Price Impact Costs and the Limit of Arbitrage

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Abstract

This paper investigates whether one can profit from the size, book-to-market, or momentum anomaly, when price-impact costs are taken into account. We implement a variety of long-short arbitrage strategies based on each such anomaly, and estimate the maximal fund size attainable before excess return vanishes. We find that the profitable fund size remains only marginal relative to the relevant funds in the industry. Our finding supports the idea that trading costs deter investors from fully exploiting apparent profit opportunities.

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Abstract

This paper investigates whether one can profit from the size, book-to-market, or momentum anomaly, when price-impact costs are taken into account. We implement a variety of long-short arbitrage strategies based on each such anomaly, and estimate the maximal fund size attainable before excess return vanishes. We find that the profitable fund size remains only marginal relative to the relevant funds in the industry. Our finding supports the idea that trading costs deter investors from fully exploiting apparent profit opportunities.

JEL Classification: G1

Keywords: Stock market anomaly; price-impact function; limit of arbitrage.

1 Introduction

Recent empirical studies have documented a number of stock-return anomalies: return spreads between certain groups of stocks are too high to be justified by standard asset pricing models. Some argue that these findings are evidence of market irrationality because there is too much money being left on the table. Others point out that markets are at least minimally rational in the sense that certain market imperfections prevent agents from exploiting these anomalies (e.g., see Rubinstein (2001)). To explore this perspective further, we first estimate realistic price-impact functions for each stock. Assuming that an arbitrageur would set up a long-short hedge fund (or a long-position-only investment like a mutual fund) to take advantage of an anomaly, we then determine the maximal amount of capital that can be accommodated without losing money on average. Our goal is to take into account not only explicit costs such as commissions and bid-ask spread, but also the price-impact costs, short-sale costs (short rebate rate) and limits on the trade and position in every stock. If the profitable fund sizes are small, it will mean that anomalies exist not because investors are irrational, but because they are probably too economically rational.

To make the scope of the paper manageable, we choose to focus on three popular anomalies: size, book-to-market (B/M), and momentum. The size and B/M anomalies arise because, contrary to the predictions of more traditional models such as CAPM, both the size and the B/M ratio of stocks are found to be significant determinants of their future excess return. The size effect was first reported in Banz (1981) and confirmed in Fama and French (1993) and others for later periods. The B/M or value effect was first documented in Basu (1983), and more recently in Fama and French (1993), Lakonishok et al. (1994), La Porta et al. (1997), and others. The momentum anomaly exists because buying past winners and selling short past losers generates abnormal returns. It was studied in Levy (1967) and Jegadeesh and Titman (1993, 2001).

To profit from a given anomaly, a direct approach is to implement a long-short arbitrage strategy as such a strategy allows the arbitrageur to be market-neutral or close to it. As a result, a long-short strategy reduces the impact of market risk and gives the anomaly effect the "best chance" to perform. Since size is inversely related to future excess returns, buying a portfolio of small capitalization stocks and shorting a portfolio of big ones constitutes an arbitrage. In contrast to size, B/M is a positive factor for future excess returns. A long-short arbitrage based on B/M therefore entails purchasing a portfolio of high B/M stocks and selling short a portfolio of low B/M ones. To benefit from the momentum anomaly, we go long past winners and short past losers. The sample period for our study is 1963-2002, during which portfolio formation (stock selection) takes place at a frequency ranging from monthly to annually, depending on the strategy. At the time of portfolio formation stocks can be either equally or value weighted. Rebalancing (weight adjustment) can occur either monthly to keep up with the weighting scheme chosen at the portfolio formation, or never during the holding period. The latter corresponds to a buy-and-hold strategy that aims to reduce turnover and hence price impact. Since short selling may actually be prohibitively costly for some small stocks, we will additionally consider strategies that involve only a long position for the most profitable anomalies.

When trading the necessary long and short positions, the arbitrageur will incur price-impact costs because stock prices are sensitive to the order direction and trade size. Large purchases tend to move the price up while sales drive it down. A bigger fund size requires larger positions to rebalance and larger trades to execute, which implies higher price-impact costs and lower returns. Due to this positive relation between fund size and price-impact costs, there exists a fund size beyond which excess return over the riskless rate will become negative. We will refer to it as the break-even fund size. This is a very conservative estimate of profitable fund size since the t-statistic of excess return is zero at the break-even fund size by construction. For this reason, we will occasionally look also at a maximal fund size at which the excess return becomes just insignificant.

The notion of price-impact function has been widely used in the microstructure literature since the work of Kyle (1985). It describes the functional relationship between the relative price change caused by a trade and the size of that trade. The shape and level of the function is one of the key differences between our study and the existing anomaly literature. In many existing papers, a constant proportional transaction cost is assumed. We model the price impact as a nonlinear function of dollar volume that nests such a linear function. Allowing for nonlinearity is important for two reasons. First, many empirical studies have found the nonlinearity of price impacts under both parametric and semi-parametric specifications (Hasbrouck (1991), Hausman et al. (1992), Keim and Madhavan (1996), Kempf and Korn (1999), and Knez and Ready (1996)). Second, since we will be interested in large trades, allowing for nonlinearity will produce a conservative estimate of break-even fund size if the price impact function is concave in absolute dollar volume.

For robustness, using the TAQ dataset, we estimate two types of price impact functions, one based on tick-by-tick price movement of an individual stock and another based on the daily change in the value-weighted average price (VWAP), cross-sectionally pooled within size decile. For the tick-by-tick measure, a nonlinear price-impact function is first estimated for each of 4,897 stocks traded on the NYSE, AMEX, and NASDAQ in 1993. We use the 1993 data because this is the earliest year the TAQ data are available, while our return series goes as far back as 1963. The estimated price impact is aggregated within size decile and then projected out of sample using Amihud's (2002) illiquidity ratio. The second measure of price impact is meant to capture the impacts and trades that possibly occur over time, such as gradual incorporation of private information, pre-trade information leakage, and the splitting of a large trade ("working" an order), if not perfectly. The cross-sectional pooling is possible since we formulate the price impact as a function of signed dollar volume. It also avoids getting extremely noisy estimates for individual stocks.

When price-impact costs are ignored, all the three anomalies generate average returns significantly higher than the riskless rate, with most profitable being the B/M and certain momentum strategies. The equally weighted B/M strategy produces an excess monthly return of 1.13% when rebalanced every month, and the buy-and-hold 12/3 momentum strategy yields 1.49%. However, this does not translate into the accommodativeness of capital after cost. When price-impact costs are taken into account, returns for these strategies decrease rapidly with the arbitrage fund size. The break-even fund sizes for these strategies are no more than several hundred million dollars.

The most accommodative strategies under costs are slight variations of these strategies, an equally weighted buy-and-hold B/M and the 6/12 momentum strategies. The break-even fund sizes for these strategies are several billion dollars. This difference results from reduced turnover due to either going buy-and-hold or increasing the holding period. Further, the momentum strategy can accommodate about $20 billion when implemented with the long position only. This number, however, ignores the implementability of a strategy that involves small size stocks. A realistic assumption would be to constrain each trade to be no more than 1% of the market capitalization of the stock being traded, since such a trade is very rare as will be demonstrated. Moreover, a position over 5% of a stock's market capitalization requires filings with SEC (Form 13D) and may be prohibitively costly. We find that, when these 1% trade restriction and 5% position limit are imposed, the break-even fund size of the winner-only momentum strategy decreases to approximately $10 billion. The fund size that produces a significantly positive return is at most several hundred million dollars for any of the above strategies.

Increasing the portfolio-formation frequency from annual to semiannual and then to quarterly has two competing effects. One might benefit from "fine-tuning" to the anomaly, while an obvious drawback is increased turnover and hence trading costs. We generally find that the latter effect is stronger; the break-even fund size decreases with portfolio formation frequency.

We compare our estimates to the actual size of all relevant hedge funds and mutual funds, since we are investigating the rationality of market participants as a whole. The idea here is to simply compare apples to apples. Each break-even fund size estimated in the previous sections should be interpreted as an additional fund size attainable to the market. Indeed, we have implicitly studied a monopolistic arbitrageur who attempts to create a single, largest fund from a set of possible strategies. Thus, our reference point should be the total anomaly-driven investment that produce price-impact costs, and not the size of funds that follow a particular strategy.

Using the TASS and the CRSP mutual fund datasets and other information, we estimate the size of relevant equity funds to be at least $650 billion as of 2002. We believe that this is a conservative estimate of money that is subject to price impact, given the size of domestic equity mutual funds totaling $2.3 trillion (in 2002). The largest of our break-even fund sizes, $10-20 billion, represent no more than 2-3% of the $650 billion. This is also well within a tolerance of weekly volatility. Moreover, this investment is not worth pursuing, since one could earn the same return by just investing in a safe deposit or Treasury securities. If he wishes to secure a significantly positive excess return, he can invest only several hundred million dollars.

If, as we argue, price-impact cost is so significant, the hedge fund industry must have experienced a deteriorated performance by now. Indeed, such news is abundant in the current media. Just to mention one, on July 20, 2004, the Federal Reserve Chairman Alan Greenspan allegedly testified,

> "Not surprisingly, the rate of return in [the hedge fund] activity is reportedly declining. I would not be surprised if, with time, many of the new entries exited, some presumably following large losses."[1]

The most related studies are Korajczyk and Sadka (2004) and Lesmond, Schill and Zhou (2004). Both of them focus on the post-cost profitability of momentum strategies and reach opposite conclusions. Korajczyk and Sadka (2004) propose a "liquidity weighted" strategy which maximizes after-cost returns under some simplifying assumptions. They find that transaction costs, including price-impact costs, do not fully explain the return continuation of certain winners-only momentum strategies, leading to a conclusion that "this anomaly remains an important puzzle." (Korajczyk and Sadka (2004, p.1040)) In contrast, Lesmond, Schill and Zhou (2004) observe that standard momentum strategies call for frequent trading in high cost securities and therefore that the apparent profit opportunity of these strategies cannot be exploited. The differences between these two papers and ours will be discussed in a later section; the bottom line is that while the numerical results are generally consistent, our interpretation is different. As noted above, we think that it is more appropriate to examine the issue from the perspective of arbitragers and investors as a whole.

The paper is organized as follows. The next section estimates the price-impact functions. Section 3 studies the profitability of anomaly-driven trading strategies. Section 4 discusses the result and investigates its robustness. The final section concludes.

[1] Reuters, as appears at
http://biz.yahoo.com/rf/040720/economy_greenspan_hedgefunds_4.html
A similar quote is also cited in Lahart (2004).

2 Estimation of Price-Impact Functions

This section describes how we estimate the price-impact functions for both individual stocks and their portfolios and discusses the results. Using a nonlinear function that nests a linear specification, we find that estimated price impact functions are concave. It is also demonstrated how concavity is important in producing conservative estimates of break-even fund size.

2.1 Model Specification

There are various ways to specify a price-impact function. The most common practice is to assume a linear relation between the (absolute or relative) price change caused by a trade and its volume. Typically, trade size is the number of shares traded, either in absolute terms or relative to the number of shares outstanding. Such linear price-impact functions may be motivated by the theory of Kyle (1985), and empirical applications can be found in Bertsimas and Lo (1998), Breen et al. (2002), and Madhavan and Dutta (1995). In contrast, we follow Hasbrouck (1991), Hausman et al. (1992), and Keim and Madhavan (1996) and allow here nonlinear price-impact functions. Knez and Ready (1996) also emphasize the importance of nonlinearity in the relationship between price improvement and excess depth.[2]

For robustness, we model price impact in two ways that differ in time frequencies and cross-sectional aggregation. The first specification measures the price impact at the tick level for each individual stock. Specifically, the price impact of a trade is defined as the relative change in the quote midpoint, which in turn is formulated as a nonlinear function of the dollar volume of that trade,

$$PI_t \triangleq \frac{Q_{t+1} - Q_t}{Q_t} = a + b\,\frac{V_t^{\lambda} - 1}{\lambda} + \varepsilon_t, \tag{1}$$

where Q_t is the quote midpoint prevailing at transaction time t, V_t is the dollar volume (price times the number of shares traded) of the trade, the error term ε_t is independently and identically distributed with mean zero and a finite variance, and a, b, and λ are constants to be estimated. To allow for asymmetric impacts of buys and sells, we estimate the model for purchases and sales separately. We call this the tick-by-tick price impact. Because of the high frequency nature, this is suitable for estimating price impact functions for each individual stock. However, since such individual estimates are often noisy, they will be aggregated at the portfolio level. Cross-sectional aggregation is discussed later.

The right hand side of the above formula is known as the Box-Cox function, where the dollar trade volume is transformed with a curvature parameter λ. Note that V_t is nonnegative by definition and

[2] Kempf and Korn (1999) also question the empirical use of a linear price impact.

that the Box-Cox transformation $(V_t^\lambda - 1)/\lambda$ converges to $\ln V_t$ as $\lambda \to 0$. For a computational reason, we restrict that $0 \leq \lambda \leq 1$.[3] This is also the restriction imposed by Hausman et al. (1992), where their ordered probit model employs a Box-Cox transformation. This captures concavity between a log function (when $\lambda = 0$) and a linear function (when $\lambda = 1$) inclusive. We do not restrict the intercept or the slope coefficient in this model. The superiority of a Box-Cox function over other nonlinear specifications will be demonstrated in the next section.

To obtain quote midpoints, we follow Lee and Ready (1991) and match each trade to the bid and ask quotes that are set at least five seconds prior to the trade.[4] This procedure adjusts missequenced transactions: most trades that precipitate a quote revision are reported with some delay. Ideally, we would like to assign to each trade the quote prevailing an instant after the trade has occurred.

Using actual transaction prices rather than quote midpoints could bias the price-impact estimation, because trades do not occur continuously. For instance, consider a situation in which the quote midpoint increases at time $t - 1$ due to a positive announcement about the value of the underlying asset, but no trade takes place in that period. If the price impact were defined in terms of actual transaction prices, then the price impact of a buy (sell) at time t would be overstated (understated). On the other hand, use of the quote midpoints matched with trades by the Lee and Ready (1991) algorithm may bias the estimates since the matching will not be perfect. We think that the bias introduced by employing actual transaction prices is bigger and hence prefer to work with quote midpoints. Hasbrouck (1991) uses quote midpoints, too, while Hausman et al. (1992) look at actual transaction prices.

To classify a trade as either a buy or a sell, we apply the method introduced by Blume et al. (1989). A purchase occurs when the transaction price p_t is strictly larger than the midpoint quote Q_t at time t while a sale occurs if p_t is strictly smaller than Q_t. Hence, trades with transaction prices closer to the ask price are interpreted as buyer-initiated, while trades with prices closer to the bid price as seller-initiated. Transactions for which $p_t = Q_t$ are indeterminate according to this categorization and discarded from our analysis.

The second measure of price impact addresses the following two points that are hardly captured by the previous one. First, traders typically "work" a large order, by splitting it into smaller pieces and execute them over time. Second, the impact of a trade may occur gradually over time. Or because of information leakage, the relevant price change might occur prior to trade. Third, a quote change may reflect the effect of several preceding trades. To incorporate these points would entail some averaging over time. Along these lines, we define our second measure of price impact as the daily change in

[3] Specifically, the restriction in the nonlinear least squares procedure is $10^{-6} \leq \lambda \leq 1$. When the estimate hits the lower bound, a log function is re-fitted.

[4] A trade classification rule based on the quote midpoint appears in Hasbrouck and Ho's (1987, p.1039) earlier paper.

value-weighted average price (VWAP) relative to the previous day's closing quote midpoint Q_{d-1},

$$PI_d \triangleq \frac{VWAP_d - Q_{d-1}}{Q_{d-1}} = a + b\,\frac{V_d^{\lambda} - 1}{\lambda} + \varepsilon_d, \tag{2}$$

where $VWAP_d$ is the weighted average of transaction prices on day d with the weights being the dollar volume of trades and V_d is the net dollar volume on day d. The observations are cross-sectionally pooled within size decile over each year. Trades and quotes are matched by the Lee and Ready (1991) algorithm.[5] Again, coefficients are estimated on net buy and sell days separately. For computational reasons, we restrict $a = 0$. This will be called a VWAP price impact. In principle, this model could also be estimated for individual stocks. However, we choose to aggregate observations cross-sectionally because a different method would ensure robustness of our results. It also avoids aggregating possibly noisy estimates of individual price impacts.

The models are estimated by the least squares method. For example, the parameters in (1) are given by

$$(\widehat{a}, \widehat{b}, \widehat{\lambda}) = \arg \min_{\substack{(a,b)\in\mathbf{R}^2,\\ \lambda\in[0,1]}} \sum_{t=1}^{N} \left[PI_t - a - b\,\frac{V_t^{\lambda} - 1}{\lambda} \right]^2, \tag{3}$$

where N denotes the sample size, and similarly for equation (2).

Huberman and Stanzl (2004) demonstrate that nonlinear price-impact functions can give rise to quasi-arbitrage, which is the availability of a sequence of trades that generates infinite expected profits with an infinite Sharpe ratio. Consider, for instance, the price-impact function in (1) with the curvature parameters for buys and sells, $\lambda_B < 1$ and $\lambda_S < 1$ respectively, and the trading strategy of "buying X shares in each of the next T consecutive periods and then selling all TX shares in period $T + 1$." If X is small and if the price-impact function has a sufficiently high curvature, such a strategy may be profitable; in case the price impact of the sale in period $T + 1$ is small relative to the price impacts of the T preceding buys, the average selling price might exceed the average purchasing price. Although the profit resulting from such a manipulation strategy is only in expected terms, its Sharpe ratio can be attractively high, as Huberman and Stanzl show.

Such price-manipulation schemes are feasible here in principle, but difficult to implement for reasonable parameter values. If $0 \le \lambda_B,\ \lambda_S \le 1$ and if the price-impact functions for buys and sells are approximately symmetric, that is, with $a_B \approx -a_S$, $b_B \approx b_S$, and $\lambda_B \approx \lambda_S$ in (1) where the B and S subscripts represent buys and sells, respectively, then price manipulation strategies that produce high expected profits and high Sharpe ratios will always require a very large number of trades. Hence, the gains from price manipulation are either nonexisting or small for realistic numbers of trades. Fortunately, our estimates turn out to yield almost symmetric price-impact functions.

[5] The directions of those trades that occur at quote midpoints are determined by the tick test.

Hasbrouck (1991) and Hausman et al. (1992) allow for the (theoretical) possibility of price manipulation in order to get more accurate price-impact estimates. As in the present study, price manipulation strategies in Hausman et al. can only be implemented by using unrealistically high numbers of trades. In Hasbrouck, however, price manipulation may be feasible with a few trades only, unless the support of the price-impact function is sufficiently restricted.

2.2 Alternative Estimation Methods

Besides the Box-Cox models given in (1) and (2), we have tried three alternative approaches to estimating the price-impact function: polynomial fitting, piecewise linear fitting, and ordered probit models. In the following, we discuss these methods. To save space, we focus on the tick-by-tick price impact for purchases.

A polynomial price impact function can be obtained by fitting

$$PI_t = \sum_{j=0}^{m} \alpha_j V_t^j + \varepsilon_t, \tag{4}$$

where m denotes the order of the polynomial. Panels (a) and (b) of Figure 1 depict the estimated price-impact functions for FHT, when a quadratic, cubic, or fourth-order polynomial is fitted.[6] We find that a polynomial price impact is generally subject to overfitting. In the case of quadratic and fourth-order polynomials, the fitted curves imply that a large buy trade would produce a negative price impact, which is difficult to justify. A piecewise linear price impact in Panel (c) exhibits similar shortcomings; it has a negative slope for large trades.

As a third alternative we consider a version of the ordered probit model described in Hausman et al. (1992), suitably modified for our analysis (results omitted for brevity); first, rather than the absolute change in transaction prices, we use the relative quote-midpoint change to measure the price impact. Second, we estimate the price-impact function separately for purchases and sales. In short, the problem with this approach is that estimates can only be obtained for large capitalization firms, for which sufficiently many quote and trade observations are available, an issue that Hausman et al. already realized. Although the stock FHT is not a random choice, the disadvantages of the alternative methods illustrated here apply to many other stocks.

Taking all of the above into consideration, we choose to employ the formulations in (1) and (2). By comparison, Panel (d) of Figure 1 depicts for FHT the estimated Box-Cox function in (1).

[6] Fingerhats Companies Inc. (FHT) is a NYSE company with an average market capitalization of approximately 988 million dollars during our estimation period, January through June 1993. This number ranks the stock in the third largest decile of all NYSE stocks.

2.3 Price Impact for Individual Stocks

The individual tick-by-tick price impact in (1) is estimated for each of 4,897 individual stocks on the NYSE, AMEX and NASDAQ using a sample period of January through June in 1993. We chose the earliest year for which the TAQ dataset is available, because our strategies go as far back as 1963. The six-month time period provides enough observations for most of the stocks. We first identify all the common stocks using the CRSP monthly file. Next, for each of these stocks, we extract from the TAQ dataset quotes with positive bid and offer prices and trades with a positive transaction price and a number of shares traded.[7] We only use trades and quotes time stamped between 9:30a.m. and 4:00p.m. from the same exchange or trading system identified as primary in CRSP. These quotes are matched by a version of the Lee and Ready (1991) algorithm described earlier. We discard stocks with less than ten matched quote-trade pairs. This procedure resulted in an initial sample of 5,173 stocks.

To get rid of outlier effects, we jettison transactions with a dollar volume in the largest one percentile for each stock. Since we measure the price impact by the relative quote midpoint and the trade size is expressed in dollars, the price jump due to a stock split introduces only a negligible estimation bias. Firms that experienced stock splits during our sample are therefore not excluded. Those stocks are thrown out for which the estimation of either the buy or the sell price-impact function did not converge after 1,000 iterations. This left us with the estimated price impact functions of 4,897 stocks.

