Price Impact Costs and the Limit of Arbitrage

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Abstract

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JEL Classification: G1

Keywords: Stock market anomaly; Price-impact function; Arbitrage; Fund size limit.

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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 bounded-rationality perspective further, in the present paper we first estimate a more realistic price-impact function for each stock. Assuming that an arbitrageur would set up a long/short hedge 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 the price-impact and trading costs, but also short-sale costs (short rebate rate) and limits on positions in any stock. If the maximal fund sizes are economically small, it will mean that anomalies exist not because investors are irrational, but because they are too economically rational.

To make the scope of the paper manageable, we choose to focus on three popular anomalies: size, book/market (B/M) and momentum. The size and the B/M anomalies arise because, contrary to the predictions of the CAPM, both the size and the B/M ratio of a stock are found to be significant determinants of its 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 and 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-sized stocks and shorting a portfolio of big stocks constitutes an arbitrage, if the positions are chosen properly. 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 and shorting a portfolio of low B/M stocks. To benefit from the momentum anomaly, we buy a portfolio of past winners and short a portfolio of past losers. The time period for our study is 1963-2000, where rebalancing takes place annually, semiannually, and quarterly. Moreover, both equally weighted and value weighted portfolios will be employed. Note that we do not optimize the long and short positions to further minimize risk or force the portfolio to be market-neutral, partly to avoid data-mining and partly due to the fact that our goal is to determine an approximate maximal fund size for each anomaly.

When trading the necessary long and short positions, the arbitrageur will incur price-impact and trading costs because stock prices are sensitive to orders and trade sizes. Purchases usually move the price up while sales drive it down. Hence, price-impact costs can reduce the returns of an investment considerably if the invested amount is big. In our case, a larger fund size requires larger positions to rebalance and bigger 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 the excess return over the riskless rate will become negative (for a reasonably shaped impact function). We will refer to it as the fund size limit or maximal fund size.

The notion of price-impact function has been widely used in the microstructure literature since the work by 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 a key difference between our study and the existing anomaly literature. In most existing studies, a constant proportional transaction-cost structure is assumed. For example, using a linear price-impact function, Sadka

(2001) shows that the momentum seasonality strategy is no more profitable when more than \$19 million is invested, and concludes that the existence of momentum seasonality does not contradict market efficiency. From the market microstructure literature, however, the general consensus is that the empirically estimated impact function is typically concave (e.g., Hasbrouk (1991)). Compared to a concave impact function, a linear function will under-estimate the trading costs for small- to mid-size trades, while over-estimating the costs of large trades (assuming a linear line is estimated to fit the same transaction data as for the concave function). Our empirical exercise also demonstrates these biases by a linear impact function. For this reason, assuming a linear trading cost function is likely to under-estimate the impact magnitude of trading costs on portfolio performance.

To determine the price-impact costs, we estimate a non-linear price-impact function for each of 5173 stocks traded on the NYSE, AMEX, and NASDAQ during our sample period.

When position limits and price-impact costs are ignored, arbitraging based on the three anomalies each generates average returns higher than the riskless rate. The most profitable long-short arbitrage is based on B/M (with equally weighted positions), yielding an excess return of 9.2% and a Sharpe ratio of 0.66. The momentum based long-short strategy with value-weighted positions produces 9% and 0.35, for the respective performance metrics. The finding that a value-weighted momentum arbitrage strategy is more profitable than an equally weighted one differs from the results in Jegadeesh and Titman (1993 and 2001) and Moskowitz and Grinblatt (1999).

When price-impact costs are taken into account, returns for each arbitrage strategy decrease rapidly with the arbitrage fund size. The maximal arbitrage fund size is the smallest based on B/M, regardless of the way the portfolios are formed. It is \$2.38 million for an equally weighted portfolio, and even smaller for value weighted portfolios. For size-based arbitrage strategies, the maximal fund sizes are respectively \$186.1 million and \$9.8 million for equally and value-weighted portfolios. The corresponding fund size limits for momentum-based arbitrage are \$141,000 and \$44.2 million. The fact that an equally weighted portfolio would accommodate less capital is surprising, because one would expect more capacity when more weights are assigned to smaller firms. However, it turns out that the return spread between winner and loser portfolios are higher for the value weighted portfolios, although the individual returns for the winner and loser portfolios are higher for the equally weighted portfolios. Furthermore, as more weights are assigned to larger firms, the resulting price-impact costs would also be lower for a value weighted portfolio. This explains why a value-weighted strategy would accommodate more fund capacity.

Not surprisingly, increasing the portfolio-rebalancing frequency from annual to semiannual and then to quarterly reduces the maximal fund size successively because as the rebalancing frequency rises, so do price-impact costs. For example, the maximal fund size for size-based arbitrage (equally weighted) drops to $119.1 million if it is rebalanced semiannually and to $34.8 million if it is rebalanced quarterly.

Extending the sample period from 1963-1991 to 1963-2000 makes all arbitrage strategies less lucrative, except the momentum-based ones. This finding is indicative of the fact that the size and B/M anomalies were less pronounced in the 1990s.

Arbitrage strategies that combine the three anomalies do not fare much better than the individual anomaly based ones. The arbitrage which supports the largest maximal fund size is a momentum-based equally-weighted portfolio that invests only in stocks in the five largest size deciles. Its maximal fund size is about $560 million.

Compared to actual hedge funds, the maximal fund sizes of the anomaly-driven arbitrages estimated here appear relatively consistent: most managers in the industry believe a "good hedge fund size" is in the lower $100's of millions.

We hence conclude that markets are minimally rational, because price-impact costs deter agents from taking advantage of the anomalies. It is often argued that either short-selling or wealth constraints, or simply the risk of an arbitrage, make the exploitation of stock market anomalies impossible. In light of this, we demonstrate that the magnitude of the estimated price-impact costs, taken alone, is already enough to accomplish that.

The paper is organized as follows. Section 2 describes how we estimate the price-impact functions. Section 3 provides a brief overview of the data used in our analysis. Section 4 quantifies the profitability and the break-even find sizes of the anomaly-driven arbitrages. It also compares the obtained break-even find sizes to actual hedge fund sizes. Section 5 concludes the paper.

2 Estimation of Price-Impact Functions

This section introduces an estimation method for the price-impact function and discusses the estimates obtained for both individual stocks and portfolios of stocks. The choice of our method will be justified by pointing out its advantages relative to alternative approaches. Our estimates have two important implications. First, the price-impact costs for stocks are generally nonlinear. Second, if a linear price-impact function is applied, the price-impact costs of small- and medium-sized trades will be underestimated, while those of large-sized trades overestimated.

