Contrarian and Momentum Returns on

Iran's Tehran Stock Exchange

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to be published in **The Journal of International Financial Markets, Institutions & Money**

Vol 17, no 5, December 2007

This paper studies Iran's emerging Tehran Stock Market. Potential foreign investors, who have been able make direct investments since 2003, should study the recent history of the exchange in order to understand the risks that accompany the high returns. Using data on stock prices and volume over the period 1997 to 2002, this study looks at the crucial question of pricing efficiency, examining the relation of current prices and volumes to future returns. We apply the analyses of Jegadeesh and Titman (1993), Conrad, Hameed, and Niden (1994), Cooper (1999), and Gervais, Kaniel, and Mingelgrin (2001) to this developing market. There is no evidence of "contrarian" behavior. Standard tests of autocorrelation and pricing efficiency find no evidence of anomalies in the short run. There is, however, evidence of "momentum" where past high performers have above-average return over an intermediate (3 - 12 month) horizon.

JEL Code: G150 - International Financial Markets

Keywords: Stock Pricing Efficiency, Momentum, Iran

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1. Introduction

International studies of markets in varying phases of development can help economists gain important insights into key institutional features that may encourage efficient outcomes. The contribution of this paper is to extend developed-market analyses of autocorrelation related to volume and return behavior to the Iranian stock market. The Tehran Stock Exchange (TSE) has attracted attention for its top, internationally competitive returns and for suggestions of murky dealings and opaque regulations (Daragahi 2004).

To preview the results, this research finds little evidence of pervasive short-term predictability in Iran's TSE stock prices, although there is strong evidence for medium-term momentum. A battery of standard tests fails to find any short-term systematic autocorrelation properties. This paper applies tests that have shown short-term relationships between volume and returns in US markets: they include the Conrad, Hameed, and Niden (1994) version of Lehmann's tests (1990), the Cooper (1999) approach, and the analysis of Gervais, Kaniel, and Mingelgrin (2001). The paper also explores medium-term momentum in the manner of Jegadeesh and Titman (1993). The reliance upon previous tests constrains this paper's analysis from data-mining to find possibly spurious relationships.

The absence of predictability suggests that, while the Tehran Stock Exchange might continue to be plagued by insider information and opaque dealings, the closing prices, at least, seem to be efficient. Therefore, it can be argued that valuations of listed companies provide some informative content to outsiders. One of a national stock market’s principal functions is to provide information to guide the allocation of investment capital. The other main function, which is to provide a desirable portfolio for savers, may remain impaired. If there are "insiders"

and "outsiders," then the insiders would appear to be numerous enough and fragmented enough to form a competitive market for securities.

Several comprehensive studies have documented momentum in world stock markets, including works by Fong, Wong and Lean 2005; Nijman, Swinkels, and Verbeek 2004; Rouwenhorst 1999; and Hameed and Kusnadi 2002 found contradictory evidence). Research on short-term autocorrelation, however, has been sparser. Short-term autocorrelation related to volume has been found in Malaysia (Hameed and Ting 2000), Chile (Parisi and Acevedo 2001), Taiwan (Shen and Wang 1998), Turkey (Antoniou, Ergul, and Holmes 1997), and Sri Lanka (Elyasiani, Perera, and Puri 1996). However, these studies used variations of older methodologies from Conrad, Hameed, and Niden (1994) or earlier; some of the specifications of the inefficiency were sub-standard enough to raise concerns about data-mining. This paper's finding that there was no relation between volume and stock return autocorrelation, contradicts previous studies of other developing markets.

This study will evaluate the Iranian Stock Exchange, using study methodologies described in four previous papers that examined developed markets. Conrad, Hameed, and Niden (1994) examined contrarian strategies to show that buying the previous week's losers and selling short the winners (as suggested by DeBondt and Thaler 1985, 1986, and Lehmann 1990) would generate statistically significant returns. Their refinement documented that volume would further clarify the relationship so that those returns would be greater for high-volume stocks.

Cooper (1999) separated the data into bins to provide evidence that the short-term behavior of subsequent returns contradicts that of Conrad, Hameed, and Niden. There is still contrarian behavior (which Cooper refers to as "reversals") but now he found that the low-volume stocks exhibited the strongest reversals while the high-volume stocks had the weakest

reversals. Cooper supported his claim by exhibiting generally monotonic relations among the volume/return data bins. Gervais, Kaniel, and Mingelgrin (2001) documented that volume alone is an important predictor in the US market: a portfolio that buys high-volume stocks and sells low-volume stocks will have significantly high future returns.