Table 1 reports the characteristics of seven representative stocks, and Table 2 shows the estimated coefficients of their tick-by-tick price-impact functions. Estimates in Panel (a) of Table 2 share the following qualitative properties: first, small-size stocks have higher price impacts. For example, compare CSII and S, where CSII belongs to the smallest size quintile of our sample, whereas S to the largest (both share similar B/M ratios in Table 1). Panel (a) of Figure 2 shows a larger price impact for CSII than S. Two parameters are relevant in defining price impact for large trades, the slope coefficient b and the curvature parameter λ in (1). The large slope coefficient of CSII outstrips the large λ (closer to linearity and therefore less curvature) of S in Table 2.

Panel (b) of Figure 2 reveals however that for a small buy order, the price impact may be negative. This is because we have not restricted the intercept in (1) to be zero. However, this is innocuous for our purpose since we are primarily interested in the effect of large trades, and if any, it would produce a conservative estimate of break-even fund size. The qualitative properties of the estimated price-impact functions for sales are roughly "symmetric" to buys, as is evident from Panels (c) and (d) of Figure 2.

As mentioned before, purchases and sales must have approximately symmetric price impacts to rule out price manipulation. Other empirical studies, however, have produced different results that may

[7] "When-issued" entries are excluded.

imply the feasibility of price manipulation. Gemmill (1996) and Holthausen et al. (1987) find that block purchases have a significantly larger price impact than block sales, and Chan and Lakonishok (1995) report the same for institutional trades. In contrast to that, Keim and Madhavan (1996) and Scholes (1972) find markets in which sales exhibit a stronger price impact.

Since a single trade rarely exceeds 1% of the firm's market capitalization, we draw the estimated price-impact functions only up to this dollar volume. This is why the price-impact functions for BONT and CSII are truncated in Panels (a) and (c) of Figure 2. To demonstrate this point, Figure 3 shows the histogram of signed dollar volume for KO and BONT. Panel (a) shows that there were 9,108 valid trades in January 1993, ranging from a sell trade of $4.3 million to a buy of $10.2 million (recall that a positive trade indicates a buy, and a negative trade a sell). Since the size of KO was $54.9 billion at the end of December 1992 (see Table 1), the largest trade during this one month period was merely 0.0186% of the market capital. The relative trade size, however, tends to be larger for smaller stocks. In Panel (b), the maximum trade for BONT during the first six months of 1993 was $0.923 million, or 2.56% of the market capital. 260 out of 2,081 trades, or one in eight trades, exceed 1% of the average market capital during the six month period. However, no single trade was larger than 5% of the market capital. A buy order of this magnitude would imply that the resulting position requires costly SEC filings, unless the pre-trade position was short.

2.4 Linear versus Nonlinear Price-Impact Functions

This section examines the difference between a linear and a nonlinear price-impact function. Allowing for nonlinearity, specifically concavity, is important for our purpose, since it will produce a conservative estimate of break-even size. In fact, the absolute price impact for the seven representative stocks were all concave in dollar volume (see Figure 2). This results from the curvature parameters that are substantially below 1 in Table 2.

The top rows of Table 3 report the estimates for a linear regression model,

$$PI_t = \alpha + \beta V_t + \varepsilon_t, \tag{5}$$

applied to the buy orders of the seven representative stocks. The estimated slope coefficients are positive and statistically significant for the three large capitalization firms on NYSE (GE, KO, S). The bottom rows of Table 3 then show differences between the linear price impact in (5) and the nonlinear one in (1), when either $50,000 or $300,000 is purchased. At $300,000, the linear function already gives a larger price impact for three of the four small firms on NASDAQ (BONT, CSII, MIKE, INGR). Obviously, a concave price impact function will give a smaller price impact than a linear one for large enough trades.

This is graphically demonstrated in Figure 4, for purchases of KO and BONT.

2.5 Aggregating Price-Impact Functions

Since the estimated price-impact functions for individual stocks can be quite noisy, it is desirable to aggregate price impacts to accurately assess the trading costs of our trading strategies. In this section, we discuss the aggregation methods for the two price-impact measures.

To aggregate the tick-by-tick price-impact function in (1), we sort all the stocks into ten size deciles S_1 (smallest), $S_2, \ldots, S_{10}$ (biggest), where the size of a stock is defined as the daily average of the stock's market capitalization between January 1993 and June 1993. The estimated price-impact function for decile j is then given by an analogue of (1),

$$\overline{a}_j + \overline{b}_j \frac{V^{\overline{\lambda}_j} - 1}{\overline{\lambda}_j}, \tag{6}$$

where $\overline{a}_j$, $\overline{b}_j$, and $\overline{\lambda}_j$ are the equally weighted average of the corresponding parameters for individual stocks. Again, parameters are averaged separately for purchases and sales.

Table 4 presents the estimated portfolio coefficients by size decile. The resulting price-impact functions are drawn in Figure 5. Like the individual one, the absolute price impact is increasing in dollar trade volume and concave for all deciles. For a given dollar volume the price impact generally decreases with the capitalization of firms, except for some range of trade size in which the ordering is reversed among a couple of deciles. The price-impact function for the smallest decile is fairly large relative to others, which justifies the exclusion of stocks in this decile in our momentum strategies. This is also implemented by Jegadeesh and Titman (2001).

Note that these estimates would be valid only for trades in the sample period, the first half of 1993. Since our strategies span from 1963 through 2002, we wish to estimate price impacts in each of these years. One way to do this is to use a measure of (il)liquidity available through the period and extrapolate our price-impact functions. Candidates for such measures include Amihud's (2002) illiquidity ratio and Pastor and Stambaugh's (2003) return reversal; both of these are constructed from lower-frequency but longer data, specifically CRSP. Hasbrouck (2003) finds that the correlation between Amihud's illiquidity ratio and a TAQ-based measure of price impact is 0.90 for portfolios.[8] From this it seems appropriate to choose Amihud's illiquidity ratio for our purpose, which is defined as

$$I_y = \frac{1}{N_y} \sum_{d \in y} \frac{|r_d|}{V_d}, \tag{7}$$

[8] Note that the correlation for individual stocks is much lower; According to Hasbrouck (2003), it is only 0.47. This signifies the importance of aggregation.

where r_d and V_d are the return and the volume, respectively, on day d, and N_y is the number of days in period (say year) y. This is computed for each stock. It is seen from (7) that this measure has a direct interpretation of a price-impact coefficient. Using Hasbrouck's (2003) dataset, we compute the portfolio illiquidity ratio for each size decile every year as the average of the illiquidity ratios of component stocks.[9] To exclude extreme values, we discard observations in the top and bottom 10 percentiles within each decile. Figure 6 shows Amihud's illiquidity ratio for size deciles 1 and 10 (normalized at 1 in year 1993). Consistent with the common sense, Panel (a) shows that the liquidity of largest stocks has improved substantially over years. Surprisingly however, there is no clear trend for the smallest stocks in Panel (b). Graphs for other deciles fall somewhere between these two and hence are omitted; most deciles are similar to Panel (a), while decile 2 looks somewhat more like Panel (b). For each decile, the normalized illiquidity ratio is multiplied to the entire price-impact function in (1) to project it out of sample.

While the above is an intuitive way to aggregate individual impacts, strictly speaking, it is subject to a technical reservation. That is, a concave function with the average parameter values will not give the average of the concave functions. This is where we call for the second measure of price impact. We estimate the VWAP price impact in (2) for each size decile by pooling the daily observations of component stocks every year, separately for buys and sells. Thus, we estimate 20 price impact functions for each year from 1993 through 2002. Figure 7 shows the estimated portfolio VWAP price-impact functions for year 2002 by size decile. Again, the absolute price impact is concave and increasing in trade volume; for a given trade volume, it is generally decreasing in market capitalization of traded stocks. Figure 8 in turn shows the time series of the buy price-impact function for the largest decile. Although there is some fluctuation, the price impact has generally decreased over years, with a substantial drop in years after the full decimalization of NYSE on January 29, 2001. To estimate out-of-sample price-impact functions in pre-1993 years, we again multiply the normalized Amihud illiquidity ratio for a size decile to the entire 1993 VWAP price-impact function for that decile.

Equipped with measures of price impacts, we may now proceed to examine the profitability of anomaly driven strategies.

3 Profitability of Anomaly-based Strategies

This section studies the profitability of long-short arbitrage strategies and their variants based on the size-, B/M-, and momentum anomalies. We measure the returns from anomaly-driven strategies as a function of the fund size, when price-impact costs are taken into account. Obviously, a bigger fund

[9] Hasbrouck's dataset ends in 2001 at the time of our analysis. We used the 2001 values for year 2002.

size requires larger trades, which implies higher price-impact costs and lower returns. The subsequent analysis will quantify this relationship. Of special interest is the break-even fund size of an arbitrage strategy: what is the maximal fund size that generates a nonnegative excess return (relative to the Federal Fund rate)?

To explain the implementation of a long-short arbitrage strategy, it suffices to start with one anomaly, say, the size anomaly. As mentioned above, the size anomaly arises because the excess return is inversely related to market capitalization. To profit from this relation, one would want to buy a portfolio of small stocks and sell short the same amount of large stocks. Unfortunately, a textbook arbitrage is infeasible in practice, mainly because of three reasons. First, the convergence of the values of the two positions can never be assured. Second, the proceeds from shorting cannot all be used to finance the long position, since in practice they have to be deposited on a margin account as collateral. Finally, price-impact and transaction costs reduce the available funds when the portfolios are rebalanced. Our long-short arbitrage strategy will take the second and third factors into consideration, while attempting to minimize the risk of nonconvergence through taking a large number of positions and through either equal-weighting or value-weighting.

Specifically, suppose we start with an initial fund size π_0 and implement a self-financing long-short arbitrage over the next T months. Denote by L_t and S_t the long and short portfolios, respectively, in month t. At the end of month 0, we invest π_0 dollars in L_1 and sell short the same dollar amount of S_1 before costs. After price-impact costs and transaction fees, we would effectively hold $b_1 = \pi_0 - PIL_1 - PIS_1 - TCL_1 - TCS_1 - ECL_1 - ECS_1$ dollars of L_1, and sell short the same dollars of S_1, where PIL_1, TCL_1, and ECL_1 represent the price-impact costs, the transaction fees, and the effective spread necessary to create our long position, and PIS_1, TCS_1, and ECL_1 denote the corresponding costs for installing our short position. To compute PIL_1 and PIS_1 we first calculate the dollar amount invested in each stock by equal or value weighting of π_0. Price impact for each stock is then computed by identifying the stock's size decile and applying either the tick-by-tick or VWAP price impact function for that decile. In doing this we use the price impact coefficients for the appropriate trade direction (buy or sell) and for the year that month 0 belongs. Multiplying the invested dollar amount to the price impact converts it into dollar costs (note that the price-impact functions in Figures 5, 7, and 8 are in percentage of dollar trade size). Summing up the dollar price impacts for all the stocks in the long and short positions gives PIL_1 and PIS_1, respectively.

We also take into account the time variation of transactions fees. Jones (2002) shows one-way average commissions for round-lot transactions in NYSE stocks from 1928. Since it is not easy to obtain a time series of commission schedule for a cross section of stocks, we apply a schedule similar to his to all stocks for relevant years. Our one-way commissions are shown in Figure 9.[10] While this is probably an underestimate of commissions for middle to small size stocks, it will produce a conservative estimate of the break-even fund size. In computing TCL_t and TCS_t, we use this as the commissions for a purchase and a regular sale. The commissions for a short sale are calculated, somewhat arbitrarily, to be 5/3 times those of the regular sale.[11] For large fund sizes, the commissions are small relative to the price-impact costs.

The effective spread is also an important component of trading costs. Hasbrouck (2003) proposes a Gibbs sampling estimate of effective spread. While this can constitute a significant portion of total costs, for conservativeness we set this to be zero for most of our analysis. When the estimated break-even fund size is very large, we use for ECL_t and ECS_t the values implied by (the time series of) Hasbrouck's (2003) estimates to further investigate the profitability of our strategy.[12]

The b_1 dollars received from shorting LSD_1 are then assumed to be deposited in a collateral account paying 80% of the Federal Fund (FF) rate. (The short selling fee is 20% of the FF rate.) Hence, at the end of month 1, the value of our total portfolio is $\pi_1 = (1 + r_{l1} - r_{s1} + 0.8r_1)b_1$, where r_{l1} is the rate of return on L_1, r_{s1} the return on S_1, and r_1 the FF rate.

At the end of each month, the portfolios are reformed (stocks are reselected) if the strategy's holding period has elapsed since the previous portfolio formation (e.g., for the momentum J/K strategies, this occurs every month if $K = 1$, and only annually if $K = 12$, for a given monthly cohort). Otherwise, stock selection is unchanged. In this case, there are two important considerations in devising trading strategies: the weighting scheme and the rebalancing frequency. Since these affect the trading costs substantially, unlike most existing studies, we pay a particular attention to their treatment. We allow portfolio weights to be rebalanced either every month or never till the next portfolio formation. The latter case corresponds to a buy-and-hold strategy, which will reduce price-impact costs and transactions fees by omitting small rebalancing trades. Alternatively, we could rebalance every $x > 1$ months, but we focus on these two extreme cases since results for other rebalancing frequencies are expected to fall somewhere in-between.

Regarding the weighting scheme, we follow the custom in the asset pricing literature and employ either equal or value weighting. Note that a value weighted portfolio in a buy-and-hold strategy remains value weighted in the absence of trading costs.[13] In other words, it yields the same return as the value weighted strategy rebalanced every month, since there is effectively no rebalancing. Our accounting

[10] This figure is read from Jones (2002, Figure 3). Since his chart ends in 2000, we use the year 2000 figure for years 2001 and 2002.

[11] It is noted that there are no regular sales at the time of portfolio installation.

[12] We thank Joel Hasbrouck for making his data available on his website.

[13] A buy-and-hold strategy initiated with equally weighted portfolios will stay neither equally nor value weighted.

scheme above also implies this. For this reason, we consider another value weighting scheme. When we say a strategy is rebalanced every month with value weighting, the stocks keep value weighted according to the market capitalization at the time of *previous* portfolio formation.[14] Thus, this results in four exclusive strategies, *ceteris paribus*, as a Cartesian product of the two weighting schemes and the two rebalancing frequencies.

This way, at the end of month 1, our portfolios are either reformed, rebalanced, or held as the strategy prescribes. This is done in a self-financing manner such that π_1 dollars are invested in L_2 and the same amount is sold short in S_2. The value of each position is $b_2 = \pi_1 - PIL_2 - PIS_2 - TCL_2 - TCS_2$, after price-impact costs and transactions fees. We compute PIL_2 and PIS_2 based only on the rebalancing amount, if any, for each stock and not on the entire π_1. At the end of month 2, the value of our total portfolio changes to $\pi_2 = (1 + r_{l2} - r_{s2} + 0.8r_2)b_2$. The amount π_2 will be the initial pre-cost investment for month 3, and so on. Thus, the portfolio dynamics are governed by

$$b_t = \pi_{t-1} - PIL_t - PIS_t - TCL_t - TCS_t - ECL_t - ECS_t \tag{8}$$

$$\pi_t = (1 + r_{lt} - r_{st} + 0.8r_t)b_t \tag{9}$$

for $t \in \{1, 2, \ldots, T\}$. The excess returns are calculated for each period by

$$R_t = \pi_t/\pi_{t-1} - 1 - r_t. \tag{10}$$

Now, the break-even fund size of an arbitrage strategy can be formally defined as the maximum fund size that makes the mean excess return nonnegative, i.e.,

$$\sup\{\pi_0 \geq 0 \mid \sum_{t=1}^{T} R_t(\pi_0) \geq 0\}. \tag{11}$$

Throughout the analysis, the break-even fund size is reported in year 2002 dollars using the inflation rate calculated from the Consumer Price Index.[15]

Strictly speaking, after subtracting the price-impact costs and transaction fees, the long position would be worth $\pi_{t-1} - PIL_t - TCL_t$ dollars, while the short position $\pi_{t-1} - PIS_t - TCS_t$. In order

[14] Of course the weights should add up to 1. If a stock drops from a portfolio due to delisting or some other reason, weights are adjusted so that remaining stocks are value weighted according to the market capitalization at the previous portfolio formation without that dropping stock.

[15] Specifically, if a strategy starts in June 1963 with initial capital π_0, then we will report π_0 times the consumer price index (CPI) at December 2002 divided by its June 1963 value. The CPI is obtained from the St. Louis FRB website, http://research.stlouisfed.org/fred2/data/CPIAUCNS.txt . Since it is recorded at the beginning of each month, a lead is taken before usage. The conversion rate was 5.92 for the size and the B/M strategies (starting in June 1963), and 5.82 for the momentum strategies (starting in December 1964).

to match the value of the two positions, we can think of our accounting practice as setting aside an amount of $PIL_t + PIS_t + TCL_t + TCS_t$ dollars in riskless bonds to pay the costs. This strategy aims at reducing the total risk by equalizing the values of the long and short positions.

Having established the portfolio accounting policy, we may now examine the profitability of anomaly based strategies in the presence of trading costs, especially price-impact costs. For brevity, we will mainly present results with the VWAP price impact. The results with the tick-by-tick price impact are similar, and therefore will be shown only when a large break-even fund size calls for thorough investigation.

3.1 Size Arbitrage Strategies

The size strategy buys the largest capitalization decile and sells short the smallest one. Following Fama and French (1993), we use the NYSE breakpoints to classify the NYSE, AMEX, and NASDAQ stocks into size deciles.[16] Only common stocks traded on these three exchanges or trading system are used (CRSP share code 10 or 11). Starting from 1963, the portfolios are formed at the end of each June and held for a year. Returns are measured monthly from July 1993 through December 2002. We also examined the period in Fama and French (1993), namely from July 1963 to December 1991, but the results are not materially different and hence omitted.

Table 5 reports the results for the size arbitrage strategy rebalanced every month, either equal weighting (Panels (a) and (b)) or value weighting (Panels (c) and (d)) is used at portfolio formation, when the VWAP price impact is used. Panel (a) shows that our size strategy renders a significantly positive monthly excess return of 0.505% before cost. The benchmark CRSP equally weighted (EW) portfolio yielded a slightly higher excess return, while we should be careful in comparing these two numbers because our strategy is a long-short arbitrage strategy (see the expression for the end-of-period portfolio value in (9)).

The first two columns in Panel (b) of Table 5 show how the mean excess return decreases with fund size, when price-impact and transaction costs are taken into account. The mean excess return is the average of excess returns in (10) over the strategy years. Unlike the maximum excess return, the minimum excess return dramatically decreases with the fund size because of the increasing price impact costs. The increase in standard deviation is primarily due to this downside risk. Obviously, the Sharp ratio worsens with fund size in the presence of trading costs. The maximal fund size that generates a nonnegative mean excess return is $139 million. Note however that the mean return is insignificant

[16] Size is defined as the price times the number of shares outstanding in the CRSP dataset. It is confirmed that our NYSE size (and B/M) breakpoints are fairly close to those available on Ken French's web site.

even at the fund size of \$1 million.

The panel also shows three important measures of tradability, the mean price impact, the mean turnover, and the average number of stocks. Using the previous notation, the mean price impact is defined as the average of PIL_t/π_{t-1} and PIS_t/π_{t-1} for the long and short positions, respectively. The mean turnover is the average of the dollar amount invested or rebalanced in month t divided by π_{t-1}. For a small fund size, the mean price impact is substantially higher for the long position than for the short position because of the higher turnover and the dominance of the small-stock price impact over other deciles (see Figure 7). The higher turnover results from the fact that small firms tend to grow faster, or on the contrary, disappear. For a large fund size, say \$5 billion and over, the short position also has a non-negligible price impact because at this point the capital allocated to each stock is substantial. Note that there are only 150 stocks in the short position, compared to 2,276 in the long position. This imbalance in the number of stocks results from the use of the NYSE breakpoints, which assigns many NASDAQ stocks to the smallest decile. The long position has probably too many stocks to manage practically. If we limited it in some way, the break-even fund size would be smaller.

Panel (c) shows the results when stocks are value weighted. The excess return is positive but insignificant even if no costs are incurred. This is primarily due to the relatively good performance of blue chip firms in late 1990s. The resulting break-even fund size is below \$1 million as shown in Panel (d).

We can expect that a buy-and-hold strategy will incur lower trading costs. This is demonstrated in Table 6. In stocks are equally weighted at portfolio formation, the turnover is only 6.6% and 3.3% for the long and the short positions, respectively (Panel (b)). These figures are less than half those of the monthly rebalancing strategy in Table 5. As a result, both positions have lower price impacts. This makes up for the lower pre-cost excess return of 0.323% (Panel (a)) and still leads to a larger break-even fund size of \$417 million. When stocks are value weighted, the strategy can accommodate \$197 million before the excess return vanishes. Note however that the excess return is insignificant at any fund size regardless of the weighting scheme.

Overall, the size arbitrage strategy is not reliably profitable in the presence of trading costs. If any, it can accommodate only several hundred million dollars at most.