2.1 Model Specification

There are various ways of specifying 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 the trade's size. Typically, trade size is the number of shares traded, either in absolute terms or relative to the number of shares outstanding. Examples of such linear price-impact functions can be found in Bertsimas and Lo (1998), Breen et al. (2000), Madhavan and Dutta (1995), or Kyle (1985). In contrast, we follow Hasbrouck (1991) and Hausman et al. (1992) and allow here nonlinear price-impact functions.

More specifically, we model the price impact of a trade, measured by the relative change of the midpoint quote ((ask+bid)/2) after the trade, as a nonlinear function of the trade's dollar value (price $\times$ quantity). In addition, unlike Hasbrouck (1991) and Hausman et al. (1992), we estimate the price-impact function for purchases and sales separately. We want to keep our model simple, while allowing for asymmetric price impacts of buys and sells.

To obtain the midpoint quotes, we follow Lee and Ready (1991) and match each transaction to bid and ask quotes that are set at least five seconds prior to the transaction. 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 transaction the quote prevailing an instant after the transaction has occurred.

Using actual transaction prices rather than midpoint quotes could bias the price-impact estimation, because trades do not occur continuously. For instance, consider a situation in which the midpoint quote increases at time $t-1$ due to a positive announcement about the value of the underlying asset, but no trades take 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, the Lee and Ready (1991) method may bias the estimates since quotes may not be perfectly matched with their contemporaneous transactions. We think that the bias introduced by employing actual transaction prices is bigger and hence prefer to work with midpoint quotes. Hasbrouck (1991) uses midpoint quotes, 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.

Let $PI_t \triangleq (Q_{t+1} - Q_t)/Q_t$ be the price impact, and V_t the dollar value of the trade at time t, where V_t is calculated using the actual transaction price p_t. Then, for purchases we model the price impact as

$$PI_t = a_B + b_B \, \frac{V_t^{\lambda_B} - 1}{\lambda_B} + \varepsilon_t, \tag{1}$$

while for sales

$$PI_\tau = a_S - b_S \, \frac{V_\tau^{\lambda_S} - 1}{\lambda_S} + \varepsilon_\tau, \tag{2}$$

where t and τ are the transaction times for buys and sales, respectively. The ε_t's and ε_τ's are independently and identically distributed with mean zero and variance σ^2.

Equations (1) and (2) imply that the relative quote change is modeled as a Box-Cox transformation of the trade size measured in dollars, where λ_B and λ_S are the curvature parameters. Note that the V_t's are all nonnegative by definition and that the Box-Cox transformation $(V_t^{\lambda_B} - 1)/\lambda_B$ converges to $\ln V_t$ if $\lambda_B \to 0$. The mappings $V_t \mapsto a_B + b_B \, \frac{V_t^{\lambda_B}-1}{\lambda_B}$ and $V_t \mapsto a_S - b_S \, \frac{V_\tau^{\lambda_S}-1}{\lambda_S}$ in (1) and (2) are interpreted as the price-impact functions for purchases and sales, respectively.

We assume that the estimated price-impact function should be nondecreasing. Although there may be large trades with a relatively small price impact, on average the price impact is bigger the larger the trade. This property is satisfied by our model defined in (1) and (2). Moreover, we postulate that PI_t is concave and PI_τ is convex, or equivalently, there are economies of scale: changes in price impact decline with trade size.

As a consequence, the curvature parameters have to satisfy $\lambda_B \leq 1$ and $\lambda_S \leq 1$. Indeed, PI_t (PI_τ) is strictly concave (convex) in V_t (V_τ) if $\lambda_B < 1$ ($\lambda_S < 1$), linear (linear) if $\lambda_B = 1$ ($\lambda_S = 1$), and convex (concave) otherwise. In addition, the inequalities, $\lambda_B < 0$ and $\lambda_S < 0$, are ruled out because the Box-Cox transformation would exhibit a horizontal asymptote in these cases, which would make the coefficient estimation in (1) and (2) more difficult. Hence, we restrict both λ_B and λ_S to lie in the interval $[0, 1]$. This is also a constraint used in Hausman et al. (1992) where their ordered probit model uses a Box-Cox transformation.

To estimate (a_B, b_B, λ_B) and (a_S, b_S, λ_S) , we minimize the nonlinear least squares in (1) and (2) separately by computing

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

and

$$(\hat{a}_S, \hat{b}_S, \hat{\lambda}_S) = \arg \min_{\substack{(a_S, b_S) \in \mathbf{R}^2, \\ \lambda_S \in [0,1]}} \sum_{t=1}^{N_S} \left[PI_\tau - a_S + b_S \, \frac{V_\tau^{\lambda_S} - 1}{\lambda_S} \right]^2, \tag{4}$$

where N_B and N_S denote the sample sizes of purchases and sales, respectively.

Note that the sum of squared residuals in (3) and (4) will be relatively high due to the discreteness of prices and quotes. Nonetheless, our model is expected to fit the discrete data reasonably, as will be argued in the next section.

Huberman and Stanzl (2001a) 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) and (2) for $\lambda_B < 1$ and $\lambda_S < 1$, 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 $0 \leq \lambda_B$, $\lambda_S \leq 1$ and if the price-impact functions for buys and sells as given in (1) and (2) are approximately symmetric, that is, $a_B \approx -a_S$, $b_B \approx b_S$, and $\lambda_B \approx \lambda_S$, 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 will yield almost symmetric price-impact functions.

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 model given in (1)-(2), we have tried three alternative approaches to estimate the price-impact function: polynomial fitting, piecewise linear fitting, and ordered probit. In the following, we discuss these methods. To save space, we focus on purchases only.

Polynomial fitting of PI_t as a function of V_t can be obtained by estimating

$$PI_t = \sum_{j=0}^{m} \alpha_j V_t^j + \varepsilon_t, \tag{5}$$

where m denotes the degree of the polynomial. Figures 1a and 1b depict the estimated price-impact functions for URIX (Uranium Resources INC is a small-sized company traded on NASDAQ), when a quadratic, a cubic, or a fourth-order polynomial is fitted.

From Figure 1a, the disadvantage of using a second-order polynomial is that the fitted curve is (steeply) downward-sloping for larger trades. The price-impact of bigger trades would thus be underestimated. Evidently, the downward kink of the fitted quadratic function is caused by a few large trades that experienced price discounts.

