order flows do not carry information about stock fundamentals—a common assumption in limits-to-arbitrage models. We then test implications of the model with net trading imbalances of margin traders.

Section 3.1 and Appendix 3 give *ex-ante* evidence that our trading imbalances are uncorrelated with fundamentals. The tests in this section provide *ex-post* evidence that our trading imbalances are uncorrelated with stock fundamentals. The imbalances are associated with statistically significant and economically large price pressure at both daily and weekly frequencies. Prices tend to revert back to pre-existing levels in a predictable manner over a five week horizon. If the imbalances *were* correlated with a factor in the economy, the factor would need to exhibit mean-reversion at daily, weekly, and monthly frequencies. We find this unlikely and now turn to testing further implications of our model.

5 Additional Empirical Implications of Our Model

Our modeling framework produces three additional, cross-sectional implications which we test below: 5.1) A stock's return variance is shown to be increasing in the variance of it's own trading imbalances; 5.2) The magnitude of the of the cross-stock impact is shown to be increasing in the correlation of fundamentals; and 5.3) The observed co-movement of stock returns can be explained, in part, by trading imbalances. We end this section with an analysis of the limits to arbitrage and after-cost Sharpe ratios.

5.1 Own-Stock Variance

We test that a stock's return variance is increasing in the variance of it's own trading imbalances. To test this, we relax an earlier assumption of our basic model and allow different variances of trading imbalances across stocks (e.g., V_z^j and V_z^k). Equation (2) remains unchanged. However, the *variance* of stock j's return becomes:

$$Var(P_2^j - P_1^j) = V_S + \lambda^2(V_\phi^2 + V_s^2)\left(V_z^j + \rho_\phi^2 V_z^k + 2\rho_z\rho_\phi(V_z^j)^{\frac{1}{2}}(V_z^k)^{\frac{1}{2}}\right)$$

Note that when ρ_ϕ and ρ_z are small, the variances of two different stocks in the market become:

$$Var(P_2^j - P_1^j) \approx V_S + \lambda^2(V_\phi^2 + V_s^2)V_z^j$$
$$Var(P_2^k - P_1^k) \approx V_S + \lambda^2(V_\phi^2 + V_s^2)V_z^k$$

The equations above show that, after controlling for variance of fundamentals, stocks subjected to more volatile trading imbalances have higher return volatility. We control for fundamentals by comparing stocks within the same industry. We use the TSE industry classification system, which maps our 131 stocks into nineteen different industries. We first calculate the variance of returns—$Var(r_t^j)$—and the variance of trading imbalances—$Var(Z_t^j)$—for each stock. We then compute the standardized variance of returns and the standardized variance of trading imbalances within each industry.[15]

The Spearman rank correlation of the standardized variance of returns and the standardized variance of trading imbalances for all the 131 stocks is 0.5880 with a 0.0000 p-value. Note the Spearman rank correlation of unstandardized variances is 0.6864 with a 0.0000 p-value. Our results support the model's prediction the variance of returns increases with the variance of own trading imbalances. The results remain unchanged after controlling for different variance of fundamentals using industry classifications.

5.2 Magnitude of Cross-Stock Impact

We test if the magnitude of cross-stock impacts is increasing in the correlation of fundamentals. To do this, we extend our multi-asset model with N stocks by allowing different pairwise correlations of fundamentals across stocks ($\rho_\phi^{j,k}$). In this extension, Equation (2)

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[15]To standardize a firm's measure "X" we take ($\frac{X - \text{cross-sectional average}}{\text{cross-sectional standard deviation}}$).

becomes:

$$P_2^j - P_1^j = S_2^j + \lambda V_\phi Z_2^j + \lambda V_\phi \sum_{k \neq j} \rho_\phi^{j,k} Z_2^k - \lambda V_s Z_1^j - \lambda V_s \sum_{k \neq j} \rho_\phi^{j,k} Z_1^k + const.$$

If we focus on a single pair of stocks (j and k), we can re-write the equation above as:

$$P_2^j - P_1^j = S_2^j + \lambda V_\phi Z_2^j + \lambda V_\phi \rho_\phi^{j,k} Z_2^k + \lambda V_\phi \sum_{i \neq j,k} \rho_\phi^{j,i} Z_2^i - \lambda V_s Z_1^j - \lambda V_s \rho_\phi^{j,k} Z_1^k - \lambda V_s \sum_{i \neq j,k} \rho_\phi^{j,i} Z_1^i + const.$$

This second equation makes it clear that the magnitude of the cross-stock impact is increasing in the fundamental correlation ($\rho_\phi^{j,k}$). In other words, trading imbalances to k have an increasingly large impact on stock j's returns as $\rho_\phi^{j,k}$ increases. Relying once more on the existence of a single factor structure in trading imbalances, we can make the following substitution $(N-2)Z_t^{EW^{**}} \equiv \sum_{i \neq j,k} Z_t^i$ and write:

$$r_t^j = \pi_0 + \pi_{111} Z_t^j + \pi_{112} Z_t^k + \pi_{113}(N-2)Z_t^{EW^{**}} + \pi_{121} Z_{t-1}^j + \pi_{122} Z_{t-1}^k + \pi_{123}(N-2)Z_{t-1}^{EW^{**}} + \varepsilon_t^j$$
$$r_t^k = \pi_0 + \pi_{211} Z_t^j + \pi_{212} Z_t^k + \pi_{213}(N-2)Z_t^{EW^{**}} + \pi_{221} Z_{t-1}^j + \pi_{222} Z_{t-1}^k + \pi_{223}(N-2)Z_{t-1}^{EW^{**}} + \varepsilon_t^k$$

We form all 8,515 pairwise combinations with the 131 stocks in our sub-sample and estimate the set of equations above for each pair. For a given pair of stocks j and k, we define the contemporaneous cross-stock coefficient as: $CCC^{j,k} \equiv \frac{\pi_{112} + \pi_{211}}{2}$. The model predicts that $CCC^{j,k}$ is increasing in the correlation of fundamentals.

We test the prediction under the assumption that two stocks in the same industry have more highly correlated fundamentals than two stocks in different industries. As Table 6 shows, the average $CCC^{j,k}$ is 0.2851 across all 8,515 pairs. The average $CCC^{j,k}$ is 0.9973 across the 567 pairs for which j and k are from the same industry. The average $CCC^{j,k}$ is only 0.2342 across the 7,948 pairs for which j and k are *not* from the same industry. We also report the median value of $CCC^{j,k}$ and the standard deviation of $CCC^{j,k}$ across pairs. It is clear that we do not have 8,515 independent observations. However, even if we assume that we have only 131 independent observations (pairs), we can reject that $CCC^{j,k}$ is the same for same-industry and different-industry pairs at the 5%-level.[16] Our results support the model's prediction the magnitude of cross-stock impact increases with fundamental correlation. Our estimate of the cross-stock impact ($CCC^{j,k}$) is over four times larger when stocks are from the same industry than when they are not.

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[16] Assume the distribution of same-industry/different-industry pairs is the same as is shown as the bottom of Table 6. In other words, assume there are nine independent pairs with j and k in the same industry and 122 independent pairs with j and k in different industries.