Finally Jegadeesh and Titman (1993) showed that, over the medium term, there are not reversals but that instead winners continue to win, while losers still lose.

2. Methodology

2.1. Volume and autocorrelation of returns

The literature has proposed several methods to explore the autocorrelation of stocks and the dependence of this relation upon volume. These methods construct portfolios based on the stock's performance retrospectively (typically over a period of a week), and then evaluate forward performance. Higher returns for some portfolios, unless they are offset by higher risk, could indicate market inefficiency or some reason why market participants do not arbitrage the predictable variation.

There have been a number of researchers who have investigated the short-term predictability of the stock market, such as DeBondt and Thaler (1985, 1986) and Lehmann (1990). Their papers propose a very simple idea: form "contrarian" portfolios of stocks based on the previous week's returns, by buying past losers and selling past winners (with some portfolio weights, $w_{i,t}$). Denote *Win* as the week-*t* returns of the portfolio of stocks that were winners in the previous week (*t–1*), so that $Win = \sum_{i=1}^{N_W} w_{i,t} R_{i,t}^{W}$. *Lose* is defined symmetrically. Lehmann

showed that the net returns were significantly positive: (*Lose* – *Win*) > 0. Lo and Mackinlay's paper pointed out an important modification, since using a market average, $\overline{R}$, to form the weights will transfer through the autoregressive properties of that average.

Subsequent papers examined the relationship of volume to these stock returns, suggesting that volume is important in distinguishing the autocorrelations. In US markets, Conrad, Hameed, and Niden (1994, subsequently CHN) reported that volume changes can separate the stocks with positive autocorrelation from those with negative autocorrelation. CHN confirmed that (*Lose* – *Win*) > 0 but suggested a further modification. They make a further classification of stocks into *WinHi* (the returns to a portfolio of winners with increasing volume), *WinLo* (winners with decreasing volume), *LoseHi*, and *LoseLo*. Then (*LoseHi* – *WinHi*) > 0 while (*LoseLo* – *WinLo*) < 0.

Cooper (1999) provided a contrary perspective using filter rules on a sample of US large-capitalization stocks. These filters separated stocks into categories, depending on the magnitude of their previous return and change in volume. Cooper ratified (*Lose* – *Win*) > 0 but contradicted CHN in volume interactions, so that (*LoseHi* – *WinHi*) < 0 while (*LoseLo* – *WinLo*) > 0.

Gervais, Kaniel, and Mingelgrin (2001) documented that volume alone is an important predictor in the US market; that in the short run, the returns to (*Hi* – *Lo*) > 0. Over a longer time horizon such as three to 12 months, however, the contrarian phenomenon is replaced by "momentum," as suggested by Jegadeesh and Titman (1993). Now momentum pushes (*Win* – *Lose*)>0 over the succeeding three to 12 months. This result has been found to be widespread across various countries (Fong, Wong and Lean 2005; Nijman, Swinkels, and Verbeek 2004) and industries (Chen and DeBondt 2004).

Using Iranian data, this paper will apply the short-term portfolio composition strategies suggested by Conrad, Hameed, and Niden (1994), Cooper (1999), and Gervais, Kaniel, and Mingelgrin (2001) and the medium-term strategy of Jegadeesh and Titman (1993).

3. Empirical results

3.1. Overview of the Tehran Stock Exchange

The data on stocks traded on the Tehran Stock Exchange (TSE) in Iran show a market that is still developing. Significant restrictions remain, most prominently the continued US restrictions on direct investment. Nonetheless, the large domestic market has been tapped and new laws at the end of 2003 paved the way for foreign direct investment (as well as indirect investment via a Bahrain fund). The currency was made freely convertible in 2002 (at a rate of about 7900 Rials to the dollar). Other factors impacting favorably on the TSE's future prospects include Iran's strategic geographical location, and its large population of over 60 million people, which makes making it second only to Turkey in the Middle East. In addition, recent annual returns of over 40% have placed it in the forefront of exchanges in developing countries.

A government privatization plan revived the moribund TSE in 1989, which by the end of 2002 listed over 300 companies. Because this study focuses on the TSE-50 we do not incorporate all these new entrants. Companies listed on the "First Board" must have capital of at least 20 billion Rials and be held sufficiently widely (the government cannot own a majority stake). Short selling is prohibited. At present we only have data from the exchange on the price and volume of trades; data on the underlying financial performance of the companies are not

currently accessible. Previous research has attempted to relate stock return autocorrelation behavior to underlying factors, such as those of Fama and French, however the necessary Iranian data are not currently available.