Increasing the degree of the polynomials would not yield monotone price-impact functions either, as Figure 1b illustrates. In addition, it introduces a new problem: overfitting due to outliers.

Piecewise linear fitting exhibits the same shortcomings as polynomial fitting. The estimated price-impact function for URIX, shown in Figure 1c, has also a negative slope for medium- and large-sized trades.

As a third alternative we consider a version of the ordered probit model described in Hausman et al. (1992), with modifications only along two dimensions. First, rather than the absolute change in transaction prices, we use the relative midpoint-quote change to measure the price impact. And second, we estimate the price-impact function separately for purchases and sales. We thus maintain the main assumptions stated in the previous section. In short, the problem with this approach is that estimates can only be obtained for big-sized firms, for which sufficiently many quote and trade observations exist, an issue that Hausman et al. already realized.

The stock URIX is not a random choice. The disadvantages of the alternative methods illustrated for this stock apply in general, but are in particular valid for small stocks.

Taking all of the above into consideration, we choose to rely on the model specification in (1) and (2). By comparison, Figure 1d depicts for URIX the Box-Cox estimation of the function in (1).

2.3 Estimates for Individual Stocks

The model in (1) and (2) is separately estimated for 5173 individual stocks (on the NYSE and NASDAQ) between January 1993 and June 1993. To get rid of outlier effects, we sort the transactions for each stock by trade size, and jettison transactions in the largest one percent of all trades. Since we measure the price impact by the relative midpoint quote and trade size is expressed in dollars, price level effects due to stock splits introduce only a negligible estimation bias. Firms that experienced stock splits during our sample are therefore not excluded. In total, we are able to estimate the price-impact functions for 4897 stocks. For each of these stocks, the price-impact function is estimated for both buys and sells. Stocks for which at least one side of the price-impact function could not be approximated are thrown out.

Table 1 reports the characteristics of seven representative stocks, and Table 2 shows the estimated coefficients of their price-impact functions. We can note the following qualitative properties of these estimates by considering buys only. 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 is in the largest quintile (both with similar B/M ratios). Table 2 and Figures 2a and 2b show that the price impact for CSII is larger than for S, for all but small trades. Even though the curvature λ_B is bigger for S, the slope b_B is substantially larger for CSII so that its price impact is bigger than for S. This finding is generally valid across the sample. The coefficient b_B is smaller and λ_B is larger for bigger firms. Since a single trade is almost always less than 1% of a company's market capitalization, say $M_{1\%}$, we draw the estimated price-impact function only on the interval [0, $M_{1\%}$]. That's why the price-impact functions are truncated in Figures 2a and 2c.

NASDAQ companies are typically smaller than NYSE companies. Thus, from the above follows that on average trading a NASDAQ stock induces a higher price impact than a NYSE stock.

The intercept a_B is negative and statistically significant(except GE). Hence, small trades either have no price impact or even receive price improvements. For example, buying \$837.50 of KO (20 shares at \$41.875 per share) or buying \$8961 of BONT (1236 shares at \$7.25 per share) causes no price impact in each case. Furthermore, a_B is noticeably smaller for small companies, which is why the price impact for big firms exceeds that for small firms when a trade is small. Purchasing \$10,000 of BONT has a higher price impact than buying \$10,000 of KO.

The qualitative properties of the estimated price-impact functions for sales are symmetrically similar for buys, as is evident from Table 2 and Figure 2. There is one noticeable difference: a_S is statistically insignificant in many cases.

For both buys and sells the curvature parameter is typically zero for small companies. This is true for almost 60% of the small firms in our sample. Recall that $\lambda_B = 0$ and $\lambda_S = 0$ imply a logarithmic price-impact function.

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

2.4 Linear vs. Nonlinear Price-Impact Functions

This section quantifies the difference between a linear and a nonlinear price-impact function. As shown below, a linear price-impact function underestimates the price impact of small and medium trades, while overestimating it for big trades. We will only discuss here the buy side, because the results for the sell side are symmetric.

The top part of Table 3 reports the estimates for a linear regression model:

$$PI_t = \alpha + \beta V_t + \varepsilon_t \tag{6}$$

applied to the seven stocks in the previous section. All estimated parameters are statistically significant and positive, except for BONT for which the intercept is negative. The bottom part of Table 3 then shows differences between the linear function in (6) and the nonlinear one in (1), when either \$50,000 or \$100,000 is purchased.

From Table 3, the linear function underestimates the price impact for all stocks if \$50,000 is traded. This downward bias is larger for smaller companies. If \$100,000 is traded, on the other hand, the linear function still underestimates the price impact for large firms, but overestimates it for small firms.

Between the linear and nonlinear price-impact functions, there are generally two intersection points for a given stock. Figure 3, which plots the linear and nonlinear price-impact functions for KO and BONT, illustrates this fact. The leftmost interval, where the linear price-impact function is higher than the nonlinear one, is negligibly small. The middle interval is the area of small to medium trades in which the linear model underestimates the price impact.

2.5 Aggregating Price-Impact Functions

Note that the impact functions for individual stocks can be quite noisy based on the sample period. To reduce its effect, we aggregate the parameter estimates within each size decile group and then apply these aggregated estimates to assess the price-impact costs of individual trades in our study. To estimate the price-impact function for each size group, we sort all our 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

$$\begin{cases} \bar{a}_{jB} + \bar{b}_{jB} \, \frac{V^{\bar{\lambda}_{jB}-1}}{\bar{\lambda}_{jB}} & \text{if } V \text{ dollars of size portfolio } j \text{ are bought,} \\ \bar{a}_{jS} - \bar{b}_{jS} \, \frac{V^{\bar{\lambda}_{jS}-1}}{\bar{\lambda}_{jS}} & \text{if } V \text{ dollars of size portfolio } j \text{ are sold,} \end{cases} \tag{7}$$

where $\bar{a}_{jB} = \sum_{s \in S_j} \hat{a}_{sB} / |S_j|$, $\bar{b}_{jB} = \sum_{s \in S_j} \hat{b}_{sB} / |S_j|$, and $\bar{\lambda}_{jB} = \sum_{s \in S_j} \hat{\lambda}_{sB} / |S_j|$, and $\hat{a}_{sB}$, $\hat{b}_{sB}$, and $\hat{\lambda}_{sB}$ denote the individual parameter estimates for stock s, and $|S_j|$ is the number of stocks in decile S_j. The parameters $\bar{a}_{jS}$, $\bar{b}_{jS}$, and $\bar{\lambda}_{jS}$ are defined analogously. Thus, the parameter values for the price-impact function of a size portfolio are computed as the equally weighted average of the stocks in the decile.