5.3   Co-Movement

We show that our model and trading imbalance data can help explain the observed co-movement of stock returns. Recent work by Morck, Yeung, and Yu (2000) has focused attention on this topic—especially in emerging markets. 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 imbalances. To do this, we begin by measuring the R^2 on a stock-by-stock basis. The following equation regresses an individual stock's excess returns on a constant and the market's excess returns:

$$r_t^j - r_t^f \quad = \quad \alpha + \beta\left(r_t^m - r_t^f\right) + \varepsilon_t^j \tag{6}$$

Table 7, Specification 1 shows the average R^2 is 0.2958 using weekly data from the 131 firms in our sub-sample. We next augment Equation (6) by orthogonalizing the market excess return $(r_t^m - r_t^f)$ with respect to our market-wide measure of trading imbalances $\left(Z_t^{EW}\right)$. The new measure is labeled $r_t^{m \perp Z^{EW}}$. For each stock j, we also decompose Z_t^{EW} into a portion that is parallel to Z_t^j and a portion that is orthogonal Z_t^j. We refer to these two new measures as $Z_t^{EW\|j}$ and $Z_t^{EW\perp j}$ respectively. The new regression equation is thus:

$$r_t^j - r_t^f \quad = \quad \gamma_0 + \gamma_1 r_t^{m \perp Z^{EW}} + \gamma_2 Z_t^{EW\|j} + \gamma_3 Z_t^{EW\perp j} + \nu_t^j \tag{7}$$

Table 7, Specification 2 shows that the average R^2 is only 0.1630 when using the orthogonalized market return on the right-hand side. Specification 5 produces an average R^2 0.3474 when all three of our new measures are used. We view the co-movement results in Table 7 as another way to present implications of our model. Equation (2) shows that stocks co-move for three reasons: 1) Fundamental information is correlated across stocks; 2) Own trading imbalances are correlated across stocks; or 3) There are cross-stock effects which induce excess co-movement above the previous two effects. From the reported R^2 measures in Table 7, we conclude that market returns (correlated fundamentals) only explain about 46% of observed co-movement. Correlated trading imbalances explain approximately 23.75% of observed co-movement. Cross-stock effects explain the remaining 30.25% of observed co-movement.[17]

Both the own trading imbalances and the cross-stock effects are important factors whenever a market has aggregate risk-bearing capacity (i.e., limits to arbitrage.) If we were to have

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[17]Our decomposition of observed co-movement is based on the following (rough) approximations. The approximations can define either $denom = 0.3474$ or $denom = 0.1630 + 0.0827 + 0.1062 = 0.3519$. The observed co-movement can then be explained by: $\frac{0.1630}{denom} \simeq 0.46$; $\frac{0.0827}{denom} \simeq 0.2375$; and $\frac{0.1062}{denom} \simeq 0.3025$

similar data from other countries, we could try to link the strength of the trading imbalances to country-level variables such as investor protection or prevalence of institutional investors. Even without data from other countries, our model provides a unified framework for analyzing co-movement. This framework points to aggregate risk-bearing capacity as being a key factor.

5.4 After-Cost Sharpe Ratios

In our model prices deviate from fundamental values. The fundamental value of stock j at date 2 is $S_1^j + S_2^j$ while the price, as seen in Equation 1, is also a function of λ, V_ϕ, Z_t^j, Z_t^k, V_s, and ρ_ϕ. This deviation is driven by aggregate risk-aversion in the market. Equation 1 shows that deviations disappear if there is unlimited risk-bearing capacity in the market (in other words, if $\lambda = 0$).

We investigate the effect of risk-aversion further. Figure 2, Panel A plots the cumulative return to the zero-cost portfolio based on our sort results. The first week's return is 72 bp as shown in Table 4. Figure 2 shows that holding the zero-cost portfolio for two weeks or longer covers transaction costs.[18]

If prices are driven too far from fundamentals, we expect optimizing investors to step-in until the expected Sharpe ratio of the zero-cost (risky) portfolio is reasonable. In Panel B, we include the iso-bars of four different after-cost Sharpe ratios (plotted on the same time vs. pre-cost return axes we use in the left-hand panel.) The steepest line shows the return needed to achieve an annual after-cost Sharpe ratio of 0.50 and 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.)[19] The fact that after-cost Sharpe ratios are bounded by economically reasonable values provides indirect support that risk-bearing capacity is an important limit to arbitrage.

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[18]Section 6.5 explains how we calculate transaction costs.

[19]To achieve an after-cost Sharpe ratio of 0.50 after eight weeks, the zero-cost portfolio would need to earn 239 bp, as indicated by the "□" in the Figure 2, Panel B. Holding the zero-cost portfolio for one week does not cover costs, thus the after-cost Sharpe ratios are negative and not shown.

6 Robustness Checks

6.1 Ratio of Coefficients

The return equation for Stock j—Equation (2)—and our main estimation regression—
Equation (5)—imply estimated coefficients should be in a fixed ratio:

$$\frac{\pi_{12}}{\pi_{11}} = \frac{\rho_\phi \lambda V_\phi}{\lambda V_\phi} = \frac{\pi_{22}}{\pi_{21}} = \frac{\rho_\phi \lambda V_s}{\lambda V_s} = \rho_\phi \qquad (8)$$

We test this restriction when estimating Regression 3 and Regression 6 in Table 3. When
using daily data, we fail to reject the restriction at the 5%-level (the p-value is 0.3503) which
provides additional support for the model. Using weekly data we are able to reject at the 5%
level. Despite this rejection, we note that the ratio of weekly coefficients shown in Table 3,
Regression 6 is economically close: $\frac{0.1152}{1.5493} \approx \frac{-0.0536}{-0.4709}$.

6.2 Expanded Sort Results

Appendix 4 contains expanded sort results. We sort stocks into ten deciles based on the past
1, 2, or 3 three values of Z_t^j at both daily and weekly frequencies. We form a portfolio that
goes long the bottom decile and short the top decile of the sorted stocks. We then track that
portfolio for the next 1, 2, or 3 periods (days or weeks).

If we concentrate on the weekly frequency, we see the zero-cost portfolio earns 72 bp if the
sort is based on the past one week and we track returns for one week in the future (the same
as in Table 4). If we sort by the past three weeks and track returns for three weeks into the
future, the return goes up to 171 bp.

Finally, the daily and weekly results extend to a calendar monthly frequency (results are not
shown in Appendix 4 but are available upon request). If we sort stocks by the past month's
Z_t^j, the zero-cost portfolio earns an average of 154 bp over the next month. Like earlier
results, this average return is statistically significant and has a 2.54 T-statistic.

6.3 Momentum in Returns

Does the zero-cost portfolio unintentionally capture momentum (or reversals) in stock re-
turns? No. Table 5 addresses this question directly. We can see that the zero cost portfolio

loads negatively on the momentum factor, while 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, slightly positively auto-correlated at a daily frequency and Appendix 6, Panel A shows this clearly. We believe this effect is driven by small, low-priced stocks and the daily price limits that exist in this market. Our sorting procedure produces mean reversion at a daily frequency *despite* the positive auto-correlation. At a weekly frequency, there is no significant auto-correlation in returns. We simply cannot use weekly returns to forecast future mean-reversion. As Panel A shows, at most, 15 bp of the 72 bp (mean-reversion) reported in Table 4 can be attributed to underlying patterns in returns. Of course, this 15 bp might actually be fully explained by the price pressure from trading imbalances as in our model.