The Tepix Index tracks all the stocks on the First Board; the TSE-50 concentrates on the 50 most heavily traded stocks, with an adequate fraction of shares publicly held. Some companies have a low net float because their shares are held principally by public or quasi-public institutions, such as those which administer war-veterans' pensions (Tehran Stock Exchange Economic Research Department 2002a). This study focuses on TSE-50 companies in order to limit concerns about microstructure, as well as to ensure comparability (Cooper's 1999 study uses a similar strategy). One reason companies might have different returns is that they have different risk profiles. It is well known that small and large companies have different risk characteristics in developed markets. In developing markets there is the further complication of liquidity: shares of small companies might not be traded for several days. Therefore, this focus upon TSE-50 companies minimizes those other confounding factors.

The data extend from September 29, 1997 (7 Mehr in 1376, according to the Persian calendar, when the TSE data begin) to November 18, 2002 (27 Aban in 1381). In some of the analyses which follow, the daily data are aggregated to weekly, using returns mid-week to mid-week (Monday-to-Monday not Wednesday-to-Wednesday, since the Iranian trading week is Saturday to Wednesday). The data were obtained from the Tehran Stock Exchange Economic Research Department (2002b).

While we might suspect that oil price fluctuations are important, an analysis of weekly returns of the broad stock index shows no correlation with oil price returns. Regressions of Tepix returns on oil price returns with up to four leads or lags yield not a single significant

coefficient; GARCH and ARMA specifications also deliver insignificant coefficients. Foster and Kharazi (2004) give an overview.

Table 1 presents summary statistics on return and volume for the TSE-50 stocks. Summary statistics of the return (expressed as a percentage) and volume growth are shown in Table 1. Volume is shown as a growth rate from the previous week and as a rate from the previous four weeks' average level.

The average daily return is 12 to 17 basis points, depending on the particular sample. The medians are lower, showing that fewer, larger gains balance smaller, steadier losses – although the minimums are more extreme than the maximums. The first-order autocorrelation is 0.10 and the second-order partial coefficient is -0.01. Since these may not be i.i.d. shocks, the standard error given in parentheses below each coefficient is only meant to convey the magnitude of the variation, not form the basis for a significance test.

Volume grows quite steadily, at an average rate of 8 or 9 percent per week, although again the much lower median indicates the role of outliers. Average daily volumes grew from 26,725 shares in the first year to 115,110 by the last (the median grew from 4270 to 12,785). As with the price series, the autocorrelations are negligible.

3.2. Returns and volume patterns in TSE50 shares

We first form portfolios of TSE50 shares in the manner of Conrad, Hameed, and Niden (1994). For each of 262 weeks we form a portfolio of winners (stocks that had a positive return that week) and losers (stocks that had a negative return that week). That week is the reference period; we examine the return over an evaluation period of one or more future weeks. We

evaluate the efficacy of buying the losers and selling the winners by measuring the returns to a combination portfolio that buys losers and sells winners. The stocks are further subdivided into high-volume and low-volume.

Table 2 shows the results for the groups of previous-week losers, winners, and combination. Each portfolio return is shown with a standard error (with Newey-West correction for four lags) and other descriptive statistics. The t-statistics are reported, testing the null hypothesis that the returns are equal to zero, as is standard in much of the literature. However, this should be interpreted as measuring the variation, rather than a formal statistical test, since in many cases the zero null is irrelevant. Only the combination portfolio (labeled "Comb") should have a zero mean under the null hypothesis, if the stocks are randomly assigned to each portfolio without risk differences. Panel A shows the portfolios based only on returns; Panel B shows the additional division into high-volume and low-volume returns.

Panel A shows that winners tended to perform better than losers in the subsequent week: winners averaged an 82-basis point (bp) return, while losers had just a 38 basis point return. This directly contradicts findings in US markets. A "combination" portfolio as CHN form it (*Lose* - *Win*) would lose 44 bp.

CHN also examined the signs and significance of (*LoseHi – WinHi*) and (*LoseLo – WinLo*). Panel B shows that high-volume winners returned an average of 84 basis points per week; high-volume losers returned 33 basis points. So the combination high-volume portfolio, (*LoseHi – WinHi*), has the wrong sign, although it is insignificant. The low-volume winners returned just 12 basis points; low-volume losers continued to lose, so that the combination low-volume portfolio (*LoseLo – WinLo*) has a significant coefficient with the "correct" sign.

Using the alternate weights that include the measure of volume, however, makes the combination low-volume portfolio returns insignificant, although all the signs are unchanged. Experiments with different time horizons and in different sub-periods also failed to find any further patterns.