Table 4 presents the estimated coefficients obtained from (7) for all ten deciles and Figure 4 draws the resulting price-impact functions. Apparently, the price-impact function for decile S_j exceeds the price-impact functions for the deciles S_{j+1}, $S_{j+2}, \ldots,$ S_{10}. Hence, the price impact is uniformly decreasing in market capitalization. Also observe that the price-impact function for the smallest size is fairly large relative to others.

Some care is necessary to interpret the magnitudes of the curvature parameters. Table 4 shows only the mean of λ_B and λ_S for each decile but not their intra-decile distributions. For example, λ_B and λ_S are biggest for the smallest size decile, even though the fraction of stocks with $\lambda_B = \lambda_S = 0$ is highest for this decile (60%). Thus, Table 4 only says that the mean of the curvature parameter is U-shaped across the deciles.

We could have also built value-weighted parameter estimates to produce Table 4 and Figure 4. However, equal weighting is more natural for the purpose.

All long-short arbitrages introduced below will require investing in a number of stocks. We use Table 4 to estimate the price impact of each trade. For a given stock, we simply identify its size decile and take the estimates for that decile in Table 4. This method is not only applied to the period 1/1993 and 6/1993, but also to all other years in our sample. For all stocks (including those which did not trade between 1/1993 and 6/1993), the size ranking is determined in each month and the price-impact costs are then estimated from Table 4. Note that the price-impact costs prior to 1993 will be underestimated by our method because liquidity was lower then, but over-estimated for the years after 1993.

3 Data

Our empirical analysis makes use of five databases: CRSP, Compustat, CRSP-Compustat Merged, TAQ, and TASS. To gauge the profitability of anomaly-based long-short arbitrages, we need both accounting data (Compustat) and historical returns (CRSP) for some anomalies. We will consider here two sample periods: 1963-1991 and 1963-2000. To estimate the price-impact functions we employ all stocks contained in both the CRSP and TAQ databases between January 1993 and June 1993, where 1993 is the earliest available year in the TAQ data. A six-month period is chosen to guarantee enough observations of trades and quotes.

For January 1993 - June 1993, we first extract from the TAQ data all common stocks traded on NYSE, AMEX, and NASDAQ that are also in CRSP ("when-issued" entries are excluded). Then, for each of these stocks, we pull out from the TAQ Quote files those quotes that have positive bid and offer prices and an exchange code that matches the CRSP primary exchange code. From the TAQ Trade File, those trades are picked that have a positive price and number of shares traded. We use trades and quotes which are time stamped between 9:30a.m. and 4:00p.m., and match them according to the Lee and Ready (1991) criterion. Only those stocks that have at least ten observations of trades and quotes remain in our sample. The above procedure results in a sample of 5,173 stocks.

The data in CRSP and Compustat are combined with the help of the linking information given in the CRSP-Compustat Merged database. The latter database yields a considerably better matching than using the CUSIP or the ticker symbol as the linking key, especially for earlier years.

In forming the size deciles, we use the NYSE breakpoints. First, all the NYSE stocks in the CRSP file are sorted into deciles by size (the absolute value of the CRSP end-of-month price times the number of shares outstanding). Then, based on those breakpoints, all the AMEX and NASDAQ stocks are also classified into deciles. This procedure is done for every month between December 1962 and December 2000.

The B/M deciles are formed independently. In each fiscal quarter between December 1962 and December 2000, we compute 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. Since the arbitrage based on B/M involves quarterly rebalancing, both Compustat Annual and Quarterly files are used to collect the accounting numbers. If an entry is missing, we use the latest available value from the previous quarters. Given the reporting delay for financial statements and the misalignment of fiscal and calendar quarters, the B/M in quarter

t is defined as the book value in fiscal quarter $t-2$ divided by size in calendar quarter $t-2$. This conservative timing convention is in line with Fama and French (1993) and is meant to be a generalization of their annual rebalancing strategy to more frequent rebalancing, while keeping unanimity. Again, the NYSE breakpoints are used to classify all stocks into deciles.

The TASS database from TASS Management Limited covers 1330 hedge funds up to May 2000 and includes information about fund size, investment strategies and styles, and invested assets and instruments.

4 Profitability of Stock Market Anomalies

This section measures the returns from anomaly-driven arbitrage as a function of the fund size, when price-impact costs are taken into account. In particular, we study here the profitability of long-short arbitrages based on the size-, B/M-, and momentum anomalies, and on combinations thereof. Obviously, a bigger fund size requires larger trades, which implies higher price-impact costs and lower returns. The subsequent analysis will quantify this negative relation between fund size and return. Of special interest is the break-even fund size of an arbitrage strategy: what is the maximal fund size that generates a positive excess return (relative to the Federal Fund rate)?

To explain the implementation of a long-short arbitrage, 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 equity. To profit from this relation, one would want to buy a portfolio of small stocks, PL, and at the same time short a portfolio of large stocks, PS , with both sides of the same dollar amount invested. Such a strategy would constitute a riskless arbitrage if its return is riskfree. Unfortunately, a textbook arbitrage like this is infeasible in practice, mainly because of three reasons. First, the convergence of the values of PS and PL can never be assured. Second, the proceeds from shorting PS cannot be used to finance the purchase of PL, since they have to be deposited on an account as collateral. And third, price-impact and transaction costs implicate the necessity of additional finance 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.

In particular, suppose we start with an initial fund size π_0 and implement a self-financing long-short arbitrage over the next T periods, which has the following feature: in each period, we short an equally weighted portfolio of all the stocks in the largest size decile and hold an equally weighted portfolio of all the stocks in the smallest decile. Our long-short arbitrage will be unleveraged in the sense that the value of the long position will exactly match the value of the short position in the beginning of each period.

Denote by SSD_t and LSD_t the equally weighted portfolios of all the stocks in the smallest and largest size decile at time t, respectively. At the beginning of period 1, we invest π_0 dollars in SSD_1 and short π_0 dollars of LSD_1. After price-impact costs and transaction fees, we effectively hold $b_1 = \pi_0 - PIL_1 - PIS_1 - TCL_1 - TCS_1$ dollars of SSD_1 in our long portfolio, and are short b_1 dollars of LSD_1, where PIL_1 and TCL_1 represent the price-impact costs and transaction fees necessary to create our long position, and PIS_1 and TCS_1 denote the corresponding costs for installing our short position. Both PIL_1 and PIS_1 are computed using Table 4 based on π_0.