In Appendix 6, Panel B, we employ a double-sort methodology in which we independently sort stocks into one of three Z_t^j bins (low, medium, and high) and one of three r_t^j bins (low, medium, and high) for a total of nine bins. Note that the low Z_t^j bins consist (on average) of negative values from selling behavior. Likewise, the low r_t^j bins consist (on average) of negative return stocks. Complementary statements can be made about the high bins as well. The double sort results are shown in Panel B. Within each Z_t^j category, stocks show *positive* momentum. By contrast, sorting stocks by Z_t^j leads to mean reversion of 36 bp for low (negative) r_t^j stocks; 30 bp for medium r_t^j stocks; and to 45 bp for high (positive) r_t^j stocks.[20] The consistent mean-reversion (after sorting by different return levels) again supports our model.

6.4 Volume-Based Trading Strategies

Campbell, Grossman, and Wang (1993) show that reversals are prevalent following high volume periods. The authors suggest the returns of a contrarian portfolio based on high-volume stocks only should be greater than the returns of the contrarian portfolio based on all stocks (i.e., greater than weekly 15 bp contrarian returns shown in Appendix 6, Panel A).

We compute the ratio of each stock's weekly turnover to the average of it's past four week's turnover. Each week, we consider only high-volume stocks based on this ratio (stocks in the top 50%). A contrarian portfolio based on decile sort (as in Panel A) produces an average

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[20]The average mean-reversion is less than the 72 bp reported in Table 4 because we are no longer using the top and bottom deciles.

weekly return of only 5 bp and not significantly different from zero. We conclude that the predictive power of our trading imbalances is not subsumed in return and/or volume measures.

6.5 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 2, 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% profit per annum after costs.

6.6 Open Prices

We re-form the zero-cost portfolio from our sorting procedure using the next period's open price and the sub-sample of 131 stocks. Average weekly returns of the zero-cost portfolio are 78 bp and are actually higher than 72 bp returns shown in Table 4.

6.7 NTD Shocks

In Section 3 we normalized our empirical trading imbalance measures (Z_t^j) to help compare across stocks. The model is actually specified in dollars (in this case Taiwanese dollars or "NTD"). We re-estimate Table 3 with weekly, NTD data (and adjust coefficients by a factor of 10^6 to make comparisons easier). For Regression 6 we get: π_{11}=2.8354 with a 8.61 T-statistic; π_{12}=0.4084 with a 9.32 T-statistic; π_{21}=-0.8696 with a -4.48 T-statistic; and π_{22}=-1565 with a -5.99 T-statistic. The adjusted R^2 of the regression is 0.1527 which is slightly below the value reported in Table 3. Note that the T-statistics are also slightly lower using Z_t^j measured in NTD rather than how we define it in Section 3. Overall, though, the results are similar regardless of which measure we use.

6.8 $\%Z_t^j$ Shocks

We test an alternative empirical definition of trading imbalances based on shares held long on margin.

$$\%Z_t^j \equiv \frac{Shares\ Held\ _t^j}{Shares\ Held\ _{t-1}^j} - 1$$

In many ways, using the measure $\%Z_t^j$ improves the results in this paper. When using $\%Z_t^j$ instead of Z_t^j, 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). When we plot returns of the cumulative returns to this zero-cost portfolio (as in Figure 1, Panel B) we see complete mean-reversion back to zero. The zero-cost portfolio has statistically significant profit in each of four equal sub-periods during our full sample period. We re-estimate Table 3 with weekly data (and adjust coefficients by a factor of ten). For Regression 6 we get: π_{11}=1.9310 with a 16.86 T-statistic; π_{12}=0.0797 with a 13.96 T-statistic; π_{21}=-0.4064 with a -8.98 T-statistic; and π_{22}=-0.0380 with a -9.21 T-statistic. The adjusted R^2 of the regression is 0.2284 which is marginally better than the value reported in Table 3.

6.9 Full Sample

We check that results do not change when we use the full unbalanced panel of 608 stocks. We re-estimate Table 3, Regression 6 and get: π_{11}=1.5920 with a 25.68 T-statistic; π_{12}=0.0499 with a 18.38 T-statistic; π_{21}=-0.3986 with a -7.90 T-statistic; and π_{22}=-0.0205 with a -7.35 T-statistic. The adjusted R^2 of the regression is 0.2233 which is marginally better than the value reported in Table 3.

We re-do the weekly sort procedure shown in Table 4 with the full sample of 608 stocks. The zero-cost portfolio earns an average of 55 basis points per week as opposed to the 72 bp shown in Table 4. In an expanded sort based on three weeks of past imbalances and tracking returns for three weeks (as described in Section 6.2), the zero-cost portfolio earns 115 bp. Thus, results are not qualitatively changed when using the full sample of 608 stocks.

We can also use the full sample to check that results do not change when we use large companies only. We re-estimate Table 3, Regression 6 and include the thirty largest companies in the market each week (based on market capitalization). The results are: π_{11}=3.4183 with a 15.07 T-statistic; π_{12}=0.4450 with a 8.37 T-statistic; π_{21}=-0.8291 with a -4.46 T-statistic; and π_{22}=-0.1774 with a -4.46 T-statistic. The adjusted R^2 of the regression is 0.2059 which is

marginally less than the value reported in Table 3. Since we are using 30 companies instead of 131, we expect T-statistics to be about half of the values reported in Table 3. They are. Interestingly, the coefficients are almost twice as big. We attribute this finding to the fact that the large companies have high trading volumes and thus provide a higher signal-to-noise ratio than the average company in the market.

6.10 Consistent Explanations

The paper uses individual investor trades made through margin accounts. Does this feature drive our results? For example, when prices fall, margin traders face margin calls, which makes them sell stock. Similarly, when prices go up, margin traders have additional borrowing capacity and can buy more stock. Such a story is consistent with the positive contemporaneous correlation of prices and own-stock trading imbalances that we report. But, such a story cannot explain predictable reversals. If anything, they would suggest price continuations and not reversals (e.g., selling due to margin calls would push prices down even further which would lead additional margin calls.) Such a story also fails to provide intuition for many of our cross-stock findings (e.g., cross-stock impacts are increasing in fundamental correlation).

Note too that Appendix 3 shows that trading imbalances are not correlated with six month money market rates. So if borrowing constraints are truly driving margin trading, this correlation should presumably not be zero. Finally, 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 induce mean-reversion in prices at daily, weekly, and monthly frequencies.

There is room in an extended version of our model to put more structure on the trading imbalances (Z_t^j) such as in DeLong et. al. (1990a). But, such structure does not change an essential feature of our model— Z_t^j is uncorrelated with (future) fundamentals. Thus, additional structure might introduce new testable implications but it would not affect the implications derived and tested in this paper. If we allow strategic behavior by the rational arbitrageurs—as in DeLong et. al. (1990a)—solutions may quickly become unwieldy. In short, we believe our model provides a concise and unified framework to explain numerous relationships between observed trading imbalances and asset prices. Extensions, while the possible subject of future research, should be able to explain relationships beyond those addressed by the current model.

7 Conclusion

This paper develops a multi-asset model to study how a finite number of risk-averse, non-myopic investors absorb order imbalances that are uncorrelated with stock fundamentals. As with earlier single-asset models, our model predicts that prices are contemporaneously positively correlated with imbalances. Similarly, the model generates predictability of returns even with fully persistent order imbalances. Contributions include the multi-asset implications the model provides.

We test the implications of our model using an new set of data from the Taiwanese Stock Exchange. The data are daily and cover hundreds of stocks over an eight-year time period. The data represent a large pool of trading imbalances coming from a defined set of traders (individuals who buy stock through margin accounts.) The trading imbalances are publicly available each trading day. We provide evidence that the traders generating our imbalance data are unlikely to trade on the basis of private information regarding stock fundamentals. Such features make our dataset particularly well-suited for testing the empirical implications of limits-to-arbitrage models.