3.2 Book-to-Market Arbitrage Strategies

A book-to-market (B/M) arbitrage strategy buys high B/M stocks and sells short low B/M stocks. We form our portfolios in each June from 1963 through 2002 and hold them for a year. Again following Fama and French (1993), B/M is calculated as the book value divided by the market capitalization at the end of the previous year.[17] NYSE breakpoints are used to classify all the stocks on NYSE, AMEX, and NASDAQ into deciles. Our strategy then buys the highest B/M decile and sells short the lowest B/M decile. Returns are measured monthly from July 1963 through December 2002.[18]

Table 7 summarizes the results for the B/M arbitrage strategy rebalanced monthly with the VWAP price impact. When equally weighted, the strategy produces a very strong excess return of 1.133%, which is almost twice that of the benchmark CRSP index (Panel (a)). In addition, the strategy return is much less volatile than the benchmark index and the size strategy; as a result, it yields a Sharpe ratio of 0.262, over twice as large as 0.108 for the CRSP index and 0.0916 for the size strategy. Panel (b) demonstrates an important difference in tradability from the size strategy; the mean turnover, the average number of stocks, and the mean price impact are all comparable between the long and the short positions. In particular, the mean turnover of the short position is much higher than that of the size strategy. Thus, its composition seems to be changing as actively as the long position. The high price impact of the short position suggests that it now contains small stocks.[19] The break-even fund size is $315 million. The value weighted strategy is again less profitable and accommodates only $37 million (Panel (d)).

Does a buy-and-hold strategy work? Table 8 says the answer is positive but with a caveat. Unlike the size strategy, the B/M strategy preserves its fundamental strength without frequent weight adjustment; the buy-and-hold strategy renders a pre-cost excess return of 1.04% and a Sharpe ratio of 0.252. Coupled with a lower turnover below 10% for both positions, it yields the break-even fund size of $4.60 billion (Panel (b)). However, interpretation of this seemingly large number requires care, since the mean excess return is insignificantly different from zero if as little as $500 million is invested. The value weighted strategy in Panel (d) can hold only $73 million.

Because of the relative profitability of the B/M strategy, we investigate the issue further using the tick-by-tick price impact. Tables 9 and 10 present the results for the monthly rebalancing and the buy-and-hold strategies, respectively. In short, the results are very similar with this alternative measure of price impact. If equally weighted, the break-even fund size is $545 million when rebalanced monthly,

[17] We calculate the book value of a firm as the Compustat balance-sheet stockholders' equity plus deferred taxes and investment tax credit less preferred stock. For preferred stock, we use the first available of the redeemable, liquidating, or carrying value. Negative-book-value firms are excluded from the analysis.

[18] Davis, Fama, and French (2000) augments the construction of B/M by Moody's data in conjunction with Compustat. The benefit of the Moody's dataset is primarily in early years when Compustat entries are not available. We also tried this method and confirmed that the results are similar to what follows. We thank Ken French for making the Moody's data available.

[19] Indeed, it is likely that both the long and short positions contain small stocks. It is known in the literature that a part of the B/M effect is in fact a small-firm effect: high B/M small stocks and low B/M small stocks exhibit the widest spread among all possible high and low B/M groups (e.g., Loughran and Ritter (2000)).

and \$4.64 billion when bought-and-held. The mean price impact is surprisingly close to the VWAP price impact regardless of the weighting scheme and the rebalancing frequency.

3.3 Size-B/M Combined Arbitrage Strategies

It is widely accepted that size and B/M span the cross section of stock returns (Fama and French (1993)). Our next task is to examine the validity of this proposition under the additional assumption of trading costs. We sort all the stocks by size and B/M independently into five-by-five cross sections. Our arbitrage strategy then buys the smallest, highest B/M group and sells short the biggest, lowest B/M group annually in each June. Other features of the strategy are unchanged from the previous section.

Panels (a) and (b) of Tables 11 and 12 present the results for the monthly rebalancing and the buy-and-hold strategies, respectively, when returns are equally weighted and costs are assessed by the VWAP price impact. Regardless of the rebalancing frequencies, the risk-return and cost profile of the equally weighted size-B/M strategy falls somewhere between the two independent strategies; the mean and the standard deviation of the pre-cost excess return, the Sharpe ratio, the mean price impact, and the mean turnover all fall between the corresponding numbers for the size (Tables 5 and 6) and the B/M (Tables 7 and 8) strategies. The break-even fund sizes are \$489 million when rebalanced monthly and \$955.3 million when bought-and-held.

When value weighted, the combined strategy works better than the size and the B/M strategy (Panels (c) and (d) of Tables 11 and 12). The mean pre-cost excess return is 0.624% and 0.563% for the monthly rebalancing and the buy-and-hold strategies, respectively, leading to break-even fund sizes of \$89 million and \$795 million. Recall why the value weighted B/M arbitrage strategy did not work–the reason is that the highest B/M decile contains small firms that tend to render superior returns. The combined strategy seems to alleviate this problem by separating the size and the B/M effects.

3.4 Momentum Strategies

Momentum strategies are known as one of the most profitable trading strategies (Jegadeesh and Titman, (1993, 2001)). We implement the standard momentum J/K strategies where J and K denote the ranking and the holding periods, respectively. Specifically, every month t from December 1964 through November 2002, stocks are sorted into deciles by the past J month returns (month $t-(J-1)$ to t). Following Jegadeesh and Titman (2001), we use stocks on the NYSE, AMEX, and NASDAQ, excluding those with a price less than \$5 and those that belong to the bottom size decile using the NYSE breakpoint. The strategy buys the decile with the highest past returns (winners) and sells short the decile with the lowest ones (losers) and holds them for the next K months (month $t+1$ to $t+K$). Thus, there are K overlapping monthly cohorts in each of the long and the short positions. The size and the \$5 price screens are meant to mitigate microstructure concerns. For this reason, we do not skip a month between the ranking and the holding periods.[20] Also, this screening will exclude stocks that are hard to short. D'Avolio (2002) finds that one third of the stocks in the bottom size decile and one third of stocks priced under \$5 appear unshortable.

Again, we consider two rebalancing frequencies, monthly rebalancing and buy-and-hold. When rebalanced monthly, the K cohorts will always be equally weighted, while the component stocks in each cohort can be equally or value weighted. In a buy-and-hold strategy, the cohorts are equally weighted only at the inception of the strategy. The component stocks in a cohort, however, can be equally or value weighted at cohort formation (every K months). Thus, under either rebalancing frequency, only $1/K$ of all the stocks are unwound in a given month to form a new cohort (stock selection). In a buy-and-hold strategy, only these stocks are subject to trading, while in a monthly rebalancing strategy all stocks are rebalanced (weight adjustment). Returns are measured from January 1965 through December 2002.

Following Jegadeesh and Titman (2001), we first examine the momentum 6/6 strategy thoroughly. Table 13 shows the results with monthly rebalancing and the VWAP price impact. While the equally weighted strategy offers the highest return ever (1.197% before cost, Panel (a)), the break-even fund size is only \$53 million (Panel (b)). The reason is the high turnover reaching upper 30%'s monthly, which is more than twice the turnovers of other strategies we have examined. The value weighted strategy produces a slightly lower return before cost but a larger break-even fund size of \$90 million because of decreased price impact. The equally weighted buy-and-hold strategy produces a monthly excess return of 1.306% before cost, but the maximal fund size is still \$271 million (Table 14, Panels (a) and (b)). The results are similar if the tick-by-tick price impact is used in Tables 15 and 16.

Table 17 tabulates the statistics for various equally-weighted buy-and-hold momentum J/K strategies, where $J \in \{3, 6, 9, 12\}$ and $K \in \{1, 3, 6, 9, 12\}$. Panel (b) confirms the findings of the existing literature that the 12/3, 12/1, and 6/6 strategies produce highest pre-cost returns. This, however, does not translate to a large break-even fund size in Panel (a); these strategies admit no more than several hundred million dollars, because of the high monthly turnovers shown in Panel (d) and hence high price-impact costs.[21] In contrast, the most accommodative strategies are the 6/9 and 6/12 strategies,

[20] Nevertheless, we performed a spot check by skipping a month between the ranking and the holding periods. The results were not materially different.

[21] Moskowitz and Granblatt (1999, p.1274) observe that the high turnover ratio of their 1/1 industry momentum strategy would appear to preclude profits after costs, despite its high return. They note that the profitability of the 6/6 industry momentum strategy will be a subject of future research (p.1272).

which can trade as much as \$1.73 billion and \$1.69 billion before the excess return vanishes. However, the fund sizes that produce a significantly positive excess return are only several hundred million dollars (not shown). In addition, Panel (c) indicates that these strategies employ an unrealistically large number of stocks, more than 3,000 in the two positions combined.[22]

Table 18 indicates that the value weighted strategy produces lower excess returns and hence smaller break-even fund sizes. Results with the tick-by-tick price impact in Tables 19 and 20 are similar in nature. To summarize, we could confirm the high pre-cost excess returns of momentum strategies, but it seems rather difficult to exploit them practically under trading costs.

4 Discussions

The experiments in the previous sections question the profitability of anomaly-based strategies when trading costs are incurred. In this section, we investigate the robustness of our results by incorporating more realistic assumptions and extending the search over wider strategy spaces. We then interpret our results and compare them to related papers.

4.1 Trade Restriction and Position Limit

So far, we have implicitly assumed that any trade can be executed in one shot. In reality, however, traders often “work” an order; a large trade is divided up into smaller pieces and executed over time. As seen in Figure 3, actual trades are rarely larger than 1% of the market capitalization. In addition, holding more than 5% of it requires costly filings with the SEC (Form 13D). For this reason, we additionally impose two restrictions on our strategies. The 1% trade restriction requires any single trade to be no larger than 1% of the market capitalization. For example, if we trade \$2.5 million of a \$100 million firm, we place two \$1 million orders and a \$0.5 million order, and compute price impact accordingly. The 5% position limit admits no position in a single stock larger than 5% of the market capitalization. If a stock’s position exceeds this limit, the excessive funds are allocated to a largest stock in the same portfolio (or cohort in momentum strategies). If the largest stock cannot accommodate the excessive fund, the rest goes to the second largest, and so on. If the position limit is reached for all stocks, it is noted and funds are value weighted. Note that for a value weighted portfolio, the 5% position limit will be binding for all stocks if and only if it is binding for one stock.

Figure 10 shows the effect of these two restrictions on the size-B/M combined strategy with the

[22] A caveat is that overlapping is likely; one stock may be contained in multiple cohorts at a given time. The actual number of different stocks are probably less than those shown in the table.

VWAP price impact. We focus here on the more profitable equally weighted strategy. The circles depict the relation between the arbitrage fund size and the mean excess return (the first two columns in Table 12). As already discussed, the break-even fund size of the "plain vanilla" strategy was $955 million.[23] When the 1% trade restriction is imposed, the break-even fund size dramatically decreases to approximately $110 million. This is due to the concavity of price impact functions. It should be noted that such a trading strategy may not be optimal in that it does not optimize the sequence of trades. Huberman and Stanzl (2003) study the problem of optimally executing a given portfolio when trades incur price impact.

When the 5% position limit alone is imposed, the break-even fund size is about $350 million. In general, the effect of the 5% position limit is ambiguous. Allocating more funds to larger stocks will result in lower price-impact costs, but it could also reduce returns. It appears that the latter dominates the former for the current strategy. When both the trade restriction and the position limit are imposed, the break-even fund size is about $170 million.

4.2 Changing Trade Frequencies

Can we improve if we form our portfolios (reselect stocks) more frequently? Our hope is that we may be able to "fine-tune" our strategies to anomalies. An obvious drawback is the increased turnover and price impact. We have already done this analysis for momentum strategies. Frequent rebalancing means a low value of K (holding period) in Tables 17-20. The message there was that the increased trading costs exceeded the benefit.

We now examine this point for the size and B/M strategies. To save space, we again focus on the equally weighted combined strategy. In addition to annual frequency, we form portfolios semiannually and quarterly.[24] Figure 11 shows the results. As the rebalancing frequency doubles from annual to semiannual and to quarterly, the break-even fund size falls from $955 million to about $380 million and to a mere $50 million. Clearly, the cost associated with frequent rebalancing ruins the possible benefit of return increase.

4.3 Short-sale Constraint and Long–position-only Strategies

One advantage of a long-short arbitrage strategy over a strategy involving only a long position is that it allows one to be near market neutral. While this typically helps reduce return variability and improve

[23] The figure apparently shows a little smaller break-even fund size of approximately $900 million. This results from the difference in interpolation. The numbers mentioned in the text are computed by a linear interpolation between two fund sizes. The graphical representation here employs a cubic Hermite interpolation.

[24] In line with the annual strategy, B/M is calculated by the book and the market values six months ago.

the Sharpe ratio, an obvious drawback is that it may be difficult to create the short position because of illiquidity or market frictions. Therefore, it is of interest to examine whether strategies involving only a long position work. Here, we focus again on one of the most accommodative strategies, the 6/12 buy-and-hold equally-weighted momentum strategy, with the VWAP price impact used for cost calculation. A further discussion of short sale constraints is provided in the Conclusion.

Table 21 summarizes the break-even fund size of the winner-only strategy. The monthly excess return is 1.013% before cost, which is slightly lower than 1.028% for the long-short arbitrage strategy in Panel (b) of Table 17. This is because the loser portfolio offers a return that is approximately 10bp lower than that of the Federal Fund on average over our sample period. The standard deviation of excess return is 7.58%, which is considerably lower than 4.43% for the arbitrage strategies (not shown). The absence of the short position and the associated price impact allows the winner-only strategy to accommodate much more capital; the break-even fund size is $21.5 billion. The mean turnover is approximately halved. Although not shown, the break-even fund size reduces to $14.6 billion with both the 1% trade restriction and the 5% position limit. When Hasbrouck's (2003) Gibbs sampling estimates of effective costs are additionally included (ECL_t and ECS_t in equation (8)), this further decreases to $10.6 billion.

While these numbers may seem fairly large, their interpretation again needs care. The fund size that offers a statistically significant excess return is much smaller than them. The t-statistic of 1.24 for $1 billion indicates that only several hundred million dollars may be invested to produce a significant positive return at any reasonable confidence level.

4.4 Comparison with Actual Hedge Fund Size

In this section, we compare our estimates to the actual size of all relevant hedge funds and mutual funds, since we are investigating the rationality of market participants as a whole. The idea here is to simply compare apples to apples. Each break-even fund size estimated in the previous sections should be interpreted as an additional fund size attainable to the market. Indeed, we have implicitly studied a monopolistic arbitrageur who attempts to create a single, largest fund from a set of possible strategies. Thus, our reference point should be the total anomaly-driven investment that produce price-impact and other costs, and not the size of funds that follow a particular strategy.

Table 22 presents the summary statistics of the size of equity hedge funds by investment approach as defined in the TASS dataset. The data come from TASS Management Limited and covers 1,501 hedge funds as of June 2002. As the table shows, the total size of equity hedge funds in the TASS dataset is $241 billion, whereof $86 billion is invested in arbitrage strategies. Because of the private nature of hedge funds, it is likely that the actual hedge fund industry is much larger than this.

According to Hennessee Group's (2003) comments submitted to an SEC hedge fund roundtable, 5,700 funds manage $592 billion as of January 2003. Of this, 62% is invested in long-short equity strategies, which amounts to roughly $350 billion or more. Added to this should be mutual funds. Table 23 shows the size of small-cap and value equity funds in the CRSP mutual fund dataset at the end of 2002.[25] From this we roughly estimate the size of relevant mutual funds to be at least $300 billion. Thus, an identified $650 billion is already deployed in the market, seeking the potential profit opportunities based on the three popular anomalies. We believe that this is a conservative estimate of money that is subject to price impact, given the size of domestic equity mutual funds totaling $2.3 trillion (in 2002). The largest of our break-even fund sizes, $10-20 billion, represent no more than 2-3% of the $650 billion. This is also well within a tolerance of weekly volatility. In addition, this investment is not worth pursuing, since one could earn the same return by just investing in a safe deposit or Treasury securities. If he wishes to secure a significantly positive excess return, he can invest only several hundred million dollars. Moreover, some of these most accommodative strategies, such as momentum strategies with a holding period of 12 months, hold too many stocks to manage practically. Even mammoth mutual funds with tens of billions of dollars in asset, such as Vanguard 500 Index, American Funds Investment Company of America, and Fidelity Magellan, invest in no more than several hundred stocks.

It should be noted that the hedge fund industry has grown considerably since the end of our sample period, December 2002. According to Hennessee Group, there are currently 7,000 hedge funds with an $845 billion asset under management as of mid 2004 (Davis (2004)). This is a huge gain from the $400 billion asset administered by 4,800 funds at the end of 2000, and 1,640 funds a decade ago. According to Davis (2004), about three quarters of annual revenue is currently generated by equity trading, with the rest coming from bonds, commodities, currencies, and options. If revenue is proportional to the assets under management, a reasonable estimate of the current size of equity hedge funds would be $600-$700 billion. We think that this growth is too rapid to be explained by the existence of possible arbitrage opportunities. Other factors include the recovery of the stock market as a whole[26] and the increased recognition of hedge funds as alternative investments. The market may have grown, or reach soon, to the point where the apparent profit opportunities are not really exploitable in a systematic manner. Indeed, as of July 2004, new hedge funds are still being created in the order of a few billion dollars despite the fact that returns are pressed (Sender (2004)). In the same month, the Federal Reserve Chairman Alan Greenspan also gave the testimony that already appeared in the Introduction of the

[25] See the table caption for definition.

[26] According to the CRSP dataset, the total market value has increased to $13.9 trillion at the end of 2003 from $11.6 trillion in 2002.

current paper.

Our results address an important question of investor rationality. The existence of market anomaly does not necessarily imply that there is too much money left on the table. Rather, investors have been continuously trying to exploit profit opportunities, as represented by the huge size of relevant hedge funds and mutual funds. Still, various market frictions, such as trading costs and short sale constraint, prevent traders from fully exploiting anomalies. Our results indicate that price impact alone may be enough to deter arbitrage.

4.5 Relation to Other Studies

The two most related papers are Korajczyk and Sadka (KS)(2004) and Lesmond, Schill and Zhou (2004). Both of them focus on the post-cost profitability of momentum strategies and reach opposite conclusions. In this section, we discuss the difference between these two papers and our results on momentum.

KS propose a "liquidity weighted" strategy which maximizes after-cost returns under some simplifying assumptions. They find that certain winner-only momentum strategies can accommodate as much as $5 billion before the profit opportunities disappear. From this they conclude that transaction costs, including price-impact costs, do not fully explain the return continuation, and that "this anomaly remains an important puzzle." (KS (2004, p.1040)) The break-even fund sizes from our winner-only strategies are larger than theirs, while our fund sizes that produce a significantly positive return are smaller. Main differences include the followings:

1. *Stock weighting.* In addition to the traditional equal and value weighting, KS minimize price impact costs by explicitly solving an optimization problem. Their optimization is a static single-period problem, which by construction excludes a buy-and-hold strategy. However, we find that equally weighted buy-and-hold strategies are the most accommodative strategies in the class of strategies we consider.

2. *Conversion ratio.* KS use the total market capitalization to convert 1997 dollars to 1999. The ratio is 29.7. We use the Consumer Price Index, and the conversion ratio for our momentum strategies is 5.82.

3. *Price impact functions.* We model returns as a concave function of dollar volume, while KS formulate either returns as a linear function of percentage turnover (Breen, Hodrick, Korajczyk (2002)), or price changes as a linear function of the number of shares traded and the trade direction

(Glosten and Harris (1988)). *Ceteris paribus*, use of a concave function will produce a lower price impact for a large enough fund size.

4. *Portfolio formation.* We exclude stocks in the smallest size decile as well as those with a price less than $5. This tends to reduce price impact. Because of these screening, we do not skip a month between the ranking and the holding periods. KS skip a month.

5. *Sample period.* KS use a 1967-1999 period. We measure returns from 1965 to 2002. Given the market performance between 1999 and 2002, our momentum returns are likely to be weaker.

6. *Risk adjustment.* KS adjust their returns for the Fama-French three risk factors and use the regression alpha. We choose to make our profit measure model-free and simply use excess return. The regression alpha would have a lower standard error than the excess return itself.

Points 1 and 2 tend to understate our break-even fund sizes relative to KS, while Points 3, 4, and 5 would overstate them.

In contrast to KS, LSZ find that stocks that generate large returns in standard momentum strategies are precisely those stocks with high trading costs. They conclude that the apparent large returns associated with momentum strategies create "an illusion of profit opportunity when, in fact, none exists." (LSZ (2004, p.349)) The biggest difference from our study is that their "trading cost measures do not explicitly include price impact costs." (LSZ (2004, p.370)) They compare the returns and costs in percentage and therefore do not report break-even fund sizes.

Unlike these two papers that focus on the profitability of a particular strategy, specifically momentum, we discuss the rationality of the aggregate market in which all popular anomaly-based strategies are practiced.

5 Conclusion

This paper examines whether one can take advantage of the size, B/M, or momentum anomaly when price-impact costs are taken into consideration. We construct long-short arbitrage strategies based on these anomalies and compute maximum fund sizes that render nonnegative excess returns after cost. We find that most profitable arbitrage strategies are equally weighted, buy-and-hold B/M and momentum strategies, which accommodate up to several billion dollars. When short sale constraint is imposed, the winners-only momentum strategies can hold approximately $20 billion before the excess return vanishes. However, the fund sizes that secure statistically significant excess returns are at most several million dollars for all anomalies. Imposing trading frictions, such as the 1% trade restriction and the

5% position limit, can only decrease the break-even fund size in favor of our results. These support the idea that markets are minimally rational in the sense of Rubinstein (2001).

While this paper attempts to incorporate important aspects of trading practice and constraints in the real market, there are still some points left for future research. First, our search for profitability is confined only to a subset of the whole strategy space, from both the cost and the benefit perspective. For example, trading costs will be less relevant in a long term contrarian strategy. Also, dynamic as well as cross-sectional optimization of costs and returns might also prove rewarding.

Second, our strategy, like any monthly or lower frequency strategy, does not fully recognize the "working" of a trade. This an example of dynamic minimization of trading costs. While our VWAP price impact was meant to address this at least partially, explicitly splitting a large trade into smaller pieces and executing them over time might prove effective in a higher-frequency strategy.