We assume that 15 basis points accrue in commissions for each purchase and each regular sale, and 25 basis points for a short sale. For typical fund sizes, the transaction fees are small relative to the price-impact costs. The b_1 dollars received from shorting LSD_1 are then assumed to be deposited in an account which pays 80% of the Federal Fund rate. Hence, at the end of period 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 SSD_1, r_{s1} the return on LSD_1, and r_1 the Federal Fund rate.

At the beginning of period 2, we rebalance our portfolio in a self-financing manner such that π_1 dollars are invested in SSD_2 and π_1 dollars are shorted of LSD_2. The value of each position is

$b_2 = \pi_1 - PIL_2 - PIS_2 - TCL_2 - TCS_2$, after price-impact costs and transaction fees. We compute PIL_2 and PIS_2 based only on the rebalancing amount for each stock and not on π_1. Both the long and the short portfolios are held until the end of period 2, and thus 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 value of our portfolio in the beginning of the third period when we rebalance again in order to be long in SSD_3 and short in LSD_3, and so on. Thus, the portfolio dynamics are governed by

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

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

for $t \in \{1, 2, \ldots, T\}$. The excess returns are calculated for each period by $R_t = \pi_t/\pi_{t-1} - 1 - r_t$. Now, the break-even fund size of an arbitrage can be formally defined as the fund size that makes the mean excess return zero, i.e., $\sup\{\pi_0 \geq 0 \mid \sum_{t=1}^{T} R_t(\pi_0) \geq 0\}$.

Actually, after subtracting the price-impact costs and transaction fees, the long position is worth $\pi_{t-1} - PIL_t - TCL_t$ dollars, while the short position's value is $\pi_{t-1} - PIS_t - TCS_t$. In order to match the value of both portfolios, we invest an amount of $PIL_t + PIS_t + TCL_t + TCS_t$ dollars in riskless bonds in each period. This strategy aims at reducing the total risk.

The long-short arbitrage based on the B/M ratio (B/M) is long the largest B/M decile and short in the smallest B/M decile in each period. The long-short arbitrage based on momentum is to buy the best winner decile and sell short the worst loser decile.

Each arbitrage will be implemented using both equal weighting and value weighting in the dollar allocation across positions. For convenience, the EW-size arbitrage denotes the size arbitrage when equally weighted portfolios are formed, whereas the VW-size arbitrage is the size arbitrage based on value weighted portfolios. EW-B/M-, VW-B/M-, EW-momentum, and VW-momentum arbitrages are analogously defined.

Recall from Section 2.5 that Table 4 underestimates the price-impact costs for the years prior to 1993. Hence, the estimated returns and break-even fund sizes reported below may be overstated for each individual arbitrage.

4.1 Arbitrage Based on Size

Table 5 reports the results for the size arbitrage over the years 1963 to 1991 and with annual rebalancing in June. This is the same time period studied by Fama and French (1993). Panels (a) and (b) present the case where all long and short portfolios are equally weighted, whereas panels (c) and (d) consider value weighted portfolios.

The first two columns in panel (b) of Table 5 show how the mean excess return (above the Federal Fund rate) decreases with the fund size, when price-impact and transaction costs are taken into account. The mean excess return is the average annual excess return between 1963 and 1991, and is between 5.7% and -0.8% for fund sizes between $100,000 to $300 million. The maximal fund size that generates a nonnegative mean excess return is close to $186 million. In contrast, if the price-impact costs were ignored, the size arbitrage would render a mean excess return of 6.67%, as panel (a) reveals.

The standard deviation of the excess return and the Sharpe ratio are decreasing with fund size, while the mean price-impact costs and the mean turnover of the size arbitrage are both increasing with fund size. The mean price-impact costs are defined as the mean of (price-impact costs)/(dollar amount invested), and the mean turnover is calculated as the mean of (dollar amount rebalanced)/(dollar amount invested). The mean price-impact costs of the long portfolio are substantially larger than that of the short portfolio. The small stocks in the long portfolio not only cause higher price-impact costs than the big stocks in the short, but the long portfolio also exhibits a higher turnover perhaps because of the higher volatility for small stocks..

As panels (c) and (d) in Table 5 illustrate, the size arbitrage with value-weighted portfolios has the same qualitative properties. However, in comparison to the EW-size arbitrage, it yields much lower returns and only slightly smaller standard deviations. The break-even fund size is only \$10 million. The main reason for this result of the VW-size arbitrage is that the long portfolio is tilted towards the larger stocks within the smallest decile, producing lower returns. The price-impact costs should be a slight positive factor for this strategy as it means larger trades for larger stocks in a given decile.

So far, we have imposed no restrictions on position size in any given stock. In reality, however, transactions involving more than 1% of the market capitalization of a stock are very difficult to execute, and holding more than 5% of a stock's market capitalization results in costly filings with the SEC (Form 13D). Hence, any trading and portfolio strategy should take these constraints into consideration. Of course, in our case, such restrictions will only matter if the fund size is sufficiently large.

What happens to the size arbitrage's return if each trade has to be no larger than 1% of the stock's total shares and/or if each position in a stock has to be no more than 5% of the stock's total shares? Figure 5 shows the effect of incorporating these two restrictions. Evidently, the returns and break-even fund sizes become lower when the constraints are binding. For example, if our size arbitrage requires 3.5% of a stock's market equity to be traded, then the position is acquired through four transactions, which will produce higher total price-impact costs than if the entire position could be established in a single trade. We assume that when the trade size is binding, the maximal possible amount is traded for each trade until the last one. In this example, first trade 1%, subsequently trade 1% two more times, and finally the remaining 0.5%. Such a trading strategy may not be optimal in that it doesn't minimize the price-impact costs. But, for simplicity, we implement it this way. Huberman and Stanzl (2001b) study the problem of optimally executing a given portfolio when trades have a price impact.

Next, we consider a position limit to be no more than 5% of a stock's market capitalization. For a value weighted portfolio, the 5% position limit is binding for one stock if and only if it is binding for all stocks in the portfolio. Therefore it immediately reaches a maximum fund size for a VW-size arbitrage, once the position limit becomes binding for only one stock:. In Figure 5, the returns of the VW-size arbitrage are plotted for fund sizes between $0 to $50 million. The 5% position limit is not binding for this range.