We show the predictions of price pressure and return predictability are strongly supported in our data. We achieve high levels of statistical significance and results are robust to several alternative specifications. We show that an order imbalance to stock k affects stock j when the two stocks have correlated fundamentals. Once more, empirical results strongly support the cross-stock effects predicted by the model.

We use a sorting methodology in order to quantify the economic significance of the price pressure and return predictability. Using a zero-cost portfolio from the sorting, we see that initial price pressure is 237 bp on an average week. After the formation period, the zero-cost portfolio exhibits positive expected returns for several weeks. The first week's return is 72 bp on average, and cumulative returns reach 188 bp over the five weeks following formation. We conclude that price pressure and return predictability are economically large and statistically significant.

Two other novel cross-stock predictions are supported in data. We show that the magnitude of the contemporaneous cross-stock impact is, on average, four times larger when a pair of firms belong to the same industry than when the pair come from different industries. We also show that, within each industry, stocks that are subject to more volatile trading imbalances tend to have higher variance of returns.

Finally, we shed light on the excess co-movement of stock returns in an emerging stock market. Our model implies that markets with more limited risk bearing capacity (due to a smaller number of arbitrageurs, for example) display higher excess co-movement of stock returns with respect to stock fundamentals. Our data indicates that excess co-movement of returns due to limited risk-bearing capacity is responsible for 54% of the total observed co-movement in Taiwan.

One theoretical framework (our model) provides a unified explanation for all the empirical findings in this paper.

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] Barber, Brad and Terrance Odean, 2000, "Trading is Hazardous to Your Wealth: The Common Stock Investment Performance of Individual Investors," *Journal of Finance*, LV, 2, April, 773-806.

[6] Bekaert, Geert and Campbell R. Harvey, 1997, "Emerging Equity Market Volatility," *Journal of Financial Economics*, 43, 1, 29-78.

[7] Bekaert, Geert and Campbell R. Harvey, 2000, "Foreign Speculators and Emerging Equity Markets," *Journal of Finance*, 45, 565-613.

[8] 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.

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

[10] 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.

[11] 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.

[12] 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.

[13] 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.

[14] Campbell, John Y. and Albert S. Kyle, 1993, "Smart Money, Noise Trading, and Stock Price Behaviour," *Review of Economic Studies,* 60, 1-34.

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

[16] Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2000, "Commonality in Liquidity," *Journal of Financial Economics*, 56, 3-28.

[17] Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2002, "Order Imbalance, Liquidity, and Market Returns," *Journal of Financial Economics*, 65 (1), July, 111-130.

[18] Chordia, Tarun, Richard Roll, and Avanidhar Subrahmanyam, 2005, "Liquidity and Market Efficiency," Working paper, Emory University.

[19] Chordia, Tarun and Avanidhar Subrahmanyam, 2004, "Order Imbalance and Individual Stock Returns: Theory and Evidence," *Journal of Financial Economics*, 72 (3), June, 485-518.

[20] DeLong, Bradford, Andrei Shleifer, Lawrence Summers and Robert Waldman, 1990a, "Positive Feedback Investment Strategies and Destabilizing Rational Speculation," *Journal of Finance*, 45(2), June, 379-395.

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

[22] 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.

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

[24] 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.

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

[26] 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.

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

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

[29] Greenwood, Robin, 2005a, "Short- and Long-Term Demand Curves for Stocks: Theory and Evidence on the Dynamics of Arbitrage," *Journal of Financial Economics*, 75, 3, March, 607-649.

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

[31] 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.

[32] Grossman, Sanford J. and Merton H. Miller, 1988, "Liquidity and Market Structure," *Journal of Finance*, 43 (3), July, 617-637.

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

[34] 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.

[35] Hasbrouck, Joel and Duane J. Seppi, 2001, "Common Factors in Prices, Order Flows, and Liquidity," *Journal of Financial Economics*, 59, 383-411.

[36] 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.

[37] Holden, Craig W. and Avanidhar Subrahmanyam, 2002, "News Events, Information Acquisition, and Serial Correlation,", *Journal of Business*, 75 (1), January, 1-32.

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

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

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

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

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

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

[44] Lee, Charles and Mark Ready, 1991, "Inferring Trade Direction from Intraday Data." *Journal of Finance* 46, 733-747

[45] 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.

[46] 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.

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

[48] 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.

[49] 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.

[50] Petajisto, Antti, 2004, "Why Do Demand Curves for Stocks Slope Down?," Working paper, Yale University.

[51] Petersen, Mitchell A., 2005, "Estiamting Standard Errors in Finance Panel Data Sets: Comparing Approaches," Working paper, Northwestern University.

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

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

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

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

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

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

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

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

[60] Wang, Jiang, 1993, "A Model of Intertemporal Asset Prices Under Asymmetric Information," *Review of Economic Studies*, 60 (2), April, 249-282.

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

Figure 1
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 ten periods. Z_t^j is our measure of trading imbalances over a day or a week. Construction of the measures is described in the text. Shares are sorted at time zero into ten deciles based on Z_t^j. The long short portfolio is long shares in the lowest decile of Z_t^j and short shares in the highest decile. This figure reports results for a sub-sample 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
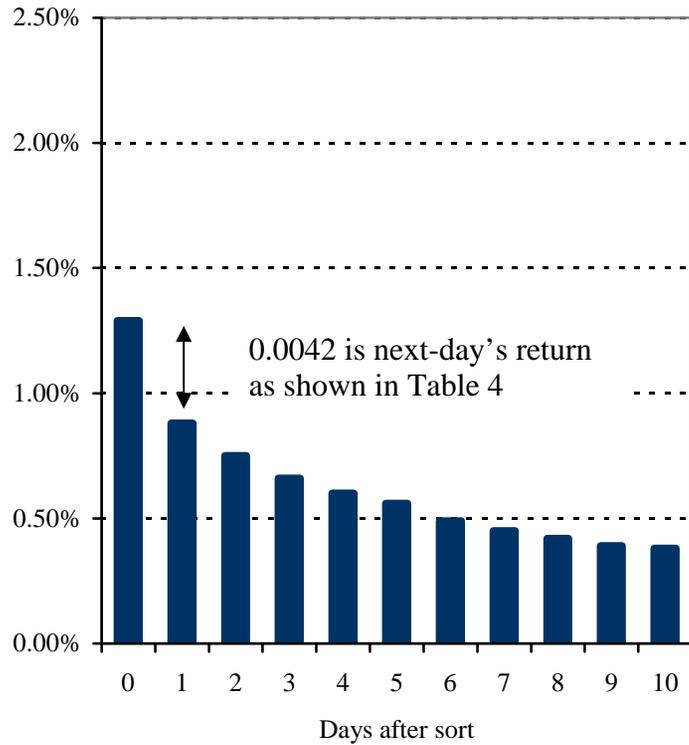
Panel B: Weekly
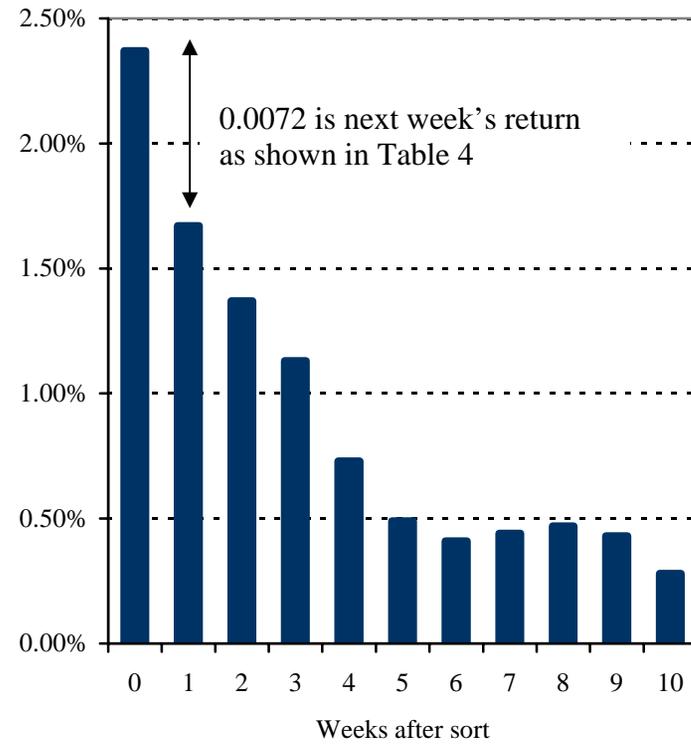
Figure 2
Limits to Arbitrage