Finally, we have kept the modeling of short-sale constraints minimal. While the results of D'Avolio (2002), Geczy, Musto, and Reed (2002), and Jones and Lamont (2002) indicate that short selling restrictions alone do not appear to explain the three anomalies that we study, the effect of the restrictions in most of our sample period is generally unknown; these three studies collectively cover only four years (1998-2001) of our sample period, and Jones and Lamont note that the relation between shorting costs and portfolio characteristics is time varying. For example, using a 1926-1933 dataset, they show that stocks with high shorting costs tend to have a higher past return, which contradicts D'Avolio's finding from 2000-2001 that momentum losers are likely to be high cost stocks.

References

[1] Amihud, Yakov, 2002, Illiquidity and stock returns: cross section and time-series effects, *Journal of Financial Markets*, 5, 31-56.

[2] Banz, Rolf W., 1981, The Relationship between Return and Market Value of Common Stocks, *Journal of Financial Economics* 9, 3-18.

[3] Basu, Sanjoy, 1983, The Relationship between Earnings Yield, Market Value, and Return for NYSE Common Stocks: Further Evidence, *Journal of Financial Economics* 12, 129-156.

[4] Bertsimas, Dimitris, and Andrew W. Lo, 1998, Optimal Control of Execution Costs, *Journal of Financial Markets* 1, 1-50.

[5] Blume, Marshall, A. Craig MacKinlay, and Bruce Terker, 1989, Order Imbalances and Stock Price Movements on October 19 and 20, 1987, *Journal of Finance* 44 (4), 827-848.

[6] Breen, William J., Laurie Hodrick, and Robert A. Korajczyk, 2002, Predicting Equity Liquidity, *Management Science* 48, 470-483.

[7] Chan, Louis K., and Josef Lakonishok, 1995, The Behavior of Stock Prices around Institutional Trades, *Journal of Finance* 50 (4), 1147-1174.

[8] Davis, Ann, 2004, "High-Flying Hedge Funds Face Tougher Scrutiny From Regulators," *Wall Street Journal*, 7/22/2004, Page A1.

[9] Davis, James L., Eugene F. Fama, and Kenneth R. French, 2000, Characteristics, Covariances and Average Returns: 1929-1997, *Journal of Finance*, 55, 389-406.

[10] D'Avolio, Gene, 2002, The Market for Borrowing Stock, *Journal of Financial Economics* 66, 271–306.

[11] Dutta, Prajit K., and Ananth Madhavan, 1995, Price Continuity Rules and Insider Trading, *Journal of Financial and Quantitative Analysis* 30 (2), 199-221.

[12] Fama, Eugene F., and Kenneth R. French, 1993, Common Risk Factors in the Returns on Stocks and Bonds, *Journal of Financial Economics* 33, 3-56.

[13] Geczy, Christopher C., David K. Musto, and Adam V. Reed, 2002, Stocks Are Special Too: An Analysis of The Equity Lending Market, *Journal of Financial Economics* 66 (2-3), 241-269.

[14] Gemmill, Gordon, 1996, Transparency and Liquidity: A Study of Block Trades on the London Stock Exchange under Different Publication Rules, *Journal of Finance* 51 (5), 1765-1790.

[15] Glosten, Lawrence R., and Lawrence E. Harris, 1988, Estimating the components of the bid/ask spread, *Journal of Financial Economics* 21, 123-142.

[16] Hasbrouck, Joel, 1991, Measuring the Information Content of Stock Trades, *Journal of Finance* 46 (1), 179-207.

[17] Hasbrouck, Joel, 2003, Trading Costs and Returns for US Equities: The Evidence from Daily Data, working paper, New York University.

[18] Hasbrouck, Joel, and Thomas S. Ho, 1987, Order Arrival, Quote Behavior, and the Return-Generating Process, *Journal of Finance* 42 (4), 1035-1048.

[19] Hausman, Jerry A., Andrew W. Lo, and A. Craig MacKinlay, 1992, An Ordered Probit Analysis of Transaction Stock Prices, *Journal of Financial Economics* 31, 319-379.

[20] Hennessee Group, 2003, "Comments of Hennessee Group LLC for the U.S. Securities and Exchange Commission, Roundtable on Hedge Funds, May 14-15, 2003" downloadable at http://www.hennesseegroup.com/Featured_Articles/SECHedgeFundRoundtable200305.pdf.

[21] Holthausen, Robert, Richard Leftwich, and David Mayers, 1987, The Effect of Large Block Transactions on Security Prices, *Journal of Financial Economics* 19, 237-267.

[22] Huberman, Gur, and Werner Stanzl, 2004, Price Manipulation and Quasi-Arbitrage, *Econometrica*, 72 (4), 1247-1275.

[23] Huberman, Gur, and Werner Stanzl, 2003, Optimal Liquidity Trading, Working Paper, Yale School of Management.

[24] Jegadeesh, Narasimhan, and Sheridan Titman, 1993, Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency, *Journal of Finance* 48 (1), 65-91.

[25] Jegadeesh, Narasimhan, and Sheridan Titman, 2001, Profitability of Momentum Strategies: An Evaluation of Alternative Explanations, *Journal of Finance* 56 (2), 699-720.

[26] Jones, Charles M., 2002, A Century of Stock Market Liquidity and Trading Costs, Working Paper, Columbia University.

[27] Jones, Charles M., and Owen A. Lamont, 2002, Short-sale constraints and stock returns, *Journal of Financial Economics* 66, 207-239.

[28] Keim, Donald B., 1983, Size-Related Anomalies and Stock Return Seasonality: Further Evidence, *Journal of Financial Economics* 12, 13-32.

[29] Keim, Donald B., and Ananth Madhavan, 1996, The Upstairs Market for Large Block Transactions: Analysis and Measurement of Price Effects, *Review of Financial Studies* 9 (1), 1-36.

[30] Kempf, Alexander, and Olaf Korn, 1999, Market Depth and Order Size, *Journal of Financial Markets* 2 (1), 29-48.

[31] Knez, Peter J. and Mark J. Ready, 1996, Estimating the Profits from Trading Strategies, *Review of Financial Studies* 9 (4), 1121-1163.

[32] Korajczyk, Robert, and Ronnie Sadka, 2004, Are Momentum Profits Robust to Trading Costs, *Journal of Finance*, 65 (3), 1039-1082.

[33] Kyle, Albert S., 1985, Continuous Auctions and Insider Trading, *Econometrica* 53 (6), 1315-1336.

[34] Lahart, Justin, 2004, Fearful Symmetry in Hedge-Fund Holdings, *Wall Street Journal*, 7/30/2004, Page C1.

[35] Lakonishok, Shleifer, and Vishny, 1994, Contrarian Investment, Extrapolation, and Risk, *Journal of Finance* 49 (5), 1541-1578.

[36] La Porta, Lakonishok, Shleifer, and Vishny, 1997, Good News for Value Stocks: Further Evidence on Market Efficiency, *Journal of Finance* 52 (2) 859-874.

[37] Lauricella, Tom, 2004, Same Managers! Same Strategy! New Fund?, *Wall Street Journal*, 7/20/2004, Page C1.

[38] Lee, Charles, and Mark Ready, 1991, Inferring Trade Direction from Intraday Data, *Journal of Finance* 46 (2), 733-746.

[39] Lesmond, David A., Michael J. Schill, and Chunsheng Zhou, 2004, "The illusory nature of momentum profits," *Journal of Financial Economics*, 71, 349-380.

[40] Levy, Robert, 1967, Relative Strength as a Criterion for Investment Selection, *Journal of Finance* 22, 595-610.

[41] Loughran, Timothy and Jay R. Ritter, 2000, Uniformly least powerful tests of market efficiency, *Journal of Financial Economics* 55, 361-390.

[42] Moskowitz, Tobias J., and Mark Grinblatt, 1999, Do Industries Explain Momentum?, *Journal of Finance* 54 (4), 1249-1290.

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

[44] Rubinstein, Mark, 2001, Rational Market: Yes or No? The Affirmative Case, Working Paper, University of California, Berkeley.

[45] Scholes, Myron S., 1972, The Market for Securities: Substitution versus Price Pressure and the Effects of Information on Share Prices, *Journal of Business* 45, 179-211.

[46] Sender, Henny, 2004, "Goldman Sachs Loses a Star Trader," *Wall Street Journal*, 7/21/2004, Page C5.

Table 1
Characteristics of Selected Stocks

This table shows the characteristics of selected stocks. All raw data are from CRSP and Compustat. Price is the closing price as of the end of December 1992. #Shares is the number of shares outstanding in thousands as of the end of December 1992. ME is the market value of equity in millions of dollars and equals Price times Number of Shares Outstanding. BE is the book value of equity in millions of dollars as of the end of the fiscal year 1992, and is given by Compustat book value of shareholders' equity plus deferred taxes less the book value of preferred stock. B/M is the book-to-market ratio and equals BE divided by ME. Volume is the sum of the number of shares traded on all trading days in December 1992 in thousands.

Ticker	Company Name	Exchange	Price	#Shares	ME	BE	B/M	Volume
GE	General Electric Co.	NYSE	85.500	854,039	73,020	27,999	0.383	21,487
KO	Coca Cola Co.	NYSE	41.875	1,309,905	54,852	3,970	0.072	32,316
BONT	Bon Ton Stores Inc.	NASDAQ	7.250	4,980	36	90	2.505	814
CSII	Communications System Inc.	NASDAQ	15.375	4,427	68	35	0.511	160
S	Sears Roebuck Co.	NYSE	45.500	345,290	15,711	9,212	0.586	17,546
INGR	Intergraph Corp.	NASDAQ	13.250	47,558	630	749	1.189	4,703
MIKE	Michaels Stores Inc.	NASDAQ	34.000	16,355	556	155	0.279	4,582

Table 2
Estimated Parameter Values of The Box-Cox Model

This table shows the estimated parameter values of the Box-Cox model. The estimated model is $PI_t = a_B + b_B (V_t^{\lambda_B} - 1)/\lambda_B + \varepsilon_t$ for buys and $PI_\tau = a_S - b_S (V_\tau^{\lambda_S} - 1)/\lambda_S + \varepsilon_\tau$ for sells with the restriction $0 \le \lambda_B, \lambda_S \le 1$, where PI_t (PI_τ) is the price impact of a trade measured as the relative quote midpoint change and V_t (V_τ) is the dollar volume. The estimation is by nonlinear least squares. t-stats are shown in parentheses. When λ_B or λ_S hits the lower bound, a log function is re-fitted. For such cases, t-stats are not reported.

	GE	KO	BONT	CSII	S	INGR	MIKE
(a) Buys							
Nobs	23,265	23,157	518	1,212	10,826	2,329	4,704
a_B ($\times 10^{-3}$)	-0.020	-0.060	-5.28	-3.89	-0.13	-0.49	-0.78
	(-1.34)	(-3.71)	(-2.75)	(-5.11)	(-3.07)	(-1.99)	(-6.69)
b_B ($\times 10^{-4}$)	0.00308	0.0109	6.53	4.91	0.0379	0.770	0.940
	(2.27)	(3.20)	(3.04)	(5.69)	(2.27)	(2.77)	(7.91)
λ_B	0.468	0.410	0.000	0.000	0.302	0.000	0.000
	(12.51)	(15.05)	(--)	(--)	(7.97)	(--)	(--)
(b) Sells							
Nobs	25,543	25,029	523	692	16,368	1,710	4,362
a_S ($\times 10^{3}$)	-0.018	0.020	1.370	2.830	0.030	0.870	0.300
	(-2.49)	(1.50)	(0.70)	(2.47)	(1.65)	(3.05)	(2.36)
b_S ($\times 10^{4}$)	-0.000774	-0.004061	-2.740000	-3.720000	-0.003922	-1.200000	-0.470000
	(-1.95)	(-3.13)	(-1.30)	(-3.01)	(-2.38)	(-3.83)	(-3.68)
λ_S	0.575	0.499	0.000	0.000	0.502	0.000	0.000
	(13.17)	(18.11)	(--)	(--)	(13.79)	(--)	(--)

Table 3
Estimated Parameter Values of The Linear Model

This table shows the estimated parameter values of the linear model and the comparison of the linear and the Box-Cox fits for buy orders. The estimated linear model is $PI_t = \alpha_B + \beta_B V_t + \varepsilon_t$, where PI_t is the price impact of a trade measured as the relative quote midpoint change and V_t is the dollar volume. The estimation is by ordinary least squares. t-stats are shown in parentheses. The price impacts for the Box-Cox model is calculated by using the estimated parameter values given in Table 2.

	Ticker Symbol						
	GE	KO	BONT	CSII	S	INGR	MIKE
Nobs	23,265	23,157	518	1,212	10,826	2,329	4,704
α_B ($\times 10^{-4}$)	0.614	0.822	3.464	1.288	1.394	1.467	1.200
	(24.22)	(21.81)	(1.11)	(1.16)	(23.12)	(3.57)	(6.83)
β_B ($\times 10^{-8}$)	0.0455	0.0829	1.075	2.657	0.0631	0.2690	0.0403
	(37.04)	(42.43)	(0.90)	(4.02)	(27.56)	(1.77)	(1.64)
(a) Price impact from $50,000 trade (bp)							
Linear	0.84	1.24	8.84	14.57	1.71	2.81	1.40
Box-Cox	0.83	1.62	17.85	14.23	1.87	3.43	2.37
Difference	0.01	-0.38	-9.01	0.35	-0.16	-0.62	-0.97
(b) Price impact from $300,000 trade (bp)							
Linear	1.98	3.31	35.72	80.99	3.29	9.54	2.41
Box-Cox	2.20	4.05	29.55	23.02	4.24	4.81	4.05
Difference	-0.22	-0.74	6.17	57.97	-0.96	4.73	-1.65

Table 4
Estimated Parameter Values for Portfolio Price Impact Functions

The estimated parameter values for the portfolio price-impact functions by size decile. First, we estimate the individual price-impact functions as described in the note to Table 2. The parameter value of a portfolio price-impact function for a given decile is computed as the equally weighted average of the individual parameter values for the stocks in the decile.

Size	a_B (x10^{-3})	b_B (x10^{-4})	λ_B	a_S (x10^{-3})	b_S (x10^{-4})	λ_S
Small	-1.98	4.56	0.245	0.16	-2.41	0.285
2	-1.95	3.15	0.198	1.16	-2.29	0.206
3	-1.69	2.48	0.155	1.13	-2.03	0.160
4	-1.65	2.53	0.121	1.13	-2.03	0.157
5	-1.53	2.44	0.113	1.10	-2.00	0.148
6	-1.59	2.33	0.108	1.41	-2.26	0.108
7	-1.52	2.10	0.108	1.24	-1.89	0.137
8	-1.22	1.49	0.133	1.19	-1.61	0.119
9	-1.00	1.11	0.168	0.99	-1.21	0.162
Big	-0.19	0.22	0.268	0.25	-0.35	0.239

Table 5
Size Arbitrage Strategy with VWAP Price Impact
Rebalanced Monthly

This table shows excess monthly returns from the size arbitrage strategy using price impact functions estimated from value-weighted average price (VWAP). The strategy buys the smallest size decile and sells short the biggest decile at the end of June from 1963 through 2002, with weights rebalanced every month to stay equally or value weighted. Calculation of size and timing of portfolio formation follow Fama and French (1993). Returns are measured from July 1963 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. Panel (a) shows the statistics for the equally weighted strategy without cost and the corresponding CRSP benchmark. Panel (b) accounts for both the price impact and transactions costs. Corresponding numbers for the value-weighted strategy are shown in Panels (c) and (d). The initial fund size is converted to 2002 dollars and shown as Arbitrage Fund Size. Mean Excess Return is the time-series average of the excess monthly returns over the sample period. Mean Price Impact and Mean Turnover are defined as the time-series average of the ratios, the dollar price impact and the dollar amount rebalanced, respectively, to the dollar amount invested before trading in the long (or short) position.

(a) Without Costs, Equally Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.505%	(1.99)	5.51%	26.00%	-14.95%	0.0916
CRSP EW	0.630%	(2.36)	5.81%	29.33%	-27.84%	0.1084

(b) With Costs, Equally Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.217%	(0.86)	5.50%	25.5%	-15.4%	0.0395	0.161%	15.5%	0.009%	7.5%
10M	0.129%	(0.51)	5.51%	25.3%	-15.5%	0.0234	0.231%	15.5%	0.027%	7.5%
50M	0.052%	(0.20)	5.52%	25.2%	-15.7%	0.0094	0.278%	15.5%	0.056%	7.5%
100M	0.011%	(0.04)	5.54%	25.2%	-15.7%	0.0021	0.298%	15.5%	0.076%	7.5%
500M	-0.107%	(-0.41)	5.61%	25.1%	-21.2%	-0.0190	0.341%	15.5%	0.150%	7.5%
1B	-0.170%	(-0.65)	5.67%	25.1%	-26.7%	-0.0300	0.357%	15.5%	0.198%	7.5%
5B	-0.347%	(-1.25)	6.02%	25.0%	-47.9%	-0.0575	0.386%	15.5%	0.344%	7.5%
10B	-0.421%	(-1.45)	6.33%	25.0%	-63.0%	-0.0665	0.393%	15.5%	0.411%	7.5%
Break-even Fund Size:		138.6M			Average # Stocks		Long:	2,276.7	Short:	150.0

Table 5, continued

(c) Without Costs, Value Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.250%	(1.05)	5.20%	23.63%	-14.66%	0.0480
CRSP VW	0.344%	(1.65)	4.53%	15.72%	-23.14%	0.0759

(d) With Costs, Value Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	-0.027%	(-0.11)	5.21%	23.3%	-14.8%	-0.0052	0.155%	16.4%	0.007%	6.6%
10M	-0.113%	(-0.47)	5.22%	23.2%	-14.9%	-0.0217	0.227%	16.4%	0.021%	6.6%
50M	-0.186%	(-0.77)	5.25%	23.1%	-14.9%	-0.0354	0.277%	16.4%	0.043%	6.6%
100M	-0.223%	(-0.92)	5.27%	23.1%	-17.8%	-0.0422	0.298%	16.4%	0.058%	6.6%
500M	-0.327%	(-1.32)	5.39%	23.0%	-30.2%	-0.0606	0.343%	16.4%	0.117%	6.6%
1B	-0.382%	(-1.51)	5.51%	23.0%	-38.8%	-0.0693	0.361%	16.4%	0.154%	6.6%
5B	-0.514%	(-1.80)	6.20%	23.0%	-73.0%	-0.0828	0.385%	16.4%	0.262%	6.6%
10B	-0.459%	(-1.46)	6.86%	23.0%	-97.2%	-0.0670	0.341%	16.4%	0.252%	6.6%
Break-even Fund Size:		<1M			Average # Stocks		Long:	2,276.7	Short:	150.0

Table 6
Size Arbitrage Strategy with VWAP Price Impact
Buy-and-Hold

This table shows excess monthly returns from the size arbitrage strategy using price impact functions estimated from value-weighted average price (VWAP). The strategy buys the smallest size decile and sells short the biggest decile at the end of June from 1963 through 2002, with no rebalancing through the holding period. Calculation of size and timing of portfolio formation follow Fama and French (1993). Returns are measured from July 1963 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. Panel (a) shows the statistics for the equally weighted strategy without cost and the corresponding CRSP benchmark. Panel (b) accounts for both the price impact and transactions costs. Corresponding numbers for the value-weighted strategy are shown in Panels (c) and (d). The initial fund size is converted to 2002 dollars and shown as Arbitrage Fund Size. Mean Excess Return is the time-series average of the excess monthly returns over the sample period. Mean Price Impact and Mean Turnover are defined as the time-series average of the ratios, the dollar price impact and the dollar amount rebalanced, respectively, to the dollar amount invested before trading in the long (or short) position.

(a) Without Costs, Equally Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.323%	(1.30)	5.43%	33.99%	-18.41%	0.0595
CRSP EW	0.630%	(2.36)	5.81%	29.33%	-27.84%	0.1084

(b) With Costs, Equally Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.183%	(0.73)	5.45%	34.0%	-18.4%	0.0335	0.081%	6.6%	0.007%	3.3%
10M	0.137%	(0.55)	5.47%	34.0%	-18.4%	0.0251	0.112%	6.6%	0.020%	3.3%
50M	0.092%	(0.36)	5.49%	34.0%	-18.4%	0.0167	0.135%	6.6%	0.043%	3.3%
100M	0.066%	(0.26)	5.51%	34.0%	-18.4%	0.0120	0.144%	6.6%	0.059%	3.3%
500M	-0.017%	(-0.07)	5.61%	33.9%	-21.2%	-0.0031	0.165%	6.6%	0.121%	3.3%
1B	-0.067%	(-0.25)	5.68%	33.9%	-26.7%	-0.0117	0.174%	6.6%	0.162%	3.3%
5B	-0.213%	(-0.76)	6.08%	33.9%	-47.9%	-0.0351	0.190%	6.6%	0.291%	3.3%
10B	-0.280%	(-0.95)	6.40%	33.9%	-63.0%	-0.0437	0.194%	6.6%	0.354%	3.3%
Break-even Fund Size:		416.8M			Average # Stocks		Long:	2,276.7	Short:	150.0

Table 6, continued

(c) Without Costs, Value Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.218%	(0.91)	5.20%	32.05%	-20.84%	0.0420
CRSP VW	0.344%	(1.65)	4.53%	15.72%	-23.14%	0.0759

(d) With Costs, Value Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.103%	(0.43)	5.22%	32.0%	-20.8%	0.0198	0.073%	6.1%	0.004%	1.4%
10M	0.066%	(0.28)	5.24%	32.0%	-20.8%	0.0127	0.102%	6.1%	0.011%	1.4%
50M	0.032%	(0.13)	5.26%	32.0%	-20.9%	0.0061	0.124%	6.1%	0.024%	1.4%
100M	0.014%	(0.06)	5.29%	32.0%	-20.9%	0.0026	0.133%	6.1%	0.032%	1.4%
500M	-0.043%	(-0.17)	5.42%	32.0%	-30.2%	-0.0080	0.155%	6.1%	0.067%	1.4%
1B	-0.076%	(-0.30)	5.54%	32.0%	-38.8%	-0.0138	0.165%	6.1%	0.091%	1.4%
5B	-0.174%	(-0.61)	6.23%	32.0%	-73.0%	-0.0279	0.179%	6.1%	0.175%	1.4%
10B	-0.181%	(-0.57)	6.88%	32.0%	-97.2%	-0.0263	0.156%	6.1%	0.205%	1.4%
Break-even Fund Size:		197.1M			Average # Stocks		Long:	2,276.7	Short:	150.0

Table 7
Book-to-market Arbitrage Strategy with VWAP Price Impact
Rebalanced Monthly

This table shows excess monthly returns from the book-to-market (B/M) arbitrage strategy using price impact functions estimated from value-weighted average price (VWAP). The strategy buys the highest B/M decile and sells short the lowest decile at the end of June from 1963 through 2002, with weights rebalanced every month to stay equally or value weighted. Calculation of B/M and timing of portfolio formation follow Fama and French (1993). Returns are measured from July 1963 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. Panel (a) shows the statistics for the equally weighted strategy without cost and the corresponding CRSP benchmark. Panel (b) accounts for both the price impact and transactions costs. Corresponding numbers for the value-weighted strategy are shown in Panels (c) and (d). The initial fund size is converted to 2002 dollars and shown as Arbitrage Fund Size. Mean Excess Return is the time-series average of the excess monthly returns over the sample period. Mean Price Impact and Mean Turnover are defined as the time-series average of the ratios, the dollar price impact and the dollar amount rebalanced, respectively, to the dollar amount invested before trading in the long (or short) position.