For an EW-size arbitrage, the 5% limit becomes binding first for the smallest stock in either the long or short portfolio, but not for others. Since we do not want to terminate the arbitrage in this case, we apply the following cascade principle: we invest the difference between the target amount for the smallest stock and the 5% of its market equity in the second smallest stock; If the 5% market cap limit becomes also binding for the second smallest stock, we invest the residual between the target amount for the second stock and the 5% of its market capitalization in the third smallest stock, and so on. Only if each stock in either the smallest or largest size decile reaches 5% of its market equity, then no further investment in the size arbitrage is possible. Note that the portfolio weights are no longer the same once our investment cascade is triggered. In Figure 5, the 5% market cap limit reduces only slightly the returns for the fund sizes shown. More generally, the effect of our cascade strategy is ambiguous. Buying more of the larger-sized stocks typically results in lower price-impact costs, but also in lower gross returns. Which of these two effects dominates can only be determined empirically.

If the size arbitrage is rebalanced more frequently, then the number of transactions rises, implying higher price-impact costs and lower returns. Figure 6 demonstrates how the fund size - return curve for annual rebalancing shifts down, when the rebalancing is done semiannually and quarterly. In addition, the top panel of Table 6 contains the break-even fund sizes for the different rebalancing frequencies. As can be seen, the break-even fund size falls quite dramatically from $186.1 million to $119.1 million and $34.8 million when the EW-size portfolio is rebalanced semiannually and quarterly, respectively.

Increasing the sample period to June 1963 – June 2000 reduces both returns and break-even fund sizes of the size arbitrage. Table 6 shows that the break-even fund sizes are particularly small when value-weighted portfolios are employed. For instance, a fund size of $277,000 already generates a zero excess return if rebalancing occurs semiannually. Again, a value-weighted strategy makes the average fund return approach zero faster than an equally weighted strategy, because the return spread is narrower among larger stocks than among smaller ones, though the larger stocks come with lower price-impact costs.

It should be remarked that in terms of the Sharpe ratio, the size arbitrage performs slightly worse than the CRSP market portfolio, as panels (a) and (c) in Table 5 indicate. Yet, the size arbitrage seems to be a good investment, because it is less risky than the CRSP market portfolio and has a return considerably higher than the riskless interest rate. Also, the benchmark CRSP market returns that we present here and below do not include the price-impact costs from buying the index portfolio.

4.2 Arbitrage Based on Book-to-Market

A B/M arbitrage is to buy all the stocks in the highest B/M decile and short all the stocks in the smallest B/M decile, each June between 1963 and 1991. Panels (a) and (c) in Table 7 demonstrate that the B/M arbitrage is profitable in comparison to the CRSP market portfolio. The mean excess return equals 9.2% for the EW-B/M arbitrage, with less than half the volatility of the CRSP equally weighted market portfolio.

The profitability of the B/M arbitrage declines fast with fund size once price-impact costs are taken into account. Table 6 and panels (c) and (d) in Table 7 reveal that the break-even fund sizes are $2.38 million for the EW-B/M arbitrage and only $20,000 for the VW-B/M arbitrage. Evidently, the turnover of both the long and short portfolios is high and causes high price-impact costs, which drives down the return. Except for the value-weighted short portfolio, the mean turnover is around 100%. We omit here the 1% trade size limit and the 5% position limit, because the break-even fund sizes are already quite small without them.

The maximal fund sizes are much smaller for a B/M based arbitrage than for a size-based arbitrage, for the following reason. In a size-based arbitrage, large stocks are the candidates to be short while small ones to buy, implying that at least one of the two sides is less subject to price impact costs. On the other hand, it is known in the literature that the B/M effect is mostly 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)). Given this small bias, the above B/M-based arbitrage strategies must tend to load up mostly small stocks on both the long and short side. Thus, a B/M-based arbitrage strategy may be hit twice with high price-impact costs, making the resulting profitable fund sizes even smaller than for a size-based arbitrage.

For the sample period from 1963 to 2000, the returns and break-even fund sizes become even lower. For instance, the break-even fund size of the EW-B/M arbitrage drops to $1.83 million. From Table 6, we also infer that the profitability of the B/M arbitrage reduces as the frequency of the rebalancing increases.

In summary, the high price-impact costs induced by the large turnover make the B/M arbitrage unprofitable even for small fund sizes. Hence, there is no need to incorporate other trading and position restrictions here. We will also omit these two restrictions in the next subsection.

4.3 Arbitrage Based on Momentum

To examine momentum-based arbitrage, we sort all stocks into deciles according to their past 12-month returns as of each June during 1964 and 1991. A momentum arbitrage strategy is to buy all the stocks in the tope decile and sell short the loser decile. After the positions are entered, they are held until the following June at which time a rebalancing will be conducted, and so on. There is no overlap in the portfolio formation or holding period.

As panels (a) and (c) in Table 8 show, a momentum arbitrage is more attractive than the

CRSP market portfolio only when value-weighted portfolios are formed. In fact, the VW-momentum arbitrage renders a 2.5 times higher excess return and 2 times higher Sharpe ratio than the CRSP value-weighted index. The standard deviation of the momentum arbitrage is 6% higher if portfolios are value-weighted and 15% lower if equally weighted, than that of the CRSP index.

The average turnover of both the long and short portfolios is fairly large and between 156% and 182% (panels (b) and (d) in Table 8). The resulting price-impact costs, however, are relatively small compared to the price-impact costs of the size and B/M arbitrages and given the high turnover. This finding can be explained by looking at the composition of the portfolios (not reported here): the long and short portfolios of a typical momentum arbitrage are less biased towards small stocks. The high turnover of a momentum arbitrage is due to the fact that past returns change over time, much more often than size and B/M do.

The bottom part of Table 6 contains the break-even fund sizes for momentum arbitrage strategies. For the EW-momentum arbitrage the maximal fund size is only \$141,000, whereas it is \$44.2 million in the VW-momentum arbitrage.

When we extend the sample period to 1963-2000, the profitability of the VW-momentum arbitrage rises, while for the EW-momentum arbitrage it falls. Rebalancing more frequently, again, erodes the returns due to higher price-impact costs, as is evident from Table 6.