This figure shows the cumulative return of the zero-cost portfolio during the ten weeks following formation. Z_t^j is our measure of trading imbalances over a day or a week. Construction of the measures is described in the text. Shares are sorted at time zero into ten deciles based on Z_t^j. The long short portfolio is long shares in the lowest decile of Z_t^j and short shares in the highest decile. This figure reports results for a sub-sample 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
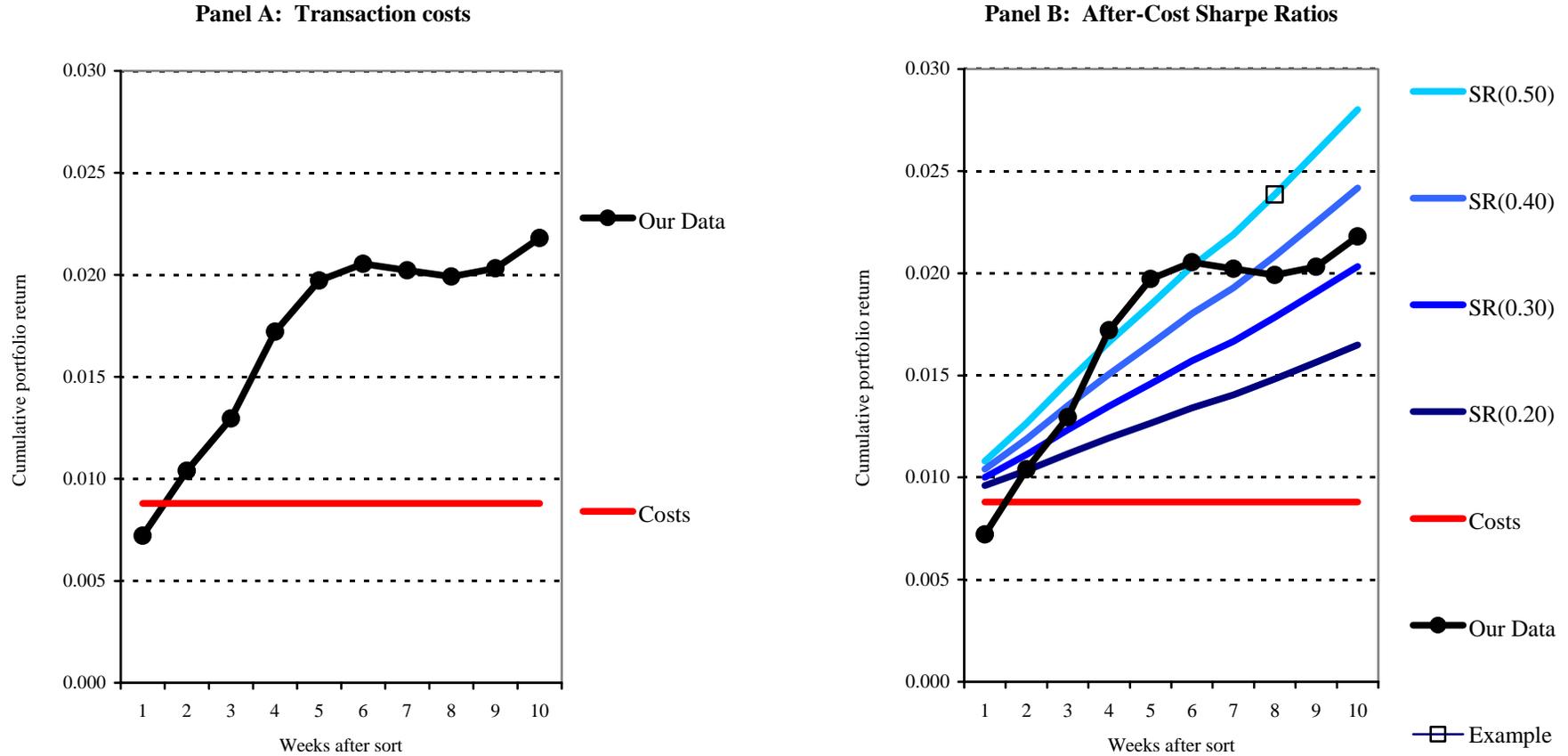
Table 1
Descriptive Statistics of Trading Imbalances

This table gives descriptive statistics of trading imbalances and aggregate holdings in our sample at the individual stock level. Z_t^j is our measure of trading imbalances over a day or a week. Holdings at any point in time is the sum of all past trading imbalances: $H_t^i = \sum_{\tau=-\infty} Z_\tau^j$ Construction of the measures is described in the text. This table also reports the absolute value of trading imbalances. Panel C gives and industry breakdown. The full sample contains 608 firms. The sub-sample 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 Z_t^j (i.e., of Company Time Series Data)

		Daily			Weekly		
		Z_t^j	$\mid Z_t^j \mid$	$H_t^j = \sum_{\tau=-\infty}^{t} Z_t^j$	Z_t^j	$\mid Z_t^j \mid$	$H_t^j = \sum_{\tau=-\infty}^{t} Z_t^j$
Full sample	Average	0.0001	0.0013	0.0725	0.0003	0.0039	0.0721
	25th-tile	0.0000	0.0007	0.0360	-0.0001	0.0023	0.0361
	50th-tile	0.0000	0.0012	0.0688	0.0001	0.0037	0.0686
	75th-tile	0.0001	0.0018	0.1049	0.0004	0.0054	0.1037
	N	608	608	608	607	607	608
Sub-sample	Average	0.0000	0.0012	0.0810	-0.0001	0.0036	0.0801
	25th-tile	0.0000	0.0007	0.0429	-0.0001	0.0021	0.0426
	50th-tile	0.0000	0.0011	0.0782	-0.0001	0.0035	0.0773
	75th-tile	0.0000	0.0016	0.1124	0.0000	0.0048	0.1101
	N	131	131	131	131	131	131

Panel B: Time-Series Measures from an Equally-Weighted Measure (Z_t^{EW})