(a) Without Costs, Equally Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	1.133%	(5.71)	4.32%	19.80%	-15.92%	0.2623
CRSP EW	0.630%	(2.36)	5.81%	29.33%	-27.84%	0.1084

(b) With Costs, Equally Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.474%	(2.38)	4.34%	19.1%	-16.5%	0.1092	0.254%	17.7%	0.206%	18.9%
10M	0.307%	(1.52)	4.40%	18.9%	-16.6%	0.0697	0.335%	17.7%	0.289%	18.9%
50M	0.166%	(0.81)	4.48%	18.8%	-18.3%	0.0370	0.397%	17.7%	0.364%	18.9%
100M	0.097%	(0.47)	4.54%	18.8%	-19.5%	0.0215	0.426%	17.7%	0.403%	18.9%
500M	-0.084%	(-0.38)	4.74%	18.7%	-23.1%	-0.0177	0.498%	17.7%	0.508%	18.9%
1B	-0.171%	(-0.76)	4.87%	18.6%	-28.0%	-0.0351	0.531%	17.7%	0.561%	18.9%
5B	-0.388%	(-1.57)	5.38%	18.5%	-46.3%	-0.0721	0.611%	17.7%	0.694%	18.9%
10B	-0.476%	(-1.82)	5.71%	18.5%	-58.6%	-0.0834	0.643%	17.7%	0.749%	18.9%
Break-even Fund Size:		315.1M			Average # Stocks		Long:	462.6	Short:	616.6

Table 7, continued

(c) Without Costs, Value Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.432%	(2.02)	4.65%	23.11%	-15.14%	0.0930
CRSP VW	0.344%	(1.65)	4.53%	15.72%	-23.14%	0.0759

(d) With Costs, Value Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.208%	(0.98)	4.64%	22.8%	-15.2%	0.0449	0.078%	14.5%	0.022%	10.1%
10M	0.093%	(0.43)	4.69%	22.6%	-15.4%	0.0198	0.161%	14.5%	0.053%	10.1%
50M	-0.045%	(-0.20)	4.85%	22.5%	-26.5%	-0.0094	0.257%	14.5%	0.093%	10.1%
100M	-0.120%	(-0.52)	5.02%	22.5%	-36.1%	-0.0240	0.307%	14.5%	0.116%	10.1%
500M	-0.270%	(-0.98)	5.98%	22.4%	-77.9%	-0.0452	0.404%	14.5%	0.168%	10.1%

Break-even Fund Size:	36.9M	Average # Stocks	Long: 462.6	Short:	616.6

Table 8
Book-to-market Arbitrage Strategy with VWAP Price Impact
Buy-and-Hold

This table shows excess monthly returns from the book-to-market (B/M) arbitrage strategy using price impact functions estimated from value-weighted average price (VWAP). The strategy buys the highest B/M decile and sells short the lowest decile at the end of June from 1963 through 2002, with no rebalancing through the holding period. Calculation of B/M and timing of portfolio formation follow Fama and French (1993). Returns are measured from July 1963 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. Panel (a) shows the statistics for the equally weighted strategy without cost and the corresponding CRSP benchmark. Panel (b) accounts for both the price impact and transactions costs. Corresponding numbers for the value-weighted strategy are shown in Panels (c) and (d). The initial fund size is converted to 2002 dollars and shown as Arbitrage Fund Size. Mean Excess Return is the time-series average of the excess monthly returns over the sample period. Mean Price Impact and Mean Turnover are defined as the time-series average of the ratios, the dollar price impact and the dollar amount rebalanced, respectively, to the dollar amount invested before trading in the long (or short) position.

(a) Without Costs, Equally Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	1.040%	(5.48)	4.13%	17.11%	-14.37%	0.2517
CRSP EW	0.630%	(2.36)	5.81%	29.33%	-27.84%	0.1084

(b) With Costs, Equally Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.667%	(3.45)	4.21%	17.0%	-14.4%	0.1586	0.156%	9.4%	0.111%	9.0%
10M	0.558%	(2.82)	4.31%	17.0%	-16.1%	0.1295	0.209%	9.4%	0.165%	9.0%
50M	0.455%	(2.23)	4.45%	17.0%	-18.7%	0.1023	0.254%	9.4%	0.220%	9.0%
100M	0.401%	(1.93)	4.53%	17.0%	-20.2%	0.0885	0.276%	9.4%	0.250%	9.0%
500M	0.251%	(1.13)	4.85%	17.0%	-24.6%	0.0517	0.335%	9.4%	0.338%	9.0%
1B	0.175%	(0.75)	5.05%	17.0%	-28.0%	0.0346	0.363%	9.4%	0.384%	9.0%
5B	-0.020%	(-0.07)	5.73%	17.0%	-46.3%	-0.0034	0.433%	9.4%	0.504%	9.0%
10B	-0.101%	(-0.36)	6.12%	17.0%	-58.6%	-0.0165	0.463%	9.4%	0.554%	9.0%
Break-even Fund Size:		4.60B			Average # Stocks		Long:	462.6	Short:	616.6

Table 8, continued

(c) Without Costs, Value Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.368%	(1.75)	4.59%	20.33%	-15.51%	0.0802
CRSP VW	0.344%	(1.65)	4.53%	15.72%	-23.14%	0.0759

(d) With Costs, Value Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.236%	(1.12)	4.58%	20.3%	-15.5%	0.0515	0.056%	8.5%	0.013%	4.1%
10M	0.146%	(0.69)	4.64%	20.3%	-15.5%	0.0316	0.123%	8.5%	0.034%	4.1%
50M	0.030%	(0.14)	4.81%	20.3%	-26.5%	0.0063	0.208%	8.5%	0.063%	4.1%
100M	-0.036%	(-0.16)	4.99%	20.3%	-36.1%	-0.0071	0.255%	8.5%	0.081%	4.1%
500M	-0.177%	(-0.64)	5.98%	20.3%	-77.9%	-0.0296	0.349%	8.5%	0.127%	4.1%

Break-even Fund Size:	73.0M	Average # Stocks	Long:	462.6	Short:	616.6

Table 9
Book-to-market Arbitrage Strategy with Tick-by-tick Price Impact
Rebalanced Monthly

This table shows excess monthly returns from the book-to-market (B/M) arbitrage strategy using price impact functions estimated from quote midpoint changes. The strategy buys the highest B/M decile and sells short the lowest decile at the end of June from 1963 through 2002, with weights rebalanced every month to stay equally or value weighted. Calculation of B/M and timing of portfolio formation follow Fama and French (1993). Returns are measured from July 1963 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. Panel (a) shows the statistics for the equally weighted strategy without cost and the corresponding CRSP benchmark. Panel (b) accounts for both the price impact and transactions costs. Corresponding numbers for the value-weighted strategy are shown in Panels (c) and (d). The initial fund size is converted to 2002 dollars and shown as Arbitrage Fund Size. Mean Excess Return is the time-series average of the excess monthly returns over the sample period. Mean Price Impact and Mean Turnover are defined as the time-series average of the ratios, the dollar price impact and the dollar amount rebalanced, respectively, to the dollar amount invested before trading in the long (or short) position.

(a) Without Costs, Equally Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	1.133%	(5.71)	4.32%	19.80%	-15.92%	0.2623
CRSP EW	0.630%	(2.36)	5.81%	29.33%	-27.84%	0.1084

(b) With Costs, Equally Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.708%	(3.56)	4.33%	19.4%	-16.3%	0.1637	0.119%	17.7%	0.112%	18.9%
10M	0.494%	(2.44)	4.40%	19.2%	-16.4%	0.1123	0.212%	17.7%	0.228%	18.9%
50M	0.312%	(1.51)	4.50%	19.1%	-18.7%	0.0692	0.292%	17.7%	0.327%	18.9%
100M	0.225%	(1.07)	4.57%	19.0%	-20.0%	0.0493	0.330%	17.7%	0.374%	18.9%
500M	0.009%	(0.04)	4.78%	18.8%	-24.7%	0.0019	0.425%	17.7%	0.491%	18.9%
1B	-0.090%	(-0.40)	4.90%	18.7%	-28.5%	-0.0184	0.468%	17.7%	0.546%	18.9%
5B	-0.329%	(-1.36)	5.27%	18.6%	-39.5%	-0.0624	0.571%	17.7%	0.677%	18.9%
10B	-0.433%	(-1.72)	5.47%	18.5%	-45.5%	-0.0791	0.615%	17.7%	0.735%	18.9%
Break-even Fund Size:		545.2M			Average # Stocks		Long:	462.6	Short:	616.6

Table 9, continued

(c) Without Costs, Value Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.432%	(2.02)	4.65%	23.11%	-15.14%	0.0930
CRSP VW	0.344%	(1.65)	4.53%	15.72%	-23.14%	0.0759

(d) With Costs, Value Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.158%	(0.73)	4.69%	22.9%	-15.2%	0.0337	0.110%	14.5%	0.039%	10.1%
10M	-0.021%	(-0.09)	4.85%	22.6%	-25.6%	-0.0043	0.222%	14.5%	0.103%	10.1%
50M	-0.172%	(-0.73)	5.10%	22.4%	-37.8%	-0.0337	0.313%	14.5%	0.161%	10.1%
100M	-0.242%	(-1.00)	5.27%	22.3%	-44.6%	-0.0460	0.354%	14.5%	0.189%	10.1%
500M	-0.405%	(-1.51)	5.82%	22.2%	-65.4%	-0.0696	0.447%	14.5%	0.257%	10.1%
1B	-0.461%	(-1.63)	6.15%	22.1%	-77.1%	-0.0750	0.477%	14.5%	0.282%	10.1%

Break-even Fund Size:	8.9M	Average # Stocks	Long:	462.6	Short:	616.6

Table 10
Book-to-market Arbitrage Strategy with Tick-by-tick Price Impact
Buy-and-Hold

This table shows excess monthly returns from the book-to-market (B/M) arbitrage strategy using price impact functions estimated from quote midpoint changes. The strategy buys the highest B/M decile and sells short the lowest decile at the end of June from 1963 through 2002, with no rebalancing through the holding period. Calculation of B/M and timing of portfolio formation follow Fama and French (1993). Returns are measured from July 1963 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. Panel (a) shows the statistics for the equally weighted strategy without cost and the corresponding CRSP benchmark. Panel (b) accounts for both the price impact and transactions costs. Corresponding numbers for the value-weighted strategy are shown in Panels (c) and (d). The initial fund size is converted to 2002 dollars and shown as Arbitrage Fund Size. Mean Excess Return is the time-series average of the excess monthly returns over the sample period. Mean Price Impact and Mean Turnover are defined as the time-series average of the ratios, the dollar price impact and the dollar amount rebalanced, respectively, to the dollar amount invested before trading in the long (or short) position.

(a) Without Costs, Equally Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	1.040%	(5.48)	4.13%	17.11%	-14.37%	0.2517
CRSP EW	0.630%	(2.36)	5.81%	29.33%	-27.84%	0.1084

(b) With Costs, Equally Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.772%	(4.04)	4.16%	17.1%	-14.4%	0.1854	0.087%	9.4%	0.078%	9.0%
10M	0.623%	(3.16)	4.29%	17.1%	-16.7%	0.1453	0.157%	9.4%	0.153%	9.0%
50M	0.490%	(2.39)	4.47%	17.0%	-20.0%	0.1097	0.220%	9.4%	0.220%	9.0%
100M	0.425%	(2.02)	4.58%	17.0%	-21.6%	0.0929	0.251%	9.4%	0.253%	9.0%
500M	0.257%	(1.14)	4.92%	17.0%	-25.9%	0.0522	0.331%	9.4%	0.337%	9.0%
1B	0.177%	(0.76)	5.11%	17.0%	-28.5%	0.0347	0.368%	9.4%	0.378%	9.0%
5B	-0.018%	(-0.07)	5.67%	17.0%	-39.5%	-0.0031	0.459%	9.4%	0.477%	9.0%
10B	-0.104%	(-0.38)	5.95%	17.0%	-45.5%	-0.0175	0.499%	9.4%	0.522%	9.0%
Break-even Fund Size:		4.64B			Average # Stocks		Long:	462.6	Short:	616.6

Table 10, continued

(c) Without Costs, Value Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.368%	(1.75)	4.59%	20.33%	-15.51%	0.0802
CRSP VW	0.344%	(1.65)	4.53%	15.72%	-23.14%	0.0759

(d) With Costs, Value Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.178%	(0.84)	4.63%	20.3%	-15.5%	0.0384	0.095%	8.5%	0.032%	4.1%
10M	0.053%	(0.24)	4.80%	20.3%	-25.6%	0.0110	0.178%	8.5%	0.070%	4.1%
50M	-0.057%	(-0.25)	5.08%	20.3%	-37.8%	-0.0113	0.249%	8.5%	0.107%	4.1%
100M	-0.110%	(-0.46)	5.26%	20.3%	-44.6%	-0.0210	0.283%	8.5%	0.125%	4.1%
500M	-0.238%	(-0.89)	5.85%	20.3%	-65.4%	-0.0407	0.361%	8.5%	0.173%	4.1%
1B	-0.286%	(-1.00)	6.19%	20.3%	-77.1%	-0.0461	0.387%	8.5%	0.193%	4.1%

Break-even Fund Size:	29.2M	Average # Stocks	Long:	462.6	Short:	616.6

Table 11
Size-B/M Arbitrage Strategy with VWAP Price Impact
Rebalanced Monthly

This table shows excess monthly returns from the size book-to-market (B/M) combined arbitrage strategy using price impact functions estimated from value-weighted average price (VWAP). First, stocks are sorted independently by size and B/M into 5 by 5 cross sections. Then the strategy buys the smallest size, highest B/M portfolio and sells short the biggest size, lowest B/M portfolio at the end of June from 1963 through 2002, with weights rebalanced every month to stay equally or value weighted. Calculation of size and timing of portfolio formation follow Fama and French (1993). Returns are measured from July 1963 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. Panel (a) shows the statistics for the equally weighted strategy without cost and the corresponding CRSP benchmark. Panel (b) accounts for both the price impact and transactions costs. Corresponding numbers for the value-weighted strategy are shown in Panels (c) and (d). The initial fund size is converted to 2002 dollars and shown as Arbitrage Fund Size. Mean Excess Return is the time-series average of the excess monthly returns over the sample period. Mean Price Impact and Mean Turnover are defined as the time-series average of the ratios, the dollar price impact and the dollar amount rebalanced, respectively, to the dollar amount invested before trading in the long (or short) position.

(a) Without Costs, Equally Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.902%	(3.74)	5.25%	26.56%	-17.18%	0.1719
CRSP EW	0.630%	(2.36)	5.81%	29.33%	-27.84%	0.1084

(b) With Costs, Equally Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.479%	(1.98)	5.26%	25.9%	-17.6%	0.0911	0.250%	17.1%	0.025%	10.8%
10M	0.356%	(1.47)	5.29%	25.7%	-17.8%	0.0673	0.328%	17.1%	0.069%	10.8%
50M	0.237%	(0.97)	5.34%	25.6%	-18.0%	0.0444	0.380%	17.1%	0.133%	10.8%
100M	0.174%	(0.70)	5.39%	25.5%	-18.1%	0.0323	0.401%	17.1%	0.174%	10.8%
500M	-0.005%	(-0.02)	5.59%	25.5%	-26.8%	-0.0009	0.444%	17.1%	0.307%	10.8%
1B	-0.094%	(-0.36)	5.75%	25.4%	-33.7%	-0.0164	0.460%	17.1%	0.380%	10.8%
5B	-0.305%	(-1.04)	6.39%	25.4%	-60.0%	-0.0478	0.485%	17.1%	0.564%	10.8%
10B	-0.357%	(-1.14)	6.81%	25.4%	-78.3%	-0.0524	0.488%	17.1%	0.613%	10.8%
Break-even Fund Size:		489.4M			Average # Stocks		Long:	646.0	Short:	105.7

Table 11, continued

(c) Without Costs, Value Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.624%	(2.72)	4.99%	25.21%	-13.20%	0.1250
CRSP VW	0.344%	(1.65)	4.53%	15.72%	-23.14%	0.0759

(d) With Costs, Value Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.267%	(1.16)	5.02%	24.7%	-13.6%	0.0532	0.210%	16.7%	0.017%	8.5%
10M	0.154%	(0.66)	5.06%	24.5%	-13.8%	0.0304	0.292%	16.7%	0.047%	8.5%
50M	0.045%	(0.19)	5.13%	24.4%	-18.8%	0.0087	0.353%	16.7%	0.094%	8.5%
100M	-0.013%	(-0.06)	5.19%	24.3%	-23.2%	-0.0025	0.379%	16.7%	0.124%	8.5%
500M	-0.175%	(-0.70)	5.47%	24.2%	-40.2%	-0.0319	0.436%	16.7%	0.228%	8.5%

Break-even Fund Size:	88.6M	Average # Stocks	Long:	646.0	Short:	105.7

Table 12
Size-B/M Arbitrage Strategy with VWAP Price Impact
Buy-and-Hold

This table shows excess monthly returns from the size book-to-market (B/M) combined arbitrage strategy using price impact functions estimated from value-weighted average price (VWAP). First, stocks are sorted independently by size and B/M into 5 by 5 cross sections. Then the strategy buys the smallest size, highest B/M portfolio and sells short the biggest size, lowest B/M portfolio at the end of June from 1963 through 2002, with no rebalancing through the holding period. Calculation of size and timing of portfolio formation follow Fama and French (1993). Returns are measured from July 1963 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. Panel (a) shows the statistics for the equally weighted strategy without cost and the corresponding CRSP benchmark. Panel (b) accounts for both the price impact and transactions costs. Corresponding numbers for the value-weighted strategy are shown in Panels (c) and (d). The initial fund size is converted to 2002 dollars and shown as Arbitrage Fund Size. Mean Excess Return is the time-series average of the excess monthly returns over the sample period. Mean Price Impact and Mean Turnover are defined as the time-series average of the ratios, the dollar price impact and the dollar amount rebalanced, respectively, to the dollar amount invested before trading in the long (or short) position.

(a) Without Costs, Equally Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.677%	(2.91)	5.07%	23.48%	-17.65%	0.1336
CRSP EW	0.630%	(2.36)	5.81%	29.33%	-27.84%	0.1084

(b) With Costs, Equally Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.436%	(1.86)	5.11%	23.4%	-17.7%	0.0853	0.142%	8.8%	0.019%	5.7%
10M	0.356%	(1.50)	5.15%	23.4%	-17.7%	0.0691	0.186%	8.8%	0.054%	5.7%
50M	0.270%	(1.12)	5.23%	23.4%	-17.7%	0.0516	0.217%	8.8%	0.108%	5.7%
100M	0.220%	(0.91)	5.28%	23.4%	-17.7%	0.0417	0.230%	8.8%	0.143%	5.7%
500M	0.072%	(0.28)	5.53%	23.4%	-26.8%	0.0129	0.259%	8.8%	0.261%	5.7%
1B	-0.007%	(-0.03)	5.71%	23.4%	-33.7%	-0.0012	0.269%	8.8%	0.328%	5.7%
5B	-0.199%	(-0.68)	6.42%	23.4%	-60.0%	-0.0311	0.287%	8.8%	0.501%	5.7%
10B	-0.250%	(-0.79)	6.84%	23.4%	-78.3%	-0.0365	0.289%	8.8%	0.548%	5.7%
Break-even Fund Size:		955.3M			Average # Stocks		Long:	646.0	Short:	105.7

Table 12, continued

(c) Without Costs, Value Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.563%	(2.53)	4.85%	23.26%	-14.06%	0.1160
CRSP VW	0.344%	(1.65)	4.53%	15.72%	-23.14%	0.0759

(d) With Costs, Value Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.366%	(1.63)	4.90%	23.2%	-14.1%	0.0747	0.123%	8.4%	0.012%	3.5%
10M	0.292%	(1.28)	4.95%	23.2%	-14.1%	0.0590	0.174%	8.4%	0.034%	3.5%
50M	0.214%	(0.92)	5.04%	23.2%	-18.8%	0.0424	0.215%	8.4%	0.070%	3.5%
100M	0.170%	(0.72)	5.10%	23.2%	-23.2%	0.0333	0.235%	8.4%	0.094%	3.5%
500M	0.039%	(0.16)	5.41%	23.2%	-40.2%	0.0072	0.278%	8.4%	0.180%	3.5%
1B	-0.027%	(-0.10)	5.67%	23.2%	-52.0%	-0.0048	0.295%	8.4%	0.230%	3.5%

Break-even Fund Size: 794.8M	Average # Stocks	Long:	646.0	Short:	105.7

Table 13

Momentum 6/6 Arbitrage Strategy with VWAP Price Impact

Rebalanced Monthly

This table shows excess monthly returns from the 6/6 momentum arbitrage strategy using price impact functions estimated from value-weighted average price (VWAP). The strategy buys the decile with the highest past six-month return and sells short the lowest return decile every month from December 1964 through November 2002. Each monthly cohort is held for six months, with weights rebalanced every month to stay equally or value weighted. Monthly cohorts are equally weighted. Portfolio formation follow Jegadeesh and Titman (2001). Returns are measured from January 1965 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. Panel (a) shows the statistics for the equally weighted strategy without cost and the corresponding CRSP benchmark. Panel (b) accounts for both the price impact and transactions costs. Corresponding numbers for the value-weighted strategy are shown in Panels (c) and (d). The initial fund size is converted to 2002 dollars and shown as Arbitrage Fund Size. Mean Excess Return is the time-series average of the excess monthly returns over the sample period. Mean Price Impact and Mean Turnover are defined as the time-series average of the ratios, the dollar price impact and the dollar amount rebalanced, respectively, to the dollar amount invested before trading in the long (or short) position.