Up to now, winner and loser stocks have been selected based on the past 12-month returns and the portfolios rebalanced once a year (in June) between 1964 and 1991. Table 9 considers momentum arbitrages, with winner and loser portfolios based on the past J-month returns and held for some K months, $J \in\in \{1, 3, 6, 9, 12\}$ and $K \in \{1, 3, 6, 12\}$. That is, rebalancing occurs every K months. For example, if $J = 3$ months and $K = 6$ months, then every six months the winner and loser portfolios are formed depending on the recent three-month returns, and the positions are then held for the next six months, and so on. We form the first winner and loser portfolios in December 1963; Thereafter, rebalancing always takes place in June and in December, using the past March-June and

September-December returns, respectively. Furthermore, the portfolios are not overlapped, so that at each point there is only one portfolio outstanding.

The break-even fund sizes and returns are presented in Table 9 for different combinations of J and K. Three observations are in order. First, momentum arbitrage is more profitable with a value-weighted allocation strategy, for all shown combinations of J and K. Second, the combinations of ($J = 6$ $K = 12$), ($J = 9$, $K = 12$), and ($J = 3$ $K = 12$) yield the highest, second highest, and third highest break-even fund sizes, respectively. This ranking holds for both equally- and value-weighted portfolios, and for both sample periods. Finally, momentum arbitrage is more profitable for the 1963-2000 period than the earlier period, suggesting a continuation of the momentum anomaly in the 1990s.

Our results seem to differ from those in Jegadeesh and Titman (1993 and 2001) and Moskowitz and Grinblatt (1999), where they find that momentum profits are higher with equally weighted than with value-weighted portfolios. Their conclusions are based on the absence of price-impact costs. In addition, their strategies rely on overlapped portfolios, that is, regardless of the values for J and K, a new portfolio is constructed each month and consequently there may be multiple overlapping portfolios in a given month. Further, they investigate earlier sample periods. But, these differences in research design do not explain why our conclusion seems to differ from theirs.

To explain why, we note that we focus on the return spread (i.e., an arbitrage portfolio), whereas they focus on the average returns on winner and loser investment portfolios. To see this, let us put aside the price-impact costs. Looking at the returns of the winner and loser portfolios separately (not presented here), we discover that both the winner and loser portfolios have higher returns when equally weighted than when value-weighted. This is because small stocks tend to have higher returns. But, the returns for the loser portfolio go down more than the returns for the winner portfolio, when the portfolio weighting changes from equal- to value-weighting. Therefore, when equally weighted, the return difference between the winner and loser portfolios is larger than when value-weighted. To make sure that our finding is not due to the particular month chosen for rebalancing, we experiment with other calendar months for rebalancing. The results are similar and hence robust.

4.4 Combined Arbitrage

Do combinations of these anomalies perform better than the individual ones? To answer this question we consider three different combined arbitrages.

First, let us combine size with B/M: buy all the stocks in the smallest size quintile and also in the highest B/M quintile, and sell short all the stocks in the largest size and in the lowest B/M quintile. Rebalancing takes place again every June between 1963 and 1991. The two-dimensional sorting is done independently for size and B/M.

As Table 10 illustrates, the EW- and the VW-size&B/M arbitrages exhibit similar return characteristics. In addition, both weighting strategies yield almost the same return as the corresponding CRSP index when price-impact costs are ignored, but have higher Sharpe ratios. The VW-size&B/M arbitrage is clearly more profitable than the VW-size arbitrage (see Table 5), although the former incurs higher price-impact costs. The break-even fund size for the VW-size&B/M arbitrage is $12.8 million, $3 million higher than that of the VW-size arbitrage (see Table 6). The EW-size&B/M arbitrage, on the other hand, beats the EW-size arbitrage only for fund sizes smaller than $500,000. Due to the relatively high price-impact costs, the returns of the EW-size&B/M arbitrage go down rapidly with fund size. As a consequence, the break-even fund size is only $13.3 million, much smaller than that of the EW-size arbitrage, which is $186.1 million.

Comparing with Table 7, we see that the EW-size&B/M arbitrage is more profitable than the EW-B/M arbitrage for all funds with more than $100,000 of capital, whereas the VW-size&B/M arbitrage outperforms the VW-B/M arbitrage for all possible fund sizes. Both findings are caused by the higher price-impact costs for the B/M arbitrages.

The second combined arbitrage is a B/M based arbitrage, except that all eligible stocks must be in the top half of each monthly stock universe based on size. Let's denote this strategy by the $(B/M)^-$ arbitrage: we buy stocks in the top B/M quintile and sell short the bottom B/M quintile of the top half of the size universe. Our goal is to estimate how much of the returns of the original B/M arbitrage are due to the size effect. The resulting performance is in Table 11, which shows that the $(B/M)^-$ arbitrage is worse than the unfiltered B/M arbitrage in most cases. It is better only when the positions are equally weighted. The VW-$(B/M)^-$ arbitrage has negative excess returns even for small fund sizes. The EW-$(B/M)^-$ arbitrage is clearly dominated by the original EW-B/M arbitrage and also less profitable than the CRSP equally weighted index. Hence, we arrive at the conclusion that the B/M anomaly is moderate for medium and large stocks.

Finally, we combine momentum with size: buy high-momentum stocks and sell short low-momentum stocks, only in the top half of the size universe (the stocks are first sorted by size and then sequentially by momentum). We call this the momentum$^-$ arbitrage. Panels (a)-(d) in Table 12 show that the break-even fund sizes of the momentum$^-$ arbitrage are large. In numbers, the break-even fund sizes of the EW- and the VW-momentum$^-$ arbitrages for the sample period 1963-1991 are approximately \$2.8 billion and \$1.3 billion, respectively, and even bigger for the sample period 1963-2000. This result can be explained by the fact that the price-impact costs here are significantly lower than for the original moment arbitrage strategies.

Given these large break-even fund sizes, we can further examine the impact of the 1% trade size and the 5% position limits. As panels (e) and (f) in Table 12 demonstrate, the break-even fund sizes decline considerably when the 1% trade size limit is imposed: \$330 million for the EW-momentum$^-$ arbitrage, and \$490 million for the VW-momentum$^-$ arbitrage. The 1% trade size upper bound thus causes each large position to be acquired using a number of smaller trades, which increases the overall price-impact costs per position and drives down the excess returns and break-even fund sizes.