CHN documented autocorrelation in US markets such that (*Lose* – *Win*) > 0, (*LoseHi* – *WinHi*) > 0, and (*LoseLo* – *WinLo*) < 0. In the TSE, we find that (*Lose* – *Win*) < 0 (and significant), (*LoseHi* – *WinHi*) < 0 (insignificant), and (*LoseLo* – *WinLo*) < 0 (significant).

Only the last matches; on the Tehran Bourse there is only modest support for predictable autocorrelations based on returns and volume consistent with "contrarian" behavior.

3.3. Filtering rules for TSE50 shares

The lack of clear results from the CHN method might arise from the weights used. Cooper (1999) constructs portfolios based on past returns and volume behavior, but rather than using variable weights, the shares are equally weighted within certain partitions. Given the magnitude of the outliers (shown in Table 1 above) the weights of CHN may be judged to be a relevant concern for the Iranian market.

The stocks are again classified as "winner" or "loser" depending on whether the previous week's return was greater or less than zero. The winner and loser stocks are gridded up into six equally spaced bins. These are defined as:

$$\begin{cases} k = 0,1,...4 \begin{cases} winner(k,A)\, if \quad kA \le R_{i,t-1} < (k+1)A \\ loser(k,A) \;\; if \; -(k+1)A \le R_{i,t-1} < -kA \end{cases} \\ k = 5 \begin{cases} winner(k,A)\, if \;\; R_{i,t-1} \ge kA \\ loser(k,A) \;\; if \; R_{i,t-1} < -kA \end{cases} \end{cases} \tag{1}$$

where *k* is the counter and A is the grid width for returns. (See Cooper 1999 for further details of how these grids are calculated.) In this study we follow the recommendation that the gridlines are set approximately at the 1%, 5%, 10%, 25%, and 50% marks (and the complements), so for price changes in the TSE A is 35 basis points.

The returns for the "loser-price" and "winner-price" filter portfolios are in Table 3. The mean of the portfolio returns is presented on the top line, followed by its standard deviation, the number of weeks during which that portfolio was formed (some weeks might have no stocks that fit that grid), and the t-statistic. Again the t-statistic is customary as a measure of the scale of the variation, even though the implied null hypothesis (of zero return) is not generally relevant.

The developed markets that Cooper analyzed showed a remarkably consistent downward relation between past and future returns so that the biggest previous losers had the largest future gains and vice versa. The market under consideration here has no similar monotonic pattern. The portfolios that did the best were based on those stocks that made modest gains the previous week. Portfolios of extreme losers did not perform exceptionally well; portfolios of extreme winners did not perform exceptionally poorly.

Recalling that the typical week averaged 12 to 17 basis points, most of the portfolios constructed were not far from that benchmark. Only a few of the winner portfolios showed much higher returns: the first grid entry (k=0 to k=1) had an average return of more than 1.5%. The next grid (k=1 to k=2) returned approximately one percent in a typical week, and the third grid returned about 70 basis points. Iran's stock market shows no evidence of reversals such as Cooper found in the US.

Cooper next examined additional filtering criteria to subdivide the price categories by volume. We create volume filter grids in the same basic manner as the price grids, but now with

asymmetric grid points to account for the distributional skew: B is the unit for positive volume changes, B=1.5; and C is the unit for negative volume changes, C=0.2 (the bottom volume change at k=5 is set to 0.99 to catch the extreme downward volume movements). Now we examine a matrix of returns depending on the previous week's price and volume.

This matrix of portfolio returns is Table 4, where the information on standard error, t-statistic, and the number of observations has been replaced with asterisks showing the levels of statistical significance. Again, this test against a zero null is not strictly relevant but it shows the magnitude of the data variation. Some of the more extreme tail grids are sparsely populated or entirely empty; this is the familiar "curse of dimensionality."

Cooper's conclusion, unlike that of CHN, found that in the US markets a portfolio that is long on low-volume losers and short on low-volume winners would have significantly positive returns, and that a high-volume combination (long on high-volume losers and short on high-volume winners) would have significantly negative returns. There is little evidence to support that conclusion on the TSE. The high-volume and low-volume groups appear very similar so that most combination portfolios would be insignificantly different from zero.

The entire Cooper analysis was performed using skip-day weeks: Cooper suggested using only the Monday-Thursday data from the previous week to form a portfolio the following Monday, to minimize the effect of bid-ask bounce. In the Iran data this procedure does not change the results presented. The analysis was also made for separate sub-periods and for different time horizons but the conclusion remains.