(a) Without Costs, Equally Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	1.197%	(4.40)	5.81%	34.41%	-44.71%	0.2059
CRSP EW	0.625%	(2.26)	5.91%	29.33%	-27.84%	0.1057

(b) With Costs, Equally Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.439%	(1.61)	5.84%	34.1%	-45.0%	0.0752	0.167%	38.1%	0.186%	37.4%
10M	0.211%	(0.77)	5.87%	33.9%	-45.1%	0.0360	0.277%	38.1%	0.300%	37.4%
50M	0.005%	(0.02)	5.91%	33.8%	-45.1%	0.0008	0.379%	38.1%	0.403%	37.4%
100M	-0.096%	(-0.35)	5.94%	33.8%	-45.1%	-0.0162	0.428%	38.1%	0.453%	37.4%
500M	-0.356%	(-1.26)	6.02%	33.7%	-45.2%	-0.0592	0.556%	38.1%	0.582%	37.4%
1B	-0.478%	(-1.68)	6.07%	33.7%	-45.2%	-0.0788	0.616%	38.1%	0.642%	37.4%
5B	-0.774%	(-2.65)	6.24%	33.6%	-45.2%	-0.1241	0.762%	38.1%	0.788%	37.4%
10B	-0.904%	(-3.04)	6.36%	33.6%	-45.2%	-0.1422	0.827%	38.1%	0.851%	37.4%
Break-even Fund Size:		52.5M				Average # Stocks	Long:	1,175.7	Short:	1,219.0

Table 13, continued

(c) Without Costs, Value Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.986%	(3.46)	6.09%	40.19%	-32.72%	0.1619
CRSP VW	0.317%	(1.47)	4.60%	15.72%	-23.14%	0.0688

(d) With Costs, Value Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.473%	(1.66)	6.09%	40.0%	-32.8%	0.0776	0.072%	32.7%	0.085%	32.5%
10M	0.287%	(1.00)	6.11%	39.9%	-32.9%	0.0470	0.155%	32.7%	0.185%	32.5%
50M	0.084%	(0.29)	6.14%	39.9%	-32.9%	0.0137	0.245%	32.7%	0.296%	32.5%
100M	-0.021%	(-0.07)	6.17%	39.9%	-32.9%	-0.0034	0.290%	32.7%	0.355%	32.5%
500M	-0.295%	(-1.00)	6.30%	39.9%	-32.9%	-0.0468	0.406%	32.7%	0.509%	32.5%

Break-even Fund Size:	90.1M	Average # Stocks	Long:	1,175.7	Short:	1,219.0

Table 14
Momentum 6/6 Arbitrage Strategy with VWAP Price Impact
Buy-and-Hold

This table shows excess monthly returns from the 6/6 momentum arbitrage strategy using price impact functions estimated from value-weighted average price (VWAP). The strategy buys the decile with the highest past six-month return and sells short the lowest return decile every month from December 1964 through November 2002. Each monthly cohort is held for six months, with no rebalancing through the holding period. At the cohort formation, component stocks are either equally or value weighted. Portfolio formation follows Jegadeesh and Titman (2001). Returns are measured from January 1965 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. Panel (a) shows the statistics for the equally weighted strategy without cost and the corresponding CRSP benchmark. Panel (b) accounts for both the price impact and transactions costs. Corresponding numbers for the value-weighted strategy are shown in Panels (c) and (d). The initial fund size is converted to 2002 dollars and shown as Arbitrage Fund Size. Mean Excess Return is the time-series average of the excess monthly returns over the sample period. Mean Price Impact and Mean Turnover are defined as the time-series average of the ratios, the dollar price impact and the dollar amount rebalanced, respectively, to the dollar amount invested before trading in the long (or short) position.

(a) Without Costs, Equally Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	1.306%	(4.97)	5.62%	37.34%	-35.38%	0.2326
CRSP EW	0.625%	(2.26)	5.91%	29.33%	-27.84%	0.1057

(b) With Costs, Equally Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.639%	(2.42)	5.64%	37.1%	-35.6%	0.1132	0.157%	30.4%	0.174%	30.5%
10M	0.418%	(1.57)	5.67%	36.9%	-35.6%	0.0737	0.263%	30.4%	0.286%	30.5%
50M	0.213%	(0.80)	5.71%	36.8%	-35.7%	0.0373	0.362%	30.4%	0.389%	30.5%
100M	0.112%	(0.42)	5.74%	36.8%	-35.7%	0.0196	0.411%	30.4%	0.439%	30.5%
500M	-0.149%	(-0.55)	5.82%	36.7%	-35.7%	-0.0256	0.537%	30.4%	0.571%	30.5%
1B	-0.271%	(-0.99)	5.87%	36.7%	-35.8%	-0.0463	0.596%	30.4%	0.632%	30.5%
5B	-0.570%	(-2.01)	6.04%	36.6%	-35.8%	-0.0943	0.740%	30.4%	0.782%	30.5%
10B	-0.701%	(-2.43)	6.16%	36.6%	-35.8%	-0.1137	0.803%	30.4%	0.847%	30.5%
Break-even Fund Size:		271.7M			Average # Stocks		Long:	1,176.1	Short:	1,219.3

Table 14, continued

(c) Without Costs, Value Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.962%	(3.37)	6.09%	40.85%	-33.03%	0.1579
CRSP VW	0.317%	(1.47)	4.60%	15.72%	-23.14%	0.0688

(d) With Costs, Value Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.465%	(1.63)	6.10%	40.7%	-33.1%	0.0762	0.073%	30.7%	0.086%	31.0%
10M	0.278%	(0.97)	6.11%	40.6%	-33.1%	0.0455	0.157%	30.7%	0.186%	31.0%
50M	0.075%	(0.26)	6.14%	40.5%	-33.2%	0.0121	0.247%	30.7%	0.297%	31.0%
100M	-0.031%	(-0.11)	6.17%	40.5%	-33.2%	-0.0050	0.292%	30.7%	0.356%	31.0%
500M	-0.306%	(-1.04)	6.30%	40.5%	-33.2%	-0.0485	0.409%	30.7%	0.511%	31.0%

Break-even Fund Size:	85.4M	Average # Stocks	Long: 1,176.1	Short:	1,219.3

Table 15
Momentum 6/6 Arbitrage Strategy with Tick-by-tick Price Impact
Rebalanced Monthly

This table shows excess monthly returns from the 6/6 momentum arbitrage strategy using price impact functions estimated from quote midpoint changes. The strategy buys the decile with the highest past six-month return and sells short the lowest return decile every month from December 1964 through November 2002. Each monthly cohort is held for six months, with weights rebalanced every month to stay equally or value weighted. Monthly cohorts are equally weighted. Portfolio formation follow Jegadeesh and Titman (2001). Returns are measured from January 1965 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. Panel (a) shows the statistics for the equally weighted strategy without cost and the corresponding CRSP benchmark. Panel (b) accounts for both the price impact and transactions costs. Corresponding numbers for the value-weighted strategy are shown in Panels (c) and (d). The initial fund size is converted to 2002 dollars and shown as Arbitrage Fund Size. Mean Excess Return is the time-series average of the excess monthly returns over the sample period. Mean Price Impact and Mean Turnover are defined as the time-series average of the ratios, the dollar price impact and the dollar amount rebalanced, respectively, to the dollar amount invested before trading in the long (or short) position.

(a) Without Costs, Equally Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	1.197%	(4.40)	5.81%	34.41%	-44.71%	0.2059
CRSP EW	0.625%	(2.26)	5.91%	29.33%	-27.84%	0.1057

(b) With Costs, Equally Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.597%	(2.19)	5.83%	34.1%	-44.9%	0.1024	0.098%	38.1%	0.099%	37.4%
10M	0.265%	(0.96)	5.89%	34.0%	-44.9%	0.0449	0.262%	38.1%	0.263%	37.4%
50M	0.012%	(0.04)	5.96%	34.0%	-44.9%	0.0020	0.387%	38.1%	0.388%	37.4%
100M	-0.102%	(-0.36)	6.00%	34.0%	-44.9%	-0.0169	0.443%	38.1%	0.444%	37.4%
500M	-0.374%	(-1.31)	6.11%	34.0%	-45.0%	-0.0613	0.577%	38.1%	0.579%	37.4%
1B	-0.495%	(-1.71)	6.17%	34.0%	-45.0%	-0.0803	0.636%	38.1%	0.639%	37.4%
5B	-0.782%	(-2.64)	6.33%	33.9%	-45.0%	-0.1234	0.776%	38.1%	0.783%	37.4%
10B	-0.907%	(-3.02)	6.42%	33.9%	-45.0%	-0.1413	0.836%	38.1%	0.846%	37.4%
Break-even Fund Size:		55.2M			Average # Stocks		Long:	1,175.7	Short:	1,219.0

Table 15, continued

(c) Without Costs, Value Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.986%	(3.46)	6.09%	40.19%	-32.72%	0.1619
CRSP VW	0.317%	(1.47)	4.60%	15.72%	-23.14%	0.0688

(d) With Costs, Value Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.371%	(1.30)	6.11%	40.0%	-32.8%	0.0607	0.116%	32.7%	0.142%	32.5%
10M	0.032%	(0.11)	6.17%	40.0%	-32.8%	0.0052	0.273%	32.7%	0.320%	32.5%
50M	-0.228%	(-0.78)	6.27%	40.0%	-32.8%	-0.0364	0.392%	32.7%	0.458%	32.5%
100M	-0.345%	(-1.17)	6.33%	40.0%	-32.8%	-0.0546	0.445%	32.7%	0.520%	32.5%
500M	-0.624%	(-2.04)	6.52%	40.0%	-32.8%	-0.0956	0.569%	32.7%	0.671%	32.5%
1B	-0.745%	(-2.39)	6.64%	40.0%	-37.6%	-0.1121	0.623%	32.7%	0.736%	32.5%

Break-even Fund Size:	14.9M	Average # Stocks	Long: 1,175.7	Short:	1,219.0

Table 16
Momentum 6/6 Arbitrage Strategy with Tick-by-tick Price Impact
Buy-and-Hold

This table shows excess monthly returns from the 6/6 momentum arbitrage strategy using price impact functions estimated from quote midpoint changes. The strategy buys the decile with the highest past six-month return and sells short the lowest return decile every month from December 1964 through November 2002. Each monthly cohort is held for six months, with no rebalancing through the holding period. At the cohort formation, component stocks are either equally or value weighted. Portfolio formation follows Jegadeesh and Titman (2001). Returns are measured from January 1965 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. Panel (a) shows the statistics for the equally weighted strategy without cost and the corresponding CRSP benchmark. Panel (b) accounts for both the price impact and transactions costs. Corresponding numbers for the value-weighted strategy are shown in Panels (c) and (d). The initial fund size is converted to 2002 dollars and shown as Arbitrage Fund Size. Mean Excess Return is the time-series average of the excess monthly returns over the sample period. Mean Price Impact and Mean Turnover are defined as the time-series average of the ratios, the dollar price impact and the dollar amount rebalanced, respectively, to the dollar amount invested before trading in the long (or short) position.

(a) Without Costs, Equally Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	1.306%	(4.97)	5.62%	37.34%	-35.38%	0.2326
CRSP EW	0.625%	(2.26)	5.91%	29.33%	-27.84%	0.1057

(b) With Costs, Equally Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.728%	(2.76)	5.64%	37.1%	-35.5%	0.1291	0.119%	30.4%	0.124%	30.5%
10M	0.416%	(1.56)	5.70%	37.1%	-35.5%	0.0730	0.271%	30.4%	0.279%	30.5%
50M	0.176%	(0.65)	5.77%	37.0%	-35.5%	0.0306	0.388%	30.4%	0.399%	30.5%
100M	0.068%	(0.25)	5.81%	37.0%	-35.5%	0.0117	0.441%	30.4%	0.454%	30.5%
500M	-0.195%	(-0.70)	5.91%	37.0%	-35.5%	-0.0329	0.568%	30.4%	0.585%	30.5%
1B	-0.311%	(-1.11)	5.97%	37.0%	-35.6%	-0.0522	0.624%	30.4%	0.644%	30.5%
5B	-0.590%	(-2.06)	6.13%	37.0%	-35.6%	-0.0963	0.758%	30.4%	0.786%	30.5%
10B	-0.713%	(-2.45)	6.22%	37.0%	-35.6%	-0.1147	0.816%	30.4%	0.848%	30.5%
Break-even Fund Size:		203.3M			Average # Stocks		Long:	1,176.1	Short:	1,219.3

Table 16, continued

(c) Without Costs, Value Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	0.962%	(3.37)	6.09%	40.85%	-33.03%	0.1579
CRSP VW	0.317%	(1.47)	4.60%	15.72%	-23.14%	0.0688

(d) With Costs, Value Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
1M	0.350%	(1.22)	6.11%	40.7%	-33.1%	0.0573	0.123%	30.7%	0.149%	31.0%
10M	0.015%	(0.05)	6.18%	40.7%	-33.1%	0.0024	0.279%	30.7%	0.324%	31.0%
50M	-0.243%	(-0.83)	6.27%	40.7%	-33.1%	-0.0388	0.397%	30.7%	0.461%	31.0%
100M	-0.359%	(-1.21)	6.33%	40.7%	-33.1%	-0.0568	0.449%	30.7%	0.523%	31.0%
500M	-0.636%	(-2.08)	6.52%	40.6%	-33.1%	-0.0975	0.573%	30.7%	0.673%	31.0%
1B	-0.757%	(-2.43)	6.64%	40.6%	-37.2%	-0.1139	0.626%	30.7%	0.739%	31.0%

Break-even Fund Size:	12.3M	Average # Stocks	Long:	1,176.1	Short:	1,219.3

Table 17
Break-even Fund Size for Various Momentum Strategies
Buy-and-hold, Equally Weighted, VWAP Price Impact

This table shows break-even fund size and other characteristics of buy-and-hold momentum arbitrage strategies using price impact functions estimated from value-weighted average price (VWAP). The strategy buys the decile with the highest past J-month return and sells short the lowest decile every month from December 1964 through November 2002. Each monthly cohort is held for K months, with no rebalancing through the holding period. At the cohort formation, component stocks are equally weighted. Portfolio formation follows Jegadeesh and Titman (2001). Returns are measured from January 1965 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. (b) Mean Excess Return is the time-series average of the excess monthly returns over the sample period. (c) Average monthly turnover is defined as the time-series average of the sum of the number of stocks in the long and the short positions. (d) Average monthly turnover is defined as the time-series average of the ratio, the dollar amount rebalanced in the two positions to the dollar amount invested before trading.

(a) Break-even fund size (in millions)

J\K	1	3	6	9	12
3	<1	<1	17.2	306.1	593.9
6	<1	8.4	271.7	1,733.2	1,693.8
9	<1	79.0	718.9	926.8	753.7
12	<1	99.3	458.0	418.0	225.0

(b) Monthly excess return before cost

J\K	1	3	6	9	12
3	0.090%	0.691%	0.851%	0.937%	0.859%
6	0.707%	1.200%	1.306%	1.295%	1.028%
9	1.127%	1.484%	1.454%	1.217%	0.913%
12	1.384%	1.486%	1.263%	0.971%	0.697%

(c) Average number of stocks (sum of the long and short positions)

J\K	1	3	6	9	12
3	416	1,236	2,440	3,618	4,770
6	408	1,213	2,395	3,552	4,684
9	402	1,194	2,360	3,501	4,619
12	395	1,176	2,326	3,452	4,555

(d) Average monthly turnover (sum of the long and short positions)

J\K	1	3	6	9	12
3	228.3%	119.7%	60.9%	41.6%	31.8%
6	172.1%	91.8%	60.8%	41.2%	31.9%
9	146.1%	78.2%	52.5%	41.2%	31.7%
12	130.0%	70.2%	47.5%	37.7%	31.8%

Table 18
Break-even Fund Size for Various Momentum Strategies
Buy-and-hold, Value Weighted, VWAP Price Impact

This table shows break-even fund size and other characteristics of buy-and-hold momentum arbitrage strategies using price impact functions estimated from value-weighted average price (VWAP). The strategy buys the decile with the highest past J-month return and sells short the lowest decile every month from December 1964 through November 2002. Each monthly cohort is held for K months, with no rebalancing through the holding period. At the cohort formation, component stocks are value weighted. Portfolio formation follows Jegadeesh and Titman (2001). Returns are measured from January 1965 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. (b) Mean Excess Return is the time-series average of the excess monthly returns over the sample period. (c) Average monthly turnover is defined as the time-series average of the sum of the number of stocks in the long and the short positions. (d) Average monthly turnover is defined as the time-series average of the ratio, the dollar amount rebalanced in the two positions to the dollar amount invested before trading.

(a) Break-even fund size (in millions)

J\K	1	3	6	9	12
3	<1	<1	5.1	106.0	406.2
6	<1	1.1	85.4	707.1	705.8
9	<1	37.9	442.0	647.7	502.4
12	<1	53.5	283.4	354.5	249.6

(b) Monthly excess return before cost

J\K	1	3	6	9	12
3	0.072%	0.475%	0.555%	0.694%	0.706%
6	0.489%	0.781%	0.962%	1.055%	0.839%
9	0.747%	1.142%	1.223%	1.045%	0.789%
12	1.111%	1.201%	1.044%	0.859%	0.629%

(c) Average number of stocks (sum of the long and short positions)

J\K	1	3	6	9	12
3	416	1,236	2,440	3,618	4,770
6	408	1,213	2,395	3,552	4,684
9	402	1,194	2,360	3,501	4,619
12	395	1,176	2,326	3,452	4,555

(d) Average monthly turnover (sum of the long and short positions)

J\K	1	3	6	9	12
3	254.7%	122.9%	62.4%	42.1%	31.9%
6	192.3%	98.6%	61.7%	41.5%	31.8%
9	161.8%	84.5%	54.4%	41.2%	31.5%
12	143.6%	75.5%	49.3%	38.0%	31.4%

Table 19
Break-even Fund Size for Various Momentum Strategies
Buy-and-hold, Equally Weighted, Tick-by-tick Price Impact

This table shows break-even fund size and other characteristics of buy-and-hold momentum arbitrage strategies using price impact functions estimated from quote-midpoint changes. The strategy buys the decile with the highest past J-month return and sells short the lowest decile every month from December 1964 through November 2002. Each monthly cohort is held for K months, with no rebalancing through the holding period. At the cohort formation, component stocks are equally weighted. Portfolio formation follows Jegadeesh and Titman (2001). Returns are measured from January 1965 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. (b) Mean Excess Return is the time-series average of the excess monthly returns over the sample period. (c) Average monthly turnover is defined as the time-series average of the sum of the number of stocks in the long and the short positions. (d) Average monthly turnover is defined as the time-series average of the ratio, the dollar amount rebalanced in the two positions to the dollar amount invested before trading.

(a) Break-even fund size (in millions)

J\K	1	3	6	9	12
3	<1	<1	16.0	213.4	440.9
6	<1	9.4	203.3	1,510.0	1,335.0
9	<1	67.5	605.1	784.1	531.9
12	3.5	84.8	396.7	330.1	111.2

(b) Monthly excess return before cost

J\K	1	3	6	9	12
3	0.090%	0.691%	0.851%	0.937%	0.859%
6	0.707%	1.200%	1.306%	1.295%	1.028%
9	1.127%	1.484%	1.454%	1.217%	0.913%
12	1.384%	1.486%	1.263%	0.971%	0.697%

(c) Average number of stocks (sum of the long and short positions)

J\K	1	3	6	9	12
3	416	1,236	2,440	3,618	4,770
6	408	1,213	2,395	3,552	4,684
9	402	1,194	2,360	3,501	4,619
12	395	1,176	2,326	3,452	4,555

(d) Average monthly turnover (sum of the long and short positions)

J\K	1	3	6	9	12
3	228.3%	119.7%	60.9%	41.6%	31.8%
6	172.1%	91.8%	60.8%	41.2%	31.9%
9	146.1%	78.2%	52.5%	41.2%	31.7%
12	130.0%	70.2%	47.5%	37.7%	31.8%

Table 20
Break-even Fund Size for Various Momentum Strategies
Buy-and-hold, Value Weighted, Tick-by-tick Price Impact

This table shows break-even fund size and other characteristics of buy-and-hold momentum arbitrage strategies using price impact functions estimated from quote-midpoint changes. The strategy buys the decile with the highest past J-month return and sells short the lowest decile every month from December 1964 through November 2002. Each monthly cohort is held for K months, with no rebalancing through the holding period. At the cohort formation, component stocks are value weighted. Portfolio formation follows Jegadeesh and Titman (2001). Returns are measured from January 1965 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. (b) Mean Excess Return is the time-series average of the excess monthly returns over the sample period. (c) Average monthly turnover is defined as the time-series average of the sum of the number of stocks in the long and the short positions. (d) Average monthly turnover is defined as the time-series average of the ratio, the dollar amount rebalanced in the two positions to the dollar amount invested before trading.