		Daily			Weekly		
		Z_t^{EW}	$\mid Z_t^{EW} \mid$	$H_t^j = \frac{1}{N}\sum_{j=1}^{N}\sum_{\tau=-\infty}^{t} Z_\tau^j$	Z_t^{EW}	$\mid Z_t^{EW} \mid$	$H_t^j = \frac{1}{N}\sum_{j=1}^{N}\sum_{\tau=-\infty}^{t} Z_\tau^j$
Full sample	Average	0.0000	0.0014	0.0850	0.0001	0.0042	0.0841
	Stdev.	0.0005	0.0005	0.0216	0.0019	0.0015	0.0220
	T	2359	2359	2360	442	442	443
Sub-sample	Average	0.0000	0.0012	0.0810	-0.0001	0.0036	0.0801
	Stdev.	0.0005	0.0005	0.0214	0.0019	0.0015	0.0220
	T	2359	2359	2360	442	442	443

Table 1
Continued

Panel C: Industry Composition

Industry	Full Sample # of Firms	31-Dec-1998 # of Firms	MktCap (NTD m)	Sub-Sample # of Firms	MktCap (NTD m)
Cement	8	8	142,875	6	131,242
Foods	20	20	182,302	6	106,151
Plastics	20	18	425,803	13	409,139
Textile	56	49	457,651	15	277,598
Electrical	33	24	156,130	5	74,606
Wire & Cable	16	16	169,444	9	147,025
Chemicals	30	23	162,215	8	54,168
Glass/Ceramics	7	7	60,424	2	45,539
Pulp/Paper	7	6	60,137	3	30,289
Steel	28	26	269,150	7	191,370
Rubber	9	9	104,434	6	71,277
Automobile	4	4	172,401	1	59,243
Electronic	221	115	3,046,223	18	1,056,146
Construction	40	33	271,731	8	95,886
Transportation	17	16	246,019	6	90,903
Tourism	7	7	50,303	2	20,049
Banking	64	47	2,123,875	9	455,953
Retailing	11	11	140,175	4	38,495
Others	10	10	152,406	3	67,757
TOTAL	**608**	**449**	**8,393,698**	**131**	**3,422,836**

Table 2
Unit Root Tests, Cross-Sectional Correlation, and Principal Component Analysis of Trading Imbalances

This table shows trading imbalances are serially uncorrelated but cross-sectionally correlated. Panel A presents the results of an Augmented Dickey-Fuller test for the presence of a unit root on the level of holdings (cumulative trading imbalances). The null is that the level of holdings follows a random walk. Panel B presents the average pairwise correlation of contemporaneous trading imbalances. Panel C reports the fraction of contemporaneous trading imbalance correlation explained by the first five principal components. The sub-sample 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: Unit Root Tests
We report the number of stocks out of 131 possible, for which the null hypothesis that holdings follow a random walk is rejected at the 5% and 10% significance levels.

Significance Levels	Daily	Weekly
5%	3	7
10%	10	16

Panel B: Average Pairwise Correlation of Trading Imbalances

	Daily	Weekly
Average	0.0612	0.1209
s.e.	0.0004	0.0001
Fraction of Pairs with Corr < 0	3.42%	4.03%

Panel C: Principal Component of Trading Imbalances
(Fraction of Total Correlation Explained)

	Daily	Weekly
1st PC	**0.0727**	**0.1347**
2nd PC	0.0202	0.0279
3rd PC	0.0178	0.0265
4th PC	0.0168	0.0208
5th PC	0.0161	0.0206

Table 3
Price Impacts, Reversals, and Cross-Stock Effects

This table shows both own-stock price impacts and cross-stock price impacts. We present results of a pooled OLS regression of stock j's return on its own contemporaneous trading imbalance (coef. π_{11}); the whole market's (excluding stock j) contemporaneous trading imbalance (coef. π_{12}); stock j's own lagged trading imbalance (coef. π_{21}); and the rest of the market's lagged trading imbalance (coef. π_{22}). "N" is the number of stocks in our sample and equal to 131. 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 allow for heteroscedasticity and clustering of contemporaneous observations.

$$r_t^j = \pi_0 + \pi_{11} Z_t^j + \pi_{12}(N-1)Z_t^{EW^*} + \pi_{21} Z_{t-1}^j + \pi_{22}(N-1)Z_{t-1}^{EW^*} + \varepsilon_t^j$$

		Daily			Weekly		
		Reg. 1	**Reg. 2**	**Reg. 3**	**Reg. 4**	**Reg. 5**	**Reg. 6**
π_{11}	**Contemp. Own Imbalance**	2.7014	---	2.0017	2.6843	---	1.5493
	(T-stat)	(44.65)	---	(54.39)	(17.83)	---	(20.33)
π_{12}	**Contemp. Cross Imbalance**		---	0.1542		---	0.1152
	(T-stat)		---	(21.54)		---	(16.08)
π_{21}	**Lagged Own Imbalance**		-0.4684	-0.7972		-0.4250	-0.4709
	(T-stat)		(-8.65)	(-26.65)		(-3.13)	(-7.82)
π_{22}	**Lagged Cross Imbalance**			-0.0562			-0.0536
	(T-stat)			(-7.84)			(-7.88)
	Adj. R²	0.0495	0.0015	0.1730	0.0593	0.0015	0.2128

Table 4
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 Z_t^j, which is net shares traded for stock j divided by total shares outstanding. Construction of the measure is described in the text. Each period (day or week) we sort stocks into ten deciles based on Z_t^j. The sub-sample 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 heteroscedasticity and autocorrelation.

Current Period Decile	*Daily*		*Weekly*	
	Next Period Return	*Stdev*	**Next Period Return**	*Stdev*
(Lowest Z_t^j) 1	0.0022	0.0195	0.0039	0.0475
2	0.0008	0.0180	0.0027	0.0439
3	0.0006	0.0172	0.0018	0.0414
4	0.0005	0.0168	0.0008	0.0400
5	0.0001	0.0164	0.0001	0.0408
6	-0.0001	0.0161	0.0001	0.0383
7	-0.0003	0.0164	-0.0002	0.0411
8	-0.0005	0.0166	0.0004	0.0432
9	-0.0008	0.0177	-0.0006	0.0431
(Highest $Z_t^j{}_t$) 10	-0.0019	0.0189	-0.0033	0.0462
Zero-Cost Portfolio				
Difference 1-10	0.0042	0.0118	0.0072	0.0288
T-stat	16.77		5.24	
N	2,358		441	

Table 5
Risk-Adjusted Returns

Returns of our zero-cost portfolio called r^{1-10} are regressed on the market's return and other factors' returns. Construction of 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 sub-sample 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.

$$r_t^{1-10} = \alpha + \beta^{MKT}\left(r_t^m - r_t^f\right) + \beta^{SMB} r_t^{SMB} + \beta^{HML} r_t^{HML} + \beta^{MOM} r_t^{MOM} + \varepsilon_t$$

	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 6
The Magnitude of Cross-Stock Price Impact

This table shows the relationship between two stocks fundamental correlation and the cross-stock price impact. For each pair of stocks "j" and "k" we estimate the regression below. The contemporaneous cross-stock coefficient is labeled $CCC^{j,k}$ and is the average of stock k's effect on stock j and stock j's effect on stock k. In the equations, Z_t^j represents stock j's trading imbalances; Z_t^k represents stock k's trading imbalances; and $(N-2)Z_t^{EW^{**}}$ is the sum across all trading imbalances except stock j and stock k. The sub-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.