Cooper, examining US data, found that past returns tend to reverse in the near future and that volume attenuates the relationship so ($LoseHi - WinHi$) < 0 while ($LoseLo - WinLo$) > 0. Unlike Cooper, we find no systematic relationship between past returns and volume and

subsequent returns. For many bins there is no significant relationship; the only significant results give a "wrong" sign: (*LoseLo* – *WinLo*) < 0. The relationships among the bins are not monotonic: the centers show more extreme returns than the tails.

3.4. Volume as a separate predictor

Gervais, Kaniel, and Mingelgrin (2001, subsequently GKM) suggested that volume alone might play an important predictive role for stock returns in developed markets. They hypothesize that the "high-volume return premium" results from shocks to "visibility" that can have a positive effect on subsequent demand. We adapt their analysis to the TSE to discover how these stock returns are influenced by past volume.

The sample is broken into non-intersecting trading intervals of 50 days with a day skipped to avoid using the same day of the week for each interval. Each trading interval is split into a 49-day reference period and a one-day formation period. The reference period establishes what volume changes would be counted as "unusual" while the formation period uses this information to create a portfolio, classing the stock among "high" or "low" volume if formation-period volume is in the top ten percent of the trading interval. At the formation date, these volume classifications are used to form portfolios (at two weights, either a zero investment or reference return weight), and held without rebalancing for the length of the test period.

The zero investment weight portfolio is long one dollar in all the high-volume stocks and short one dollar in all of the low-volume stocks The reference return weight is long one dollar in each high-volume stock in a particular formation period (offset by adequate short positions in the low-volume stocks), so implicitly giving more weight to periods where more stocks meet this

criterion. GKM found positive net returns on a portfolio that is long on high-volume shares and short on low-volume shares, regardless of weighting and over a variety of horizons from one day to 100 days.

In the Iran data there are 24 non-overlapping daily trading intervals. Summary statistics for the number of stocks in the "High-Volume" and "Low-Volume" portfolios are shown in Table 5. As would be expected, of the 50 stocks, approximately five are trading in the ten-percent top or bottom range (based on its own historical data) on any given day or week. The low correlation shows that the pattern in the assignment of stocks to each bin is not biased.

Table 6 shows the cumulative returns of these "High-Volume" and "Low-Volume" portfolios for the two weighting schemes, with GMM standard errors. Initially the high-volume stocks have a greater return than the low-volume stocks; however within 20 trading days the positions are reversed. In the first day after the portfolio was formed, the high-volume portfolio outperformed the low-volume portfolio by 8-20 basis points (depending on the weights). However, after 10 to 20 trading days the relative performances are reversed, with the low-volume shares outperforming the high-volume portfolios.

GKM also constructed portfolios based on weekly data; experiments with weekly data, as well as with sub-periods found no systematic relationship. Where GKM found uniformly positive and generally significant coefficients, regardless of time horizon or weighting in their study of US markets, the analysis of the TSE finds no pattern to either sign or significance. GKM found that $High - Low > 0$ by both weights; in Iran we find that the signs fluctuate erratically depending on the weights.

3.5. Momentum over the medium-term horizon

Finally we can examine the performance of the TSE-50 stocks over medium time horizons: 3 months, 6 months, 9 months, and 12 months. This analysis, which was pioneered by Jegadeesh and Titman (1993), looks at stocks over the past J periods (where J is typically 3, 6, 9, and 12 months) to find the top and bottom deciles. Shares in the top decile (R10) are bought and shares in the lowest decile (R1) are sold (all are equally weighted) and the returns are evaluated over K-period horizons, where K is 3, 6, 9, or 12 months. If stocks have "momentum," then this portfolio will have positive returns over the medium horizon.

The returns to these Iranian portfolios are in Table 7. These returns all skip a week between the end of the formation period and the beginning of the evaluation period, in order to minimize the effects of bid-ask bounce. As is common in these studies, the periods overlap, so we use Newey-West autocorrelation-consistent standard errors with lags up to the number of evaluation periods (K). Below each return is a t-statistic testing if that return is zero, which is standard in the literature even for cases where the zero return is not an interesting counterfactual. The null hypothesis of zero is applicable to the differences: we would expect that the difference in return between the top decile stocks (R10) and the bottom decile (R1), would be zero, unless there were some systematic difference in risk. Finding that ($R10 - R1$) > 0 implies that there is momentum.

These results consistently show that the stocks in the top decile tended to outperform those in the lowest decile, by 3 to 11 percent, depending on the formation and evaluation period. The smallest outperformance is for the J=3, K=3 strategy, with just a 3.07 percentage point

difference in returns. The largest are for J=9, K=6 and K=6, J=9, which outperform by 11.07 and 11.05 percentage points, respectively. The t-statistics are consistently high. Using alternate weights or sub-periods keeps this conclusion stable. Jegadeesh and Titman (2001) document the behavior of US stocks at even longer horizons, for which this study lacks adequate data.