(a) Break-even fund size (in millions)

J\K	1	3	6	9	12
3	<1	<1	<1	16.9	55.0
6	<1	<1	12.3	145.8	150.6
9	<1	7.0	68.4	124.8	89.4
12	<1	8.8	39.0	47.3	33.5

(b) Monthly excess return before cost

J\K	1	3	6	9	12
3	0.072%	0.475%	0.555%	0.694%	0.706%
6	0.489%	0.781%	0.962%	1.055%	0.839%
9	0.747%	1.142%	1.223%	1.045%	0.789%
12	1.111%	1.201%	1.044%	0.859%	0.629%

(c) Average number of stocks (sum of the long and short positions)

J\K	1	3	6	9	12
3	416	1,236	2,440	3,618	4,770
6	408	1,213	2,395	3,552	4,684
9	402	1,194	2,360	3,501	4,619
12	395	1,176	2,326	3,452	4,555

(d) Average monthly turnover (sum of the long and short positions)

J\K	1	3	6	9	12
3	254.7%	122.9%	62.4%	42.1%	31.9%
6	192.3%	98.6%	61.7%	41.5%	31.8%
9	161.8%	84.5%	54.4%	41.2%	31.5%
12	143.6%	75.5%	49.3%	38.0%	31.4%

Table 21
Break-even Fund Size for Winners-Only 6/12 Momentum Strategy
Buy-and-hold, Equally Weighted, VWAP Price Impact

This table shows break-even fund size and other characteristics of buy-and-hold winners-only momentum arbitrage strategies using price impact functions estimated from value-weighted average price (VWAP). The strategy buys the decile with the highest past 6 month return every month from December 1964 through November 2002. There is no short position. Each monthly cohort is held for 12 months, with positions fixed through the holding period. At the cohort formation, component stocks are equally weighted. Portfolio formation follows Jegadeesh and Titman (2001). Returns are measured from January 1965 through December 2002 and shown in excess of the Federal Fund (FF) rate. The short position is assumed to be financed by a cash position with a margin rate at 80% of the FF rate. (b) Mean Excess Return is the time-series average of the excess monthly returns over the sample period. (c) Average monthly turnover is defined as the time-series average of the sum of the number of stocks in the long and the short positions. (d) Average monthly turnover is defined as the time-series average of the ratio, the dollar amount rebalanced in the two positions to the dollar amount invested before trading.

(a) Without Costs, Equally Weighted

	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio
Strategy	1.013%	(2.85)	7.58%	37.85%	-32.65%	0.1336
CRSP EW	0.625%	(2.26)	5.91%	29.33%	-27.84%	0.1057

(b) With Costs, Equally Weighted

							Long Position		Short Position	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max Excess Return	Min Excess Return	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
100M	0.657%	(1.85)	7.59%	37.6%	-32.8%	0.0866	0.279%	16.0%	--	--
1B	0.442%	(1.24)	7.60%	37.5%	-32.8%	0.0581	0.492%	16.0%	--	--
5B	0.230%	(0.64)	7.63%	37.3%	-32.8%	0.0302	0.702%	16.0%	--	--
10B	0.124%	(0.35)	7.65%	37.3%	-32.9%	0.0162	0.807%	16.0%	--	--
30B	0.010%	(0.03)	7.68%	37.2%	-32.9%	0.0013	0.920%	16.0%	--	--
50B	-0.059%	(-0.16)	7.70%	37.2%	-32.9%	-0.0077	0.989%	16.0%	--	--
70B	-0.149%	(-0.41)	7.74%	37.2%	-32.9%	-0.0193	1.077%	16.0%	--	--
100B	-0.209%	(-0.57)	7.78%	37.1%	-32.9%	-0.0269	1.136%	16.0%	--	--
Break-even Fund Size:		21.45B				# Stocks	Long:	2,287.6	Short:	--

Table 22
Size of Equity Hedge Funds by Investment Approach

Size of equity hedge funds by investment approach in the TASS dataset as of June 2002. The investment approach is not exclusive.

		Size ($ million)					
Investment Approach	#funds	Mean	Median	Minimum	Maximum	Sum	%total
Arbitrage	445	194.4	55.0	0.206	10,968	86,491	35.9%
Bottom Up	878	183.3	36.1	0.206	27,800	160,963	66.8%
Contrarian	109	117.4	23.9	0.206	3,500	12,793	5.3%
Directional	131	115.4	22.1	0.144	4,906	15,113	6.3%
Discretionary	253	255.2	34.6	0.059	27,800	64,569	26.8%
Diversified	198	163.2	48.6	0.029	2,400	32,321	13.4%
Fundamental	808	140.5	31.5	0.029	13,276	113,532	47.1%
Long Bias	497	140.6	31.6	0.029	5,169	69,874	29.0%
Market Neutral	404	187.4	47.2	0.320	10,968	75,720	31.4%
Non Directional	204	208.9	40.1	0.829	10,968	42,607	17.7%
Opportunistic	522	206.8	35.3	0.206	27,800	107,928	44.8%
Relative Value	397	163.3	35.4	0.059	10,968	64,812	26.9%
Short Bias	561	205.2	30.9	0.150	27,800	115,137	47.8%
Systematic Quant	364	123.4	22.0	0.029	5,437	44,934	18.6%
Technical	368	158.7	22.0	0.029	27,800	58,416	24.2%
Top Down Macro	378	162.3	26.8	0.059	13,276	61,357	25.5%
Trend Follower	190	101.0	23.2	0.144	2,400	19,196	8.0%
Other	95	179.5	34.5	0.520	4,906	17,054	7.1%
Total	1,501	160.6	33.5	0.029	27,800	241,021	100.0%

Table 23
Size of Small-cap and Value Equity Mutual Funds

Size of small-cap and value equity mutual funds in the CRSP Mutual Fund dataset at the end of 2002. The investment approach is neither exclusive nor exhaustive. We define equity mutual funds as those funds having an ICDI objective of either AG, BL, GI, IN, LG, SF, TR, or UT. Of these, small-cap funds are further defined as those with an SI objective of "SCG," or the word "small" or "micro" in their name. Value funds are those with "value" in their name.

		Size ($ million)					
Investment Approach	#funds	Mean	Median	Minimum	Maximum	Sum	%total
Small-cap	1,072	172.2	35.2	0.000074	15,104.2	184,567	7.98%
Value	1,004	162.2	32.7	0.001000	7,250.1	162,824	7.04%
Small-cap or value	1,792	173.6	32.9	0.000074	15,104.2	311,162	13.45%
Total	7,286	317.5	31.0	0.000074	56,750.8	2,313,377	100.00%

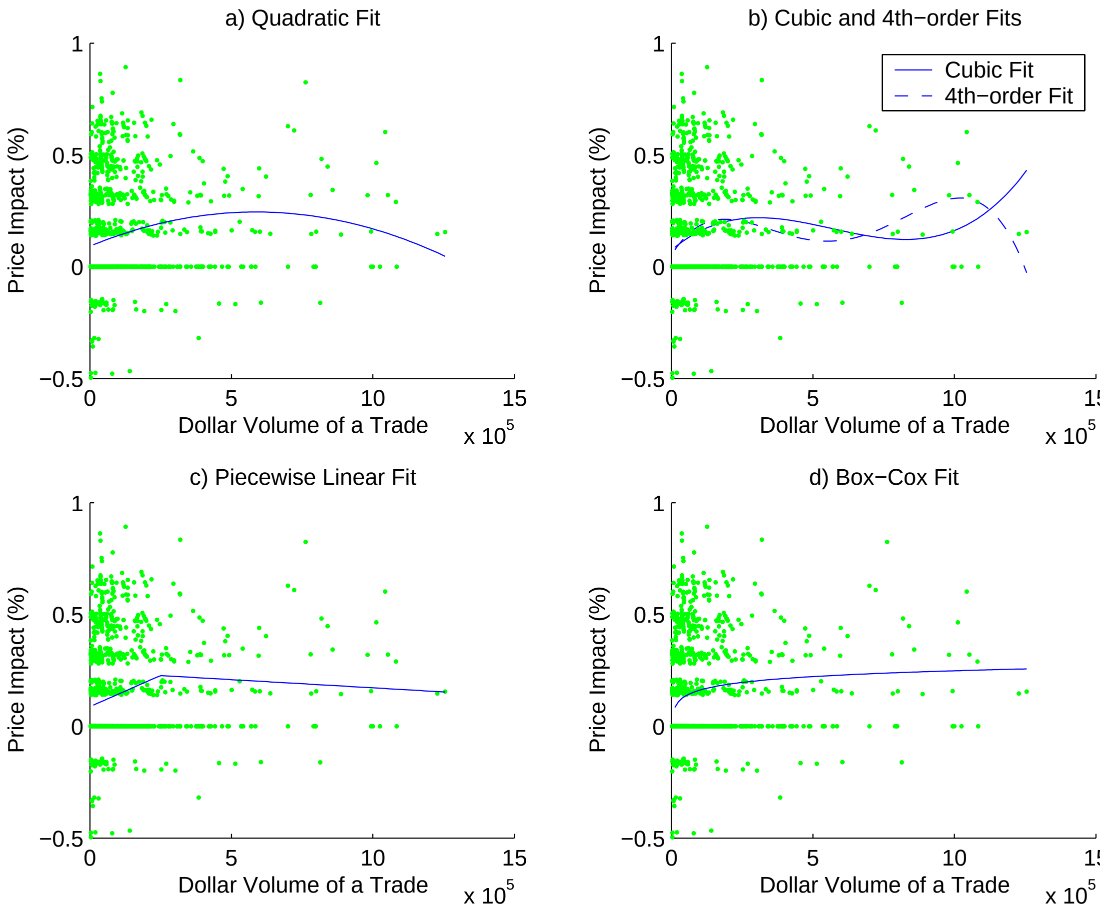

Figure 1: Comparison of the polynomial, piecewise linear, and Box-Cox fits. Dots represent actual trades. All graphs share the same observations, buys of FHT. Panels a) and b) show the quadratic fit and the cubic and fourth-order fits, respectively. Panel c) depicts the piecewise linear fit with a break point at the 90th percentile. Panel d) shows the fitted Box-Cox function as defined in Section 2.1.

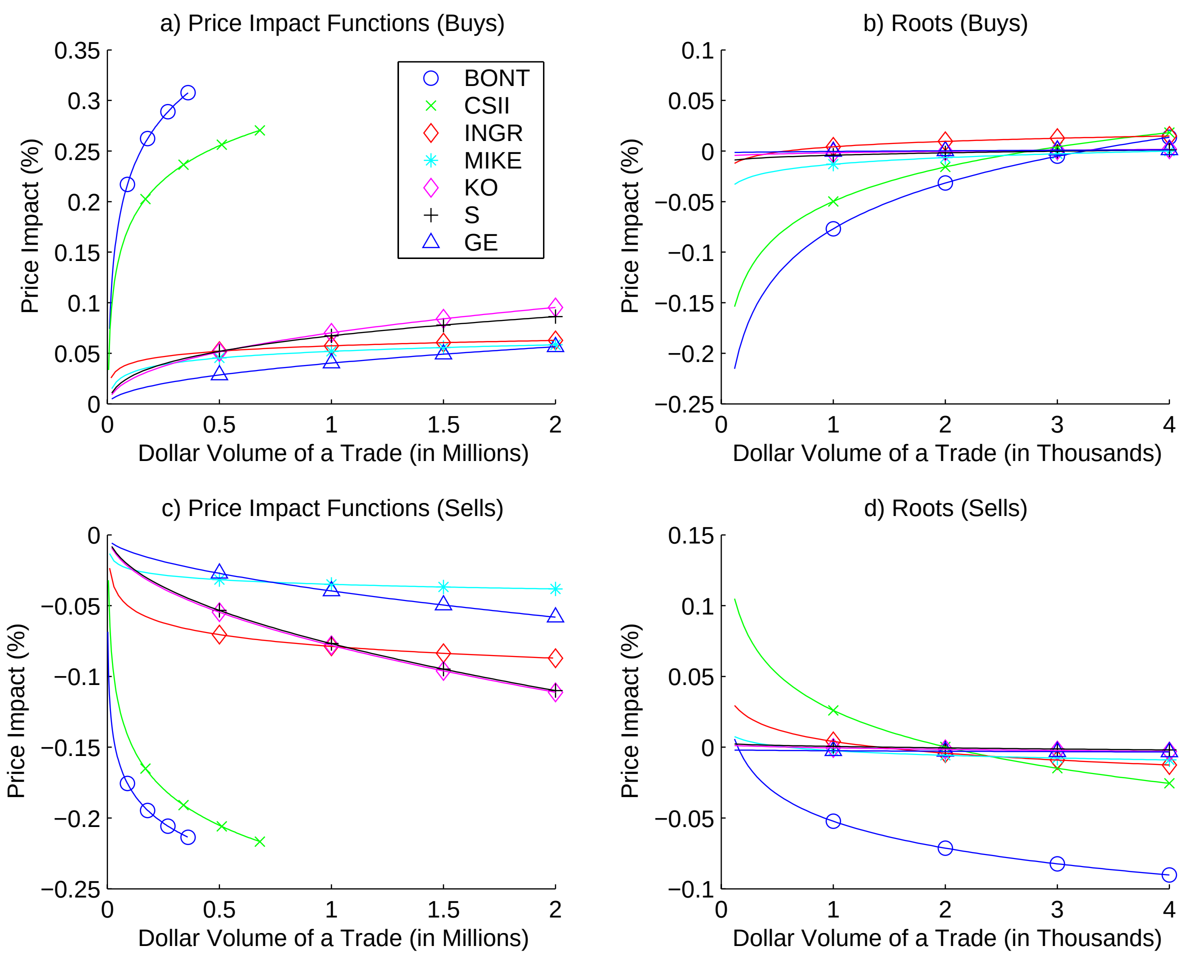

Figure 2: Estimated price-impact functions for the seven representative stocks. The estimated model is described in Section 2.1. Panel a) shows the shapes of the estimated price-impact functions for buy orders. In Panel b), the roots of each curve are shown. Panels c) and d) present the price-impact functions for sell orders.

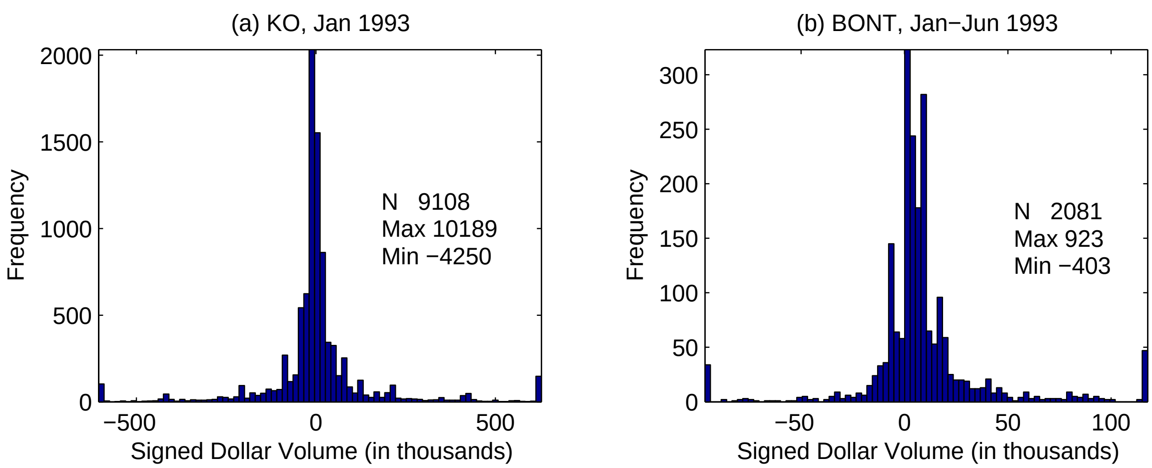

Figure 3: Distribution of signed dollar volume.

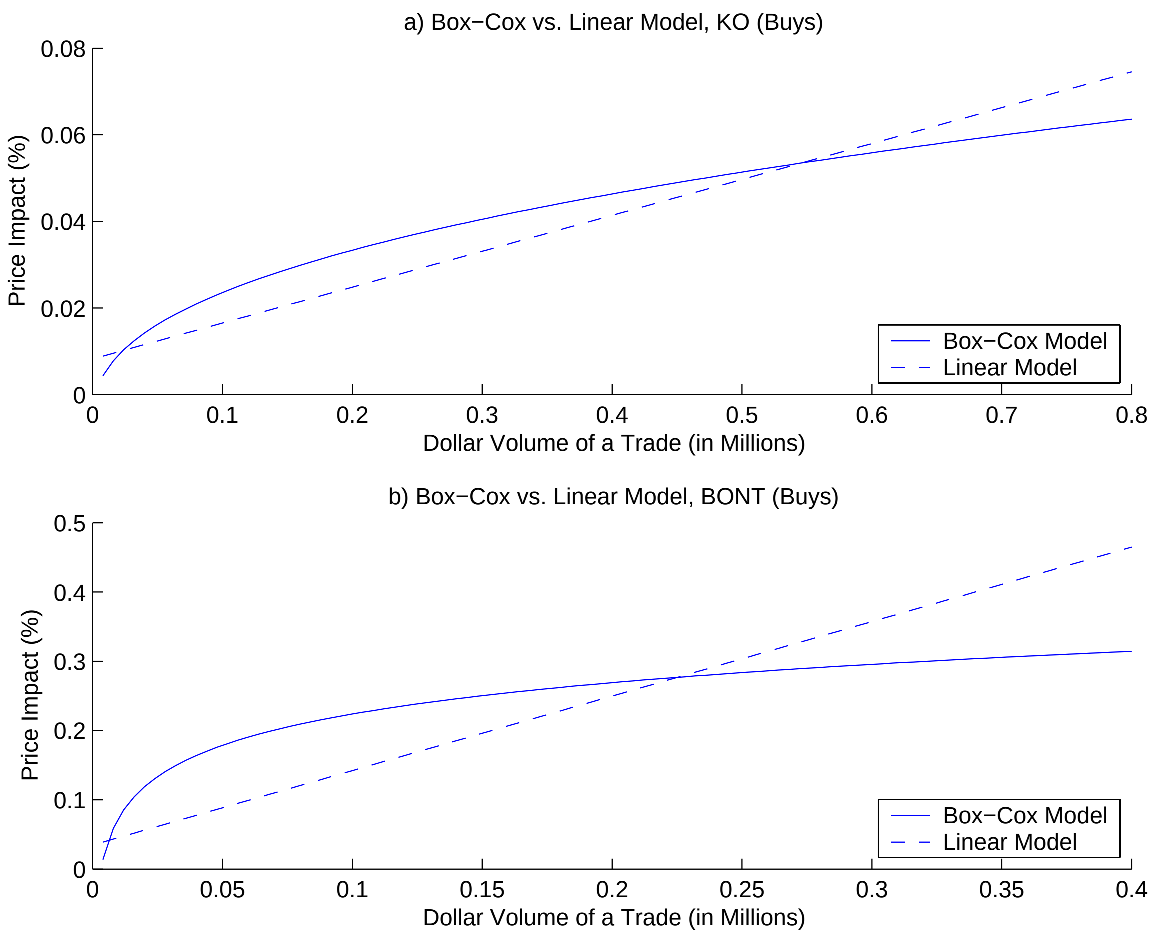

Figure 4: Comparison between the Box-Cox and the linear models. The Box-Cox model is described in Section 2.1 and the linear model in Section 2.4. Panels a) and b) show the estimates for the buy orders of KO and BONT, respectively.