$$r_t^j = \pi_0^j + \pi_{111}Z_t^j + \pi_{112}Z_t^k + \pi_{113}(N-2)Z_t^{EW^{**}} + \pi_{121}Z_{t-1}^j + \pi_{122}Z_{t-1}^k + \pi_{123}(N-2)Z_{t-1}^{EW^{**}} + \varepsilon_t^j$$

$$r_t^k = \pi_0^k + \pi_{211}Z_t^j + \pi_{212}Z_t^k + \pi_{213}(N-2)Z_t^{EW^{**}} + \pi_{221}Z_{t-1}^j + \pi_{222}Z_{t-1}^k + \pi_{223}(N-2)Z_{t-1}^{EW^{**}} + \varepsilon_t^k$$

$$CCC^{j,k} \equiv \frac{\pi_{112} + \pi_{211}}{2}$$

	All Pairs	**Pairs With j and k in Same Industry**	**Pairs With j and k in Different Industries**
Average $CCC^{j,k}$	0.2851	0.9973	0.2342
Median $CCC^{j,k}$	0.2024	0.7661	0.1715
Stdev $CCC^{j,k}$	0.7669	1.0792	0.7130
Num. Pairs	*8,515*	*567*	*7,948*

Table 7
Excess 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_t^j. Factors include: the market excess return ($r_t^m - r_t^f$); the portion of the market excess return that is orthogonal to a market-wide measure of trading imbalances ($r_t^{m \perp Z^{EW}}$); the portion of the market-wide measure of trading imbalances that is parallel to stock j's trading imbalance ($Z_t^{EW // j}$); and the portion of the market-wide measure of trading imbalances that is orthogonal to stock j's trading imbalance ($Z_t^{EW \perp j}$). 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 Measures	Average R^2	Stdev. of R^2	Num. Stocks
1	$r_t^j - r_t^f = \alpha + \beta^m \left(r_t^m - r_t^f \right) + \varepsilon_t^j$	0.2958	0.0945	131
2	$r_t^j - r_t^f = \gamma_0 + \gamma_1 \left(r_t^{m \perp Z^{EW}} \right) + v_t^j$	0.1630	0.0905	131
3	$r_t^j - r_t^f = \gamma_0 + \gamma_2 \left(Z_t^{EW // j} \right) + v_t^j$	0.0827	0.0624	131
4	$r_t^j - r_t^f = \gamma_0 + \gamma_3 \left(Z_t^{EW \perp j} \right) + v_t^j$	0.1062	0.0396	131
5	$r_t^j - r_t^f = \gamma_0 + \gamma_1 \left(Z_t^{m \perp Z^{EW}} \right) + \gamma_2 \left(Z_t^{EW // j} \right) + \gamma_3 \left(Z_t^{EW \perp j} \right) + v_t^j$	0.3474	0.0911	131

Appendix 1: Model

At date 3 assets pay liquidating dividends which we can write as $P_3^j = (S_1^j + S_2^j + \Phi_3^j)$ and $P_3^k = (S_1^k + S_2^k + \Phi_3^k)$. At date 2, we solve for prices and demands. Risk averse agents choose holdings in order to maximize date 3 wealth. The CARA-normal framework implies the following optimal demand at date 2:

$$
\begin{bmatrix} X_2^j \\ X_2^k \end{bmatrix} = \frac{1}{\lambda} \left(Var_2 \begin{bmatrix} S_1^j + S_2^j + \Phi_3^j \\ S_1^k + S_2^k + \Phi_3^k \end{bmatrix} \right)^{-1} E_2 \begin{bmatrix} S_1^j + S_2^j + \Phi_3^j - P_2^j \\ S_1^k + S_2^k + \Phi_3^k - P_2^k \end{bmatrix}
$$

$$
\begin{bmatrix} X_2^j \\ X_2^k \end{bmatrix} = \frac{1}{\lambda} \begin{bmatrix} V_\Phi & \rho_\phi V_\Phi \\ \rho_\phi V_\Phi & V_\Phi \end{bmatrix}^{-1} \begin{bmatrix} S_1^j + S_2^j - P_2^j \\ S_1^k + S_2^k - P_2^k \end{bmatrix}
$$

Market clearing at date 2 implies: $X_2^j = 1 - (Z_1^j + Z_2^j)$ and $X_2^k = 1 - (Z_1^k + Z_2^k)$. Substituting the market clearing condition into the optimal demand equation and solving for prices yields prices at date 2.

On date 1, risk averse agents choose holdings in order to maximize date 3 wealth, given their optimal decisions at date 2 and their knowledge about future equilibrium prices. The date 3 wealth is:

$$
W_3 = X_2^j(P_3^j - P_2^j) + X_2^k(P_3^k - P_2^k) + X_1^j(P_2^j - P_1^j) + X_1^k(P_2^k - P_1^k)
$$

We substitute the optimal $\{X_2^j, X_2^k\}$ and the equilibrium values of $\{P_3^j, P_3^k, P_2^j, P_2^k\}$ into the equation directly above to get the wealth equation as a function of two control variables $\{X_1^j, X_1^k\}$:

$$
\begin{aligned}
W_3 &= X_1^j \left(S_1^j + \lambda V_\Phi \left(Z_1^j + \rho_\phi Z_1^k \right) - RV_\Phi - P_1^j \right) + X_1^k \left(S_1^k + \lambda V_\Phi \left(Z_1^k + \rho_\phi Z_1^j \right) - RV_\Phi - P_1^k \right) \\
&\quad - Z_1^j \Phi_3^j + X_1^j S_2^j + \lambda V_\Phi \left((X_1^j + 2Z_1^j - 1) + \rho_\phi \left(X_1^k + 2Z_1^k - 1 \right) \right) \\
&\quad Z_2^j - Z_1^k \Phi_3^k + X_1^k S_2^k + \lambda V_\Phi ((X_1^k + 2Z_1^k - 1) + \rho_\phi \left(X_1^j + 2Z_1^j - 1 \right)) Z_2^k \\
&\quad - Z_2^j \Phi_3^j + \lambda V_\Phi (Z_2^j)^2 + 2\rho \lambda V_\Phi Z_2^j Z_2^k - Z_2^k \Phi_3^k + \lambda V_\Phi (Z_2^k)^2
\end{aligned}
$$

The risk averse investors must choose $\{X_1^j, X_1^k\}$ in order to maximize $E[e^{-\lambda W_3}]$, given an observed realization of $\{S_1^j, S_1^k\}$. It turns out that W_3 is a quadratic function of normal random variables. Therefore, we can apply the following result:

Let $Y \sim N(\mu, \Sigma)$ and A is symmetric, then:

$$E[\exp(C + B'Y - Y'AY)] =$$

$$|\Sigma|^{-\frac{1}{2}} |2A + \Sigma^{-1}|^{-\frac{1}{2}} \exp(C + B'\mu + \mu'A\mu + \frac{1}{2}(B' - 2\mu'A')(2A + \Sigma^{-1})^{-1}(B - 2A\mu))$$

Where $Y \equiv \begin{bmatrix} \Phi_3^j & S_2^j & Z_2^j & \Phi_3^k & S_2^k & Z_2^k \end{bmatrix}$. The market clearing conditions at date 1 are $X_1^j = 1 - Z_1^j$ and $X_1^k = 1 - Z_1^k$. Setting derivatives with respect to X_1^j and X_1^k equal to zero, and using the market clearing condition at date 1, yields the equilibrium prices at date 1.

Appendix 2: Sub-sample 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. This stock has non-zero margin holdings throughout our sample period. 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 within a pre-determined time frame. 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 sub-sample of companies with positive margin holdings for the entire time the stock is listed. There are 131 such companies. We carry out all tests with the full sample of 608 firms as well as the sub-sample of 131 firms.