This is the only result where the behavior of Iranian returns is similar to the behavior of returns on the US market. Jegadeesh and Titman found that $(R10 - R1) > 0$ in a variety of horizons from 3 to 12 months; this study of the TSE finds the same results. It seems that, in common with developing markets, the TSE can exhibit medium-term momentum without short-term inefficiencies (see Sims 1990 for a theoretical description).

4. Conclusions

The Tehran Stock Exchange shows a fascinating combination of market behavior: according to certain measures the exchange might seem more efficient than developed markets, while interviews with participants highlight prices made in surreptitious and possibly underhand ways (Daragahi 2004). The short-term pricing abnormalities documented in developed markets in the past, such as the profitability of "contrarian" strategies (particularly when linked with volume information), are not present in this developed market. Even in the presence of large numbers of uninformed "naïve" investors, pricing can still be efficient, although with interesting nonlinear dynamics (see McMillan 2005 for examples). This seems to be the case for Iran; our understanding of the interplay of financial markets and their development should be informed by this distinction.

A battery of tests is used to examine the Iranian data for evidence of short-term autocorrelations related to past returns or volume. The short-term portfolio composition strategies suggested by Conrad, Hameed, and Niden (1994), Cooper (1999), and Gervais, Kaniel, and Mingelgrin (2001) found that US markets showed anomalous, "contrarian" behavior. However the same tests applied to the Tehran Stock Exchange data show no significant contrarian effects. This finding, of no relation between volume and stock return autocorrelation, is the opposite of previous studies of other developing markets.

Conrad, Hameed, and Niden propose three tests that would indicate contrarian returns; the behavior of the TSE corresponds with only one of those tests. Cooper found marked patterns of reversals in grids of returns and volumes; on the TSE there are no such patterns. Gervais, Kaniel, and Mingelgrin found that high-volume stocks outperform low-volume stocks; on the TSE there are again no such patterns.

Momentum is the only major anomaly that is found in developed markets as well as Iran. Over longer horizons of three to 12 months, we find significant evidence of "momentum" patterns of returns, where the top-performing firms over a past horizon of one to four quarters continue to outperform for the next one to four quarters.

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Table 1: Summary statistics for returns and volume growth for TSE-50

	Mean	Median	Std Dev	Min	25th Ptile	75th Ptile	Max	rho 1 (std dev)	rho 2 (std dev)
5-day returns	0.1551	0.0165	0.7183	-11.87	-0.0868	0.3954	4.876	0.104 (0.146)	-0.013 (0.110)
% vol change (daily)	9.39	0.003	424.74	-1.00	-0.50	1.08	6006	-0.045 (0.047)	-0.017 (0.054)
% vol change (over past 4 weeks' avg)	7.82	-0.16	483.65	-1.00	-0.62	0.59	6727	-0.007 (0.052)	-0.027 (0.043)

Summary statistics for weekly returns (expressed as a percentage) and percent growth in volume. Weekly returns are mid-week to mid-week. The whole sample is from Sept. 29, 1997 to Nov. 18, 2002. Percent volume change shows trading volume relative to the previous four weeks' moving average.

Table 2: Profits to contrarian return-based strategy on TSE-50

	percent return	std. err.	min	max	t = stat/stderr
Panel A: using returns only					
Win	0.8201	0.2653	-1.6437	28.8927	3.0915
Lose	0.3844	0.1614	-5.3348	12.9682	2.3811
Comb: (Lose – Win)	-0.4357	0.1548	-15.9244	3.3682	-2.8149
Panel B: using return weights but volume/return to sort					
Win, Hi	0.8369	0.2832	-1.5587	27.9606	2.9548
Win, Lo	0.1221	0.0220	-0.3209	1.9194	5.5573
Lose, Hi	0.3325	0.1343	-24.3258	26.5788	2.4755
Lose, Lo	-0.0224	0.0267	-4.6453	4.3802	-0.8385
Comb: (LoseHi – WinHi)	-0.5044	0.2845	-52.2864	17.0785	-1.7726
Comb: (LoseLo – WinLo)	-0.1445	0.0368	-5.2980	2.4607	-3.9259

The "Win" portfolios are formed of winner stocks with returns greater than zero; the "Lose" portfolios are loser stocks with returns less than zero; "Comb" combine both to be short winners and long losers. "High" portfolios use high-volume stocks; "Low" use low-volume. Portfolio weights use only return information, as described in the text. The return (expressed in percentage terms) of each is an average over the sample of 262 weeks. The standard error uses Newey-West corrections with four lags; it is also expressed in percent. The t-statistic is the ratio of the percent return to the standard error.