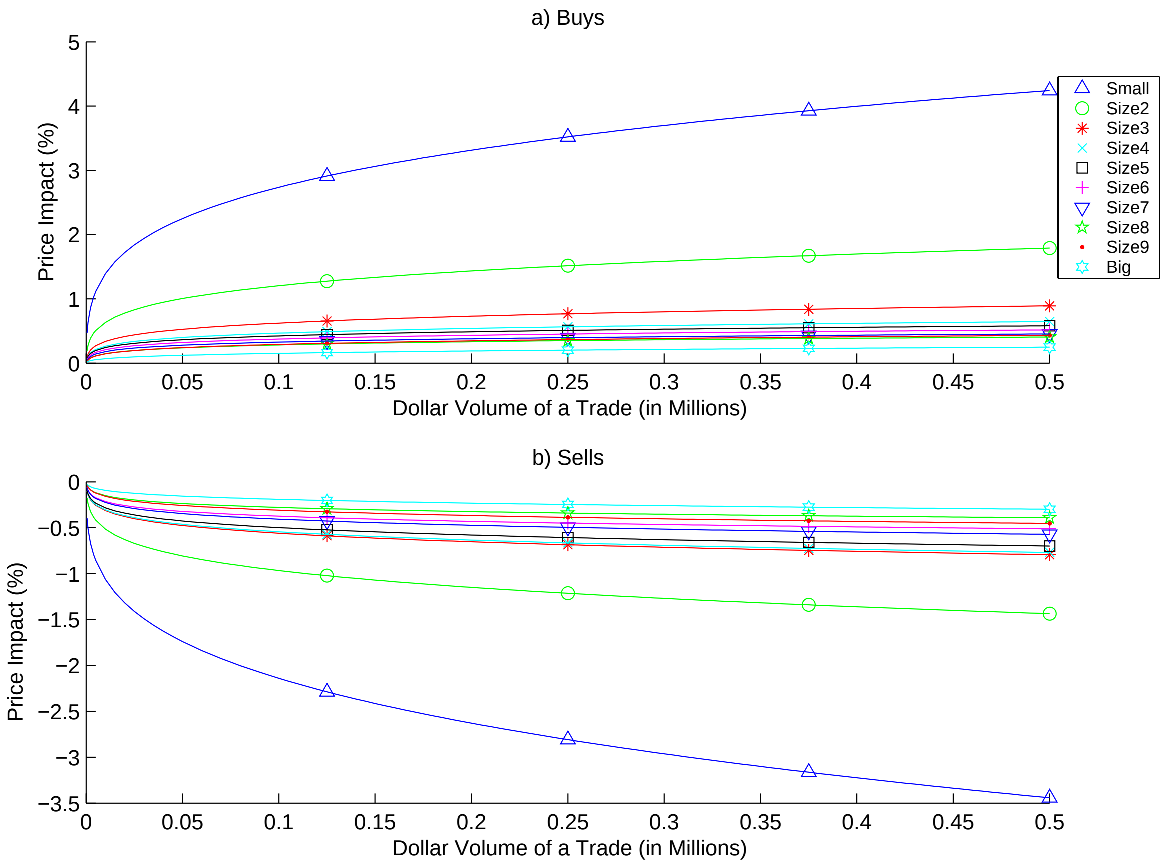

Figure 5: Estimated portfolio price-impact functions by size decile. First, price-impact functions for individual stocks are estimated by the Box-Cox model as described in Section 2.1. The parameter values of a portfolio price-impact function is then computed as the equally weighted average of the parameter values of the individual price-impact functions over stocks in the corresponding size decile. Panels a) and b) show the price-impact functions for buy and sell orders, respectively.

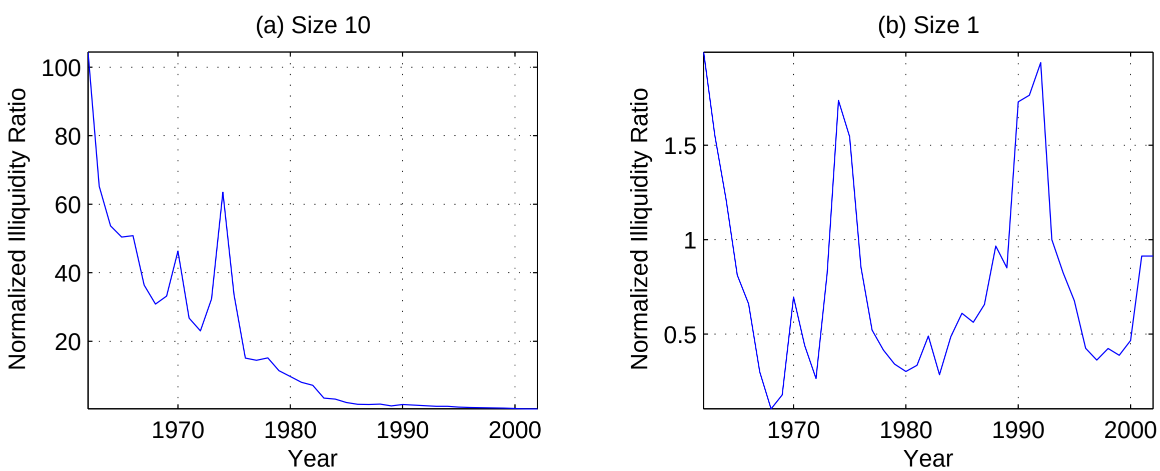

Figure 6: Amihud illiquidity ratio for size deciles. The ratio is normalized so that it is 1 in year 1993.

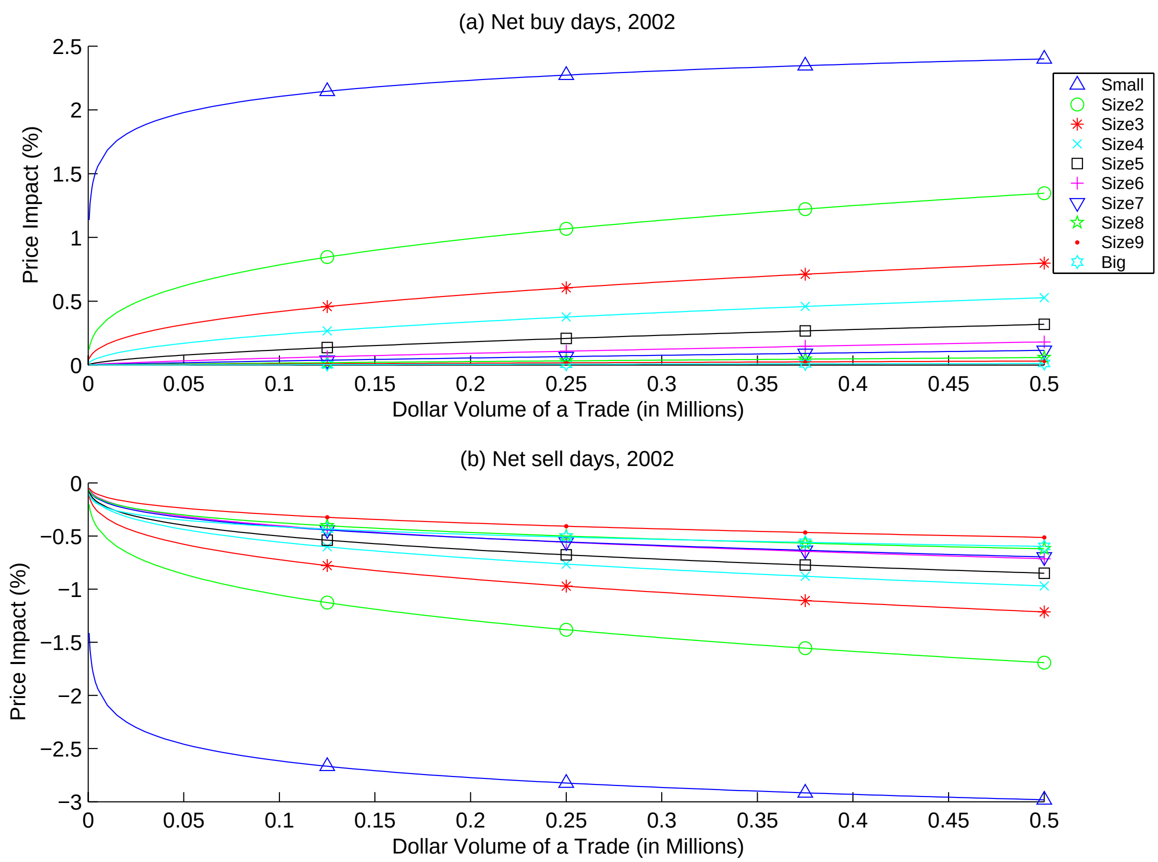

Figure 7: Portfolio VWAP price-impact functions by size decile.

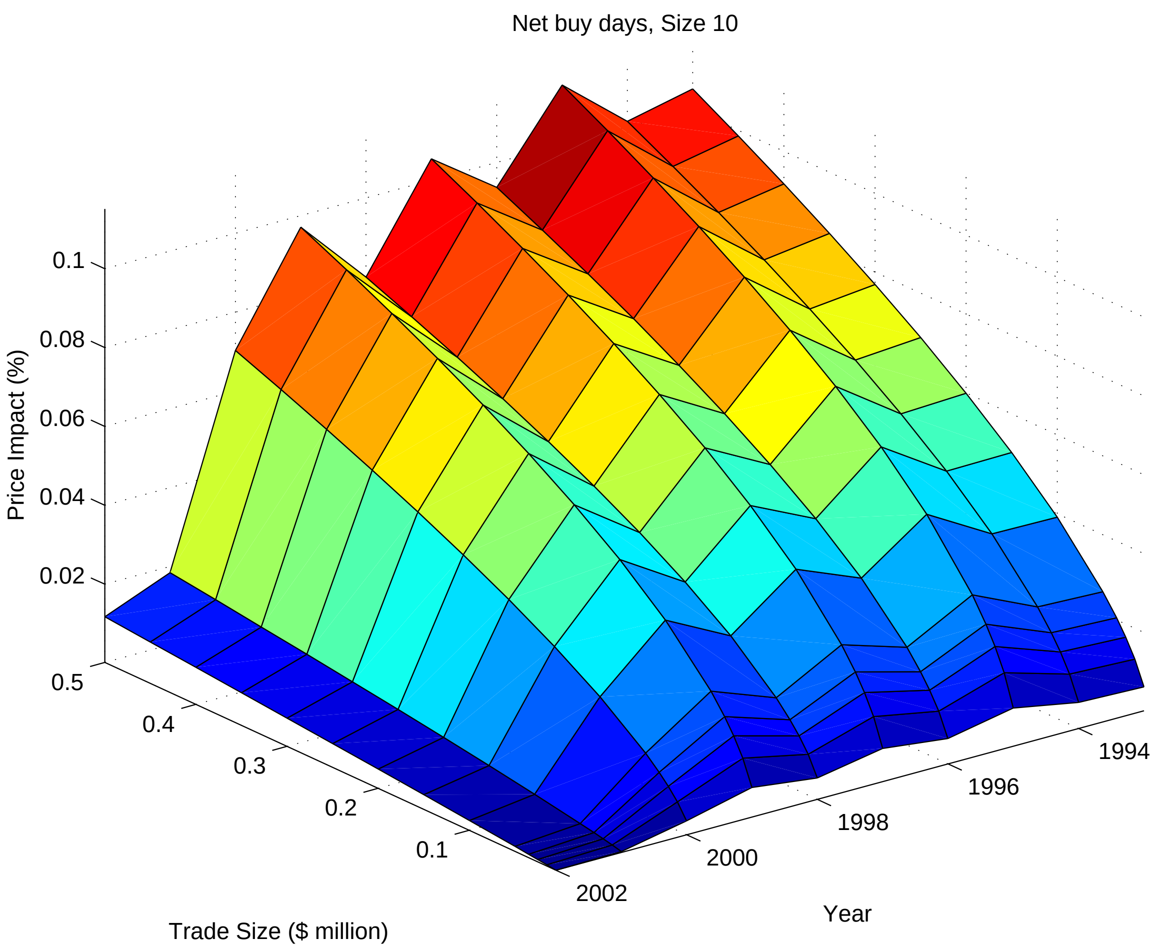

Figure 8: Pooled VWAP price-impact functions by year, largest decile, buys.

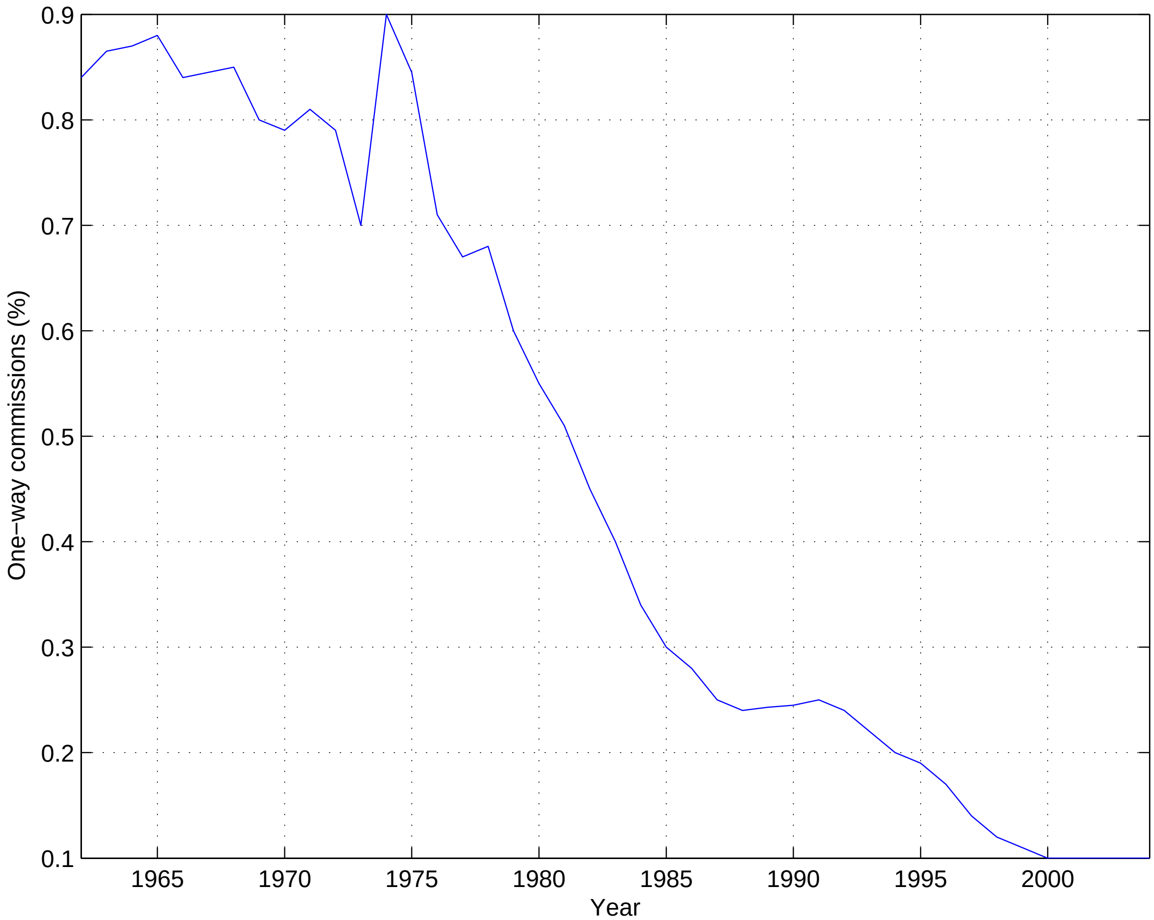

Figure 9: One-way commissions by year.

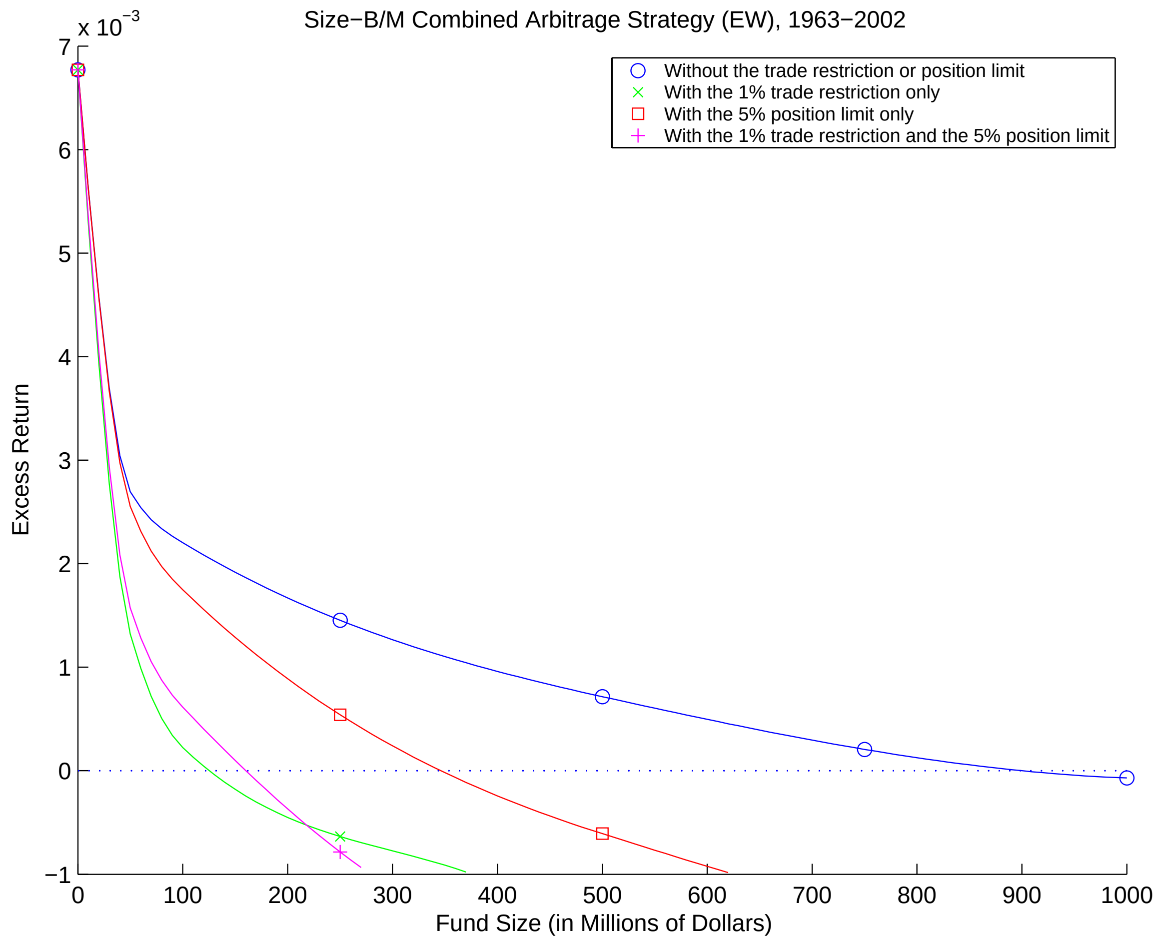

Figure 10: Excess returns of the size-B/M combined arbitrage strategy are plotted against arbitrage fund size with or without the 1% trade restriction and the 5% position limit.

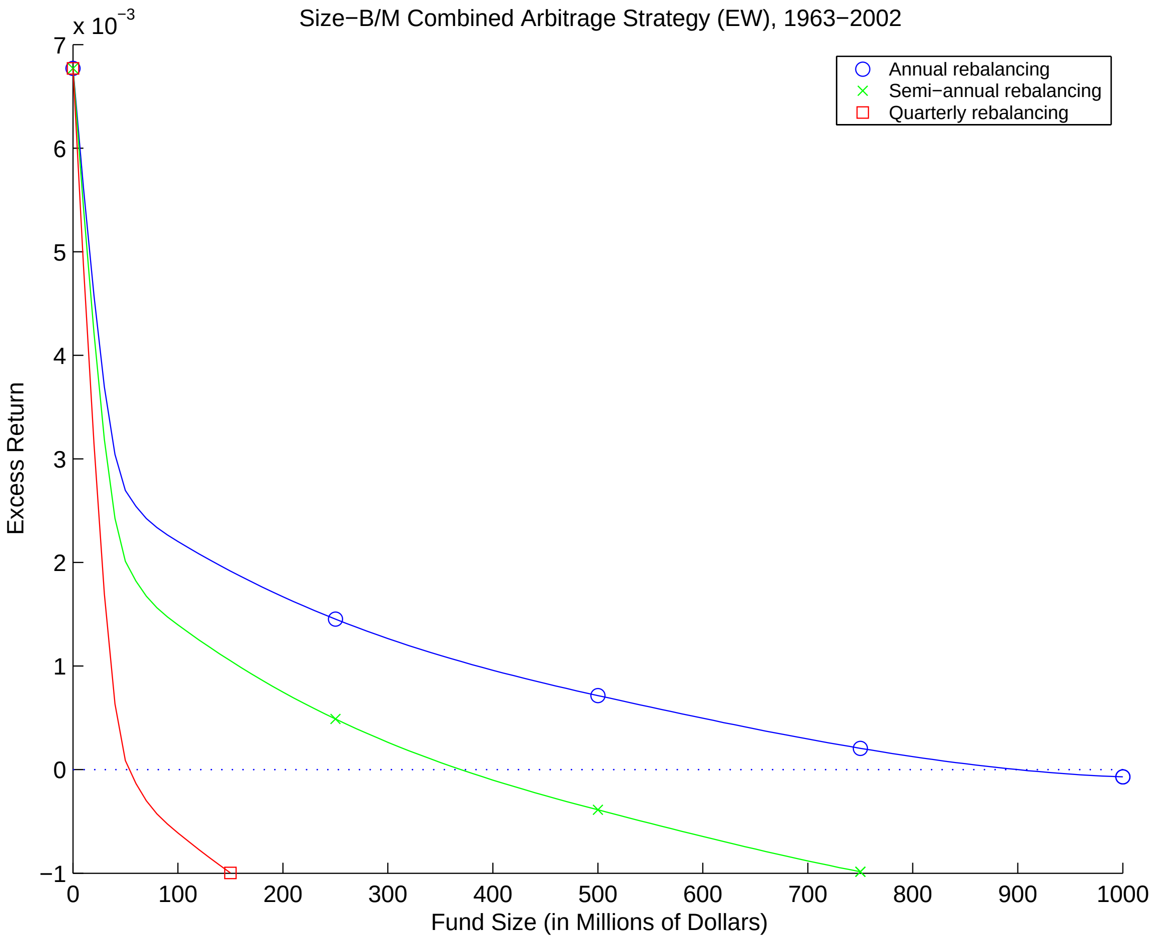

Figure 11: Excess returns of the size-B/M combined arbitrage strategy for various rebalancing frequencies, plotted against fund size. Excess returns are after both price-impact and transactions costs. The 1% market cap trade restriction and the 5% market cap position limit are not imposed.