C

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 we use $H_\tau^j = \sum Z_\tau^j$ which is defined as shares held long on margin for stock j 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 (sub-sample 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.

D
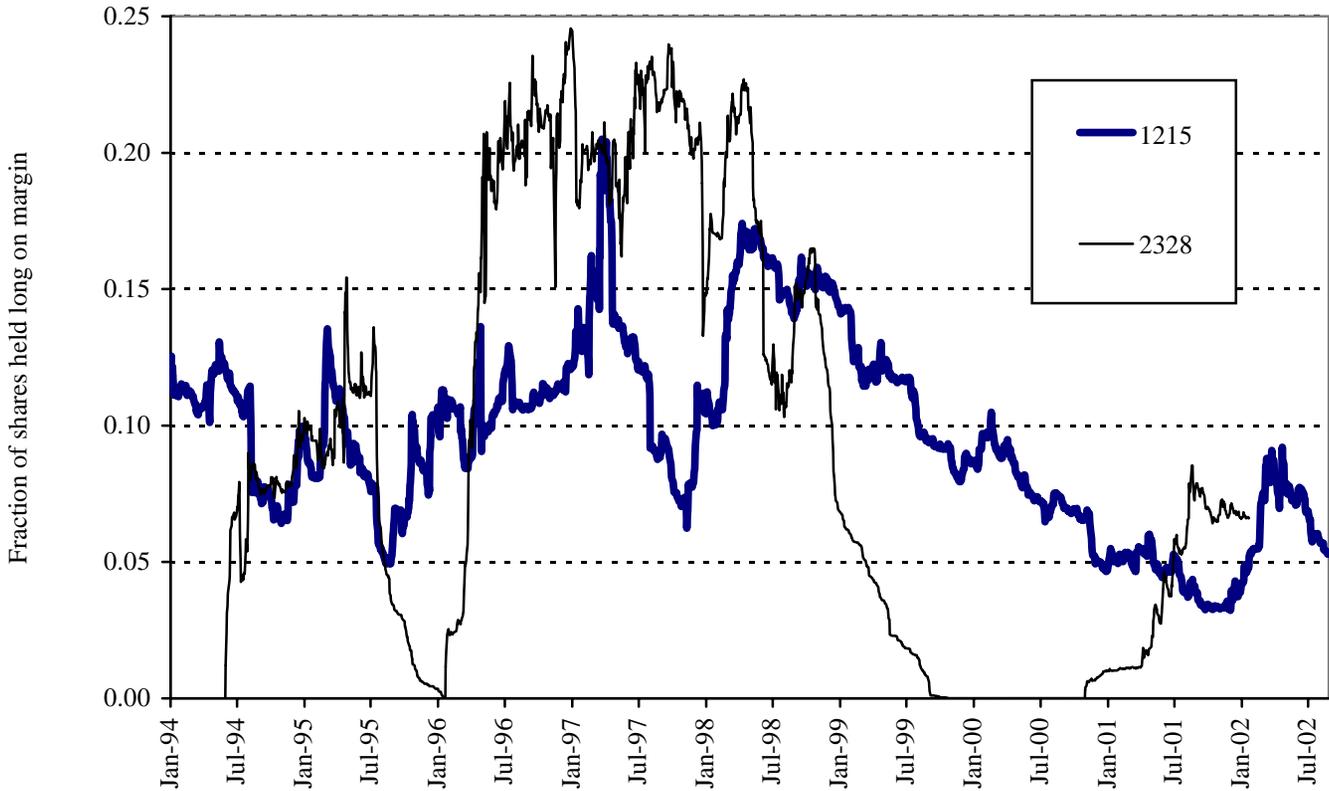
Appendix 3: Additional Tests Relating to Z_t^j

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 investors who generate our data are not (in aggregate) using their margin accounts to track the market. In other words, they are not using margin accounts to lever-up the market portfolio. 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.

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 as can be seen by the the fact the the average pair-wise correlations in Table 2, Panel B are significantly less than one.

Correlation Table

We show our net trading imbalance measure (Z_t^j) has low correlation with economic variables.

Series	Freq.	Corr with Z_t^{EW}	P-Value	Num. of Obs.
Change in 6 mo money mkt rate	Daily	<0.01	0.95	2,256
Change in Premium on Taiwan Fund	Weekly	-0.07	0.13	438
Change in Comm. Paper Rate	Monthly	-0.07	0.50	104
Loans at Domestic Banks	Monthly	-0.04	0.71	104

E

Appendix 4
Expanded Sort Results

This table shows expanded results of a sorting procedure based on uninformed trading. In order to compare holdings and changes in holdings across stocks we use Z_t^j, which is net shares traded for stock j divided by total shares outstanding. Construction of the measure is described in the text. We sort stocks into ten deciles based on the past 1, 2, or 3 three values of Z_t^j at both daily and weekly frequencies. We form a portfolio that goes long the bottom decile and short the top decile of the sorted stocks. We then track that portfolio for the next 1, 2, or 3 periods (days or weeks). The sub-sample 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 heteroscedasticity and autocorrelation.

# of Formation Days in Past	*Return over Future Days*			*# of Formation Weeks in Past*	*Return over Future Weeks*		
	1	*2*	*3*		*1*	*2*	*3*
1	0.0042	0.0055	0.0064	*1*	0.0072	0.0104	0.0130
	(16.77)	(14.18)	(13.29)		(5.24)	(5.13)	(4.92)
2	0.0037	0.0051	0.0061	*2*	0.0066	0.0104	0.0142
	(14.84)	(12.12)	(11.04)		(4.40)	(4.69)	(4.79)
3	0.0033	0.0048	0.0056	*3*	0.0067	0.0117	0.0171
	(13.24)	(11.13)	(9.51)		(4.82)	(5.18)	(5.45)

F

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
Return Momentum

This table tests for momentum and volume effects. Panel A shows the results of a traditional (single sort) test for momentum. Panel B sorts independently by current returns (r_t^j) and current trading imbalances (Z_t^j). All results show next period's returns (r_{t+1}^j). The sub-sample 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: Single-Sort on Returns (Momentum) Results
Next Period's Returns (r_{t+1}^j) Shown

	Daily		*Weekly*	
Current Period Decile	**Next Period Return**	*Stdev*	**Next Period Return**	*Stdev*
(Lowest r_t^j) 1	-0.0016	0.0198	0.0017	0.0507
2	-0.0001	0.0182	0.0019	0.0428
3	0.0001	0.0175	0.0006	0.0414
4	-0.0002	0.0170	0.0010	0.0416
5	-0.0002	0.0167	0.0009	0.0407
6	-0.0002	0.0165	0.0009	0.0407
	-0.0003	0.0164	-0.0004	0.0405
8	-0.0000	0.0171	-0.0015	0.0405
9	0.0001	0.0181	-0.0006	0.0422
(Highest $r_t^j{}_t$) 10	0.0027	0.0200	0.0002	0.0495
Momentum Port. 10-1	0.0042	0.0171	-0.0015	0.0419
Contrarian Port. 1-10	-0.0042	0.0171	0.0015	0.0419
T-stat	*-6.71*		*0.76*	
N	*2,360*		*442*	

H

Panel B: Independent Double-Sort by Trading Imbalances and Returns
Next Week's Returns (r_{t+1}^{j}) Shown

	Low Z_t^{j}	Medium Z_t^{j}	High Z_t^{j}	Effect From Z_t^{j}
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	