Table 3: Returns for portfolios constructed based on first-order return filters

		k=0 to k=1	k=1 to k=2	k=2 to k=3	k=3 to k=4	k=4 to k=5	k=5 and lower
Lose	**mean**	0.0692	0.1066	0.1322	0.0281	0.0412	0.0421
	std. dev.	1.7012	1.1951	1.0887	0.6167	0.3648	0.6511
	N	255	214	155	80	32	32
	t-stat	0.6492	1.3045	1.5114	0.4071	0.6525	0.3655
Win	**mean**	1.7617	0.9891	0.7028	0.2172	0.1414	-0.0143
	std. dev.	2.1749	1.8387	1.4329	0.8816	0.7081	0.8201
	N	259	250	218	155	84	107
	t-stat	13.0361	8.5054	7.2421	3.0675	1.8300	-0.1808

Loser filters for the previous week's price returns; these buy only stocks that lost in the previous week. Winner filters for previous week's price returns; these buy only stocks that had positive returns in the previous week. The tables report the mean, standard deviation, number of weeks for which there were stocks in that portfolio, and t-statistic. The t-statistic is not meant as a formal statistical test but to convey the magnitude of the variation. For each week and portfolio subset the stocks are equally weighted.

Table 4: Returns to portfolios composed using filters based on price and volume

		Lose						Win					
	k=	**5**	**4**	**3**	**2**	**1**	**0**	**0**	**1**	**2**	**3**	**4**	**5**
Lo	**5**	-	-	0.0016	0.0053	-0.0005	-0.0084	0.0076	0.0023	0.0141	-	-	-
	4	-	-	-	0.0067	0.0045	-0.0167	0.0227	0.0082	0.0063	-0.0025	-0.0003	-0.0046
	3	-	0.0043	-	-0.0007	-0.017	-0.0079	0.0626*	0.0324	0.0148	-0.0047	0.0033	0.0002
	2	-	-	-0.0016	-0.0134	-0.0099	-0.005	0.0532*	0.0983*	0.0352	0.0107	0.0166	0.0046
	1	-0.005	0.0027	-0.0024	0.0457	-0.0201	-0.0087	0.3286***	0.1769***	0.1253**	0.0453	-0.0037	0.0006
	0	0.0178	0.0022	0.0002	0.0492	0.0151	-0.0478	0.395***	0.2306***	0.1871***	0.0212	0.0468	-0.021
Hi	**0**	0.0209	0.0366	0.0134	0.0441	0.1092**	0.1222**	0.5128***	0.3458***	0.1595***	0.0868	0.0425	0.0223
	1	-0.0102	-0.0106	0.0049	0.0112	-0.0076	0.0165	0.1114**	0.0788*	0.0693*	0.015	0.0166	-0.0008
	2	-0.0012	0.0065	-0.0012	0.0002	0.0281	0.0014	0.0437	0.0245	0.033	0.0193	-0.0001	-0.0111
	3	0.0153	-	-0.0009	-0.0027	0.0229	-0.0019	0.0207	0.0134	0.0108	0.0059	-0.0031	-0.013
	4	0.0037	0.0005	0.0053	0.0049	-0.0017	-0.0006	0.0483	0.0242	0.0009	-0.0044	-0.0006	0.0055
	5	0.0008	-0.0001	0.0088	-0.0183	-0.0164	0.026	0.1552***	0.0363	0.0464	0.0247	0.0235	0.0028

Filters for the previous week's price returns, buying only stocks that won/lost in the previous week. The volume subsets further divide portfolios based on the previous week's volume growth, as explained in the text. The tables report just the mean, with asterisks to convey the magnitude of the variation: *** means that the t-statistic would imply significance greater than 1%; ** means that the t-statistic would imply significance from 1% to 5%; * means that the t-statistic would imply significance from 5% to 10%. For each week and portfolio subset the stocks are equally weighted.

Table 5: Stock portfolios based on volume criteria, GKM methodology

	High-volume	Low-volume
Average number of stocks in portfolio	4.58	4.88
Median number of stocks	4	4
Std. Dev. of number of stocks	2.41	2.17
Minimum number of stocks	1	2
Maximum number of stocks	11	9
Corr(High, Low)	-0.11	

The "High-Volume" portfolio selects stocks that, at the end of each 50-day trading interval (or, for the "weekly," ten-week trading interval), had trading volumes in the top ten percent of that interval; "Low-Volume" stocks were in the bottom ten percent. The table gives summary statistics for the number of stocks in each of the 24 daily trading intervals (23 weekly intervals).

Table 6: Cumulative returns to portfolios based on volume criteria

Panel A: Full Sample					
weight: **zero investment portfolio**	**1**	**10**	**20**	**50**	**100**
Average return for High-volume portfolio	0.3080	1.9419	2.6883	3.5548	9.8295
Std Err	*(0.1055)*	*(0.3510)*	*(0.3793)*	*(0.7172)*	*(1.4947)*
Average return for Low-volume portfolio	0.0700	1.0925	2.9651	6.9442	12.1956
Std Err	*(0.1150)*	*(0.4333)*	*(0.6564)*	*(1.0573)*	*(1.3285)*
Average return for Combination portfolio	0.1988	0.8494	-0.2768	-3.3894	-2.3661
Std Err	*(0.1445)*	*(0.5576)*	*(0.7581)*	*(1.2776)*	*(1.9998)*
t-statistic	1.3759	1.5232	-0.3651	-2.6529	-1.1831
weight: **reference return portfolio**	**1**	**10**	**20**	**50**	**100**
Average return for High-volume portfolio	0.4313	1.6179	2.1285	3.5441	10.0088
Std Err	*(1.2112)*	*(4.1142)*	*(5.2950)*	*(9.3437)*	*(15.4767)*
Average return for Low-volume portfolio	0.1270	1.5024	2.7143	6.6582	12.5937
Std Err	*(1.3969)*	*(5.1279)*	*(6.9501)*	*(10.0438)*	*(13.7270)*
Average return for Combination portfolio	0.0759	-0.0566	-0.4032	-1.5734	-1.0847
Std Err	*(0.0333)*	*(0.1254)*	*(0.1686)*	*(0.2703)*	*(0.4170)*
t-statistic	2.2792	-0.4509	-2.3913	-5.8199	-2.6011

The High-volume and Low-volume portfolios are created at the end of each 50-day trading interval, based on whether the stock's performance on the last day put it in the top (High-volume) or bottom (Low-volume) ten percent of that day and the previous 49 days. The "Combination" portfolio buys the top-volume stocks and sells the low-volume stocks; this t-test can be interpreted as examining whether there is a differential rate of return between the two categories. Cumulative returns are given in percentage points over horizons of 1, 10, 20, 50, and 100 days. The standard errors are based on GMM estimates. Weighting is explained in the text.

Table 7: Momentum returns over 3-12 month horizons

Skip-week monthly returns

		K = 3	K = 6	K = 9	K = 12
J = 3	**R1**	0.0185	0.0421	0.0672	0.0961
		(1.91)	(2.95)	(4.53)	(5.08)
	R10	0.0492	0.1072	0.1558	0.1986
		(7.04)	(8.13)	(7.87)	(8.43)
	R10 - R1	0.0307	0.0650	0.0886	0.1025
		(3.12)	(3.84)	(4.29)	(5.01)
J = 6	**R1**	0.0151	0.0322	0.0615	0.1062
		(1.22)	(1.71)	(2.73)	(4.39)
	R10	0.0588	0.1222	0.1719	0.2103
		(5.78)	(8.15)	(8.77)	(10.82)
	R10 - R1	0.0436	0.0900	0.1105	0.1041
		(2.89)	(4.19)	(5.71)	(7.96)
J = 9	**R1**	0.0067	0.0271	0.0749	0.1150
		(0.42)	(1.13)	(3.36)	(5.49)
	R10	0.0685	0.1378	0.1851	0.2129
		(5.91)	(11.22)	(12.29)	(14.83)
	R10 - R1	0.0618	0.1107	0.1101	0.0979
		(3.26)	(4.32)	(6.85)	(7.77)
J = 12	**R1**	0.0041	0.0356	0.0723	0.1101
		(0.23)	(1.45)	(3.48)	(5.00)
	R10	0.0647	0.1216	0.1615	0.1888
		(5.70)	(10.07)	(8.91)	(8.93)
	R10 - R1	0.0605	0.0860	0.0892	0.0787
		(2.77)	(3.17)	(5.30)	(4.89)

Each entry shows the return (t-statistic is in parentheses) of the equally weighted portfolio of stocks from the indicated decile of returns (from R1, the lowest decile, to R10, the highest), where the formation is made over the previous J months. The returns are evaluated over the next K months. The "R10 – R1" portfolio buys R10 and sells R1; this t-test can be interpreted as examining whether there is a differential rate of return between the two categories.