If the 5% position limit (based on the total market cap of each stock) is also imposed, then it typically becomes binding for certain months in our sample period. For example, this limit is hit at \$560 million for the EW-momentum$^-$ arbitrage and at \$443.6 million for the VW-momentum$^-$ arbitrage. At these fund sizes, the mean excess returns and the Sharpe ratios are 0.8% and 0.04 for the former, and 2.5% and 0.23 for the latter arbitrage. Interestingly, the restriction is binding for the EW-momentum$^-$ arbitrage at a level exceeding the break-even fund size when only the 1% trade size limit is imposed. The reason for this is the following: our cascade investment strategy from Section 4.1 demands that more money flows to larger stocks; now, since the price-impact costs decrease quicker than the gross returns, the EW-momentum$^-$ arbitrage becomes more profitable at a given fund size.

4.5 Comparison with Actual Hedge Fund Sizes

Table 13 presents summaries of actual hedge fund sizes across styles (based on the TASS classification). As the Table shows, the total amount of money invested in the hedge fund industry was around \$184.5 billion in 2000, whereof \$56 billion were invested in arbitrage strategies. Furthermore, the smallest style is represented by the "trend followers," who managed only \$14.6 billion.

Each break-even fund size estimated in the previous sections has to be interpreted as the maximal fund size attainable for the whole set of hedge funds in a particular type of arbitrage. Indeed, Section 4 implicitly studies a monopolistic arbitrageur who attempts to create the largest possible fund size for each anomaly. Hence, given the numbers in the last column of Table 13, all our estimated break-even fund sizes seem too small to be economically attractive to existing or new hedge funds.

5 Conclusion

This paper examines whether one can take advantage of the size, B/M, or momentum anomaly when price-impact costs and/or position limits are taken into consideration. Long-short arbitrages based on these anomalies are constructed and the break-even fund sizes are estimated. We find that all break-even fund sizes are small relative to actual hedge fund sizes and conclude that markets are minimally rational in the sense that price-impact costs prevent agents from exploiting the anomalies. A by-product of our analysis is the finding that the momentum arbitrage yields higher returns when value-, rather than equally, weighted portfolios are formed.

Again, as discussed earlier, our calculations tend to underestimate the price-impact costs, because we have used the first six months of 1993 to estimate the coefficients. Another reason is that we have ignored the delay and opportunity costs of trading throughout our analysis. However, incorporating these additional factors would only make the profitable fund sizes even smaller than reported in the paper. Thus, they would only make our main conclusion even stronger: these anomalies do not suggest market inefficiency, and they are rather indicative of market frictions.

In the future, we want to pursue two avenues of research. The first involves studying other stock market anomalies, like the seasonality effect (e.g., see Keim (1983)) for example, and test whether markets are minimally rational with respect to these anomalies. The second topic concerns the estimation of the price-impact costs for stocks that are either illiquid or face selling or shorting constraints.

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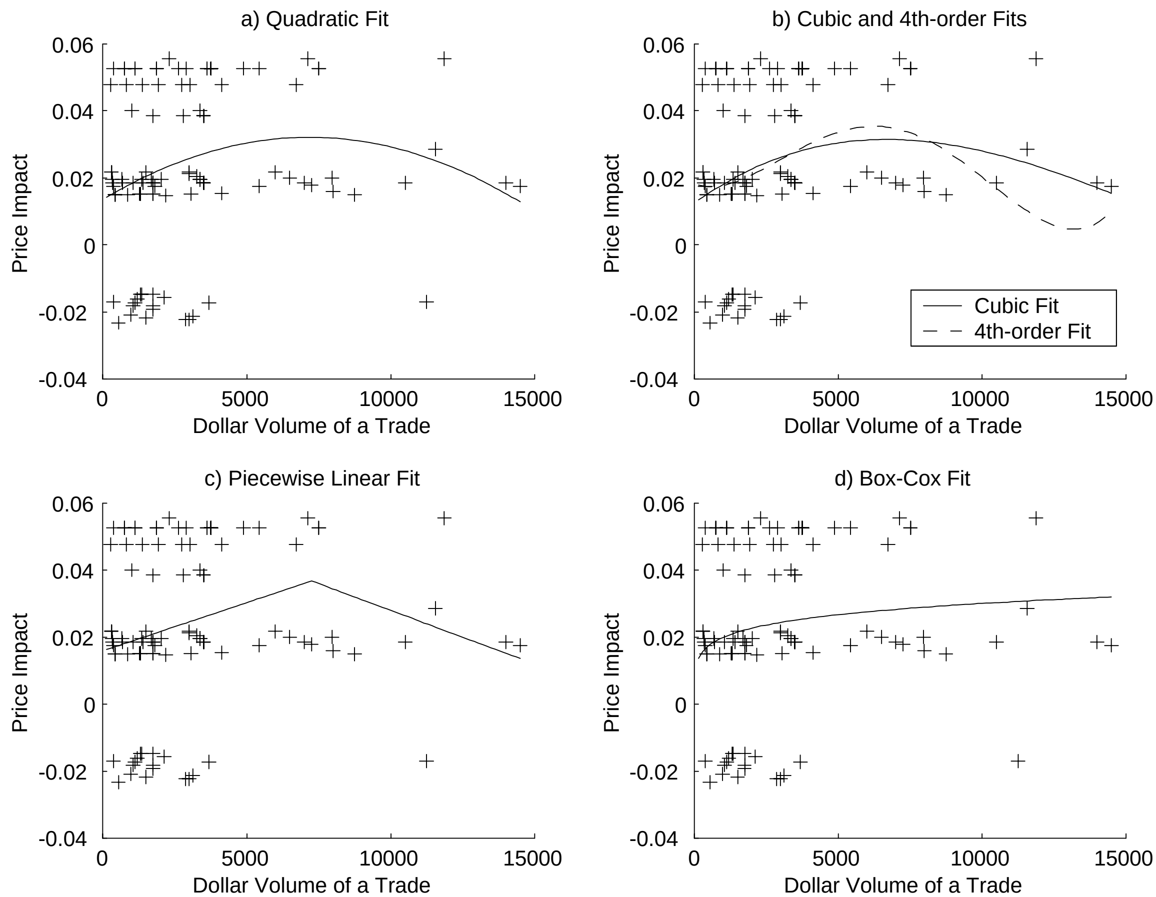

Figure 1: Comparison of the polynomial, piecewise linear, and Box-Cox fits. The actual price impacts are plotted against the dollar volume of the actual trades. All graphs share the same observations, namely, the buy orders of URIX. Figures a) and b) show the quadratic fit and the cubic and fourth-order fits, respectively. Figure c) depicts the piecewise linear fit with a break point at the 90th percentile. Figure d) shows the fitted Box-Cox function as defined in Section 2.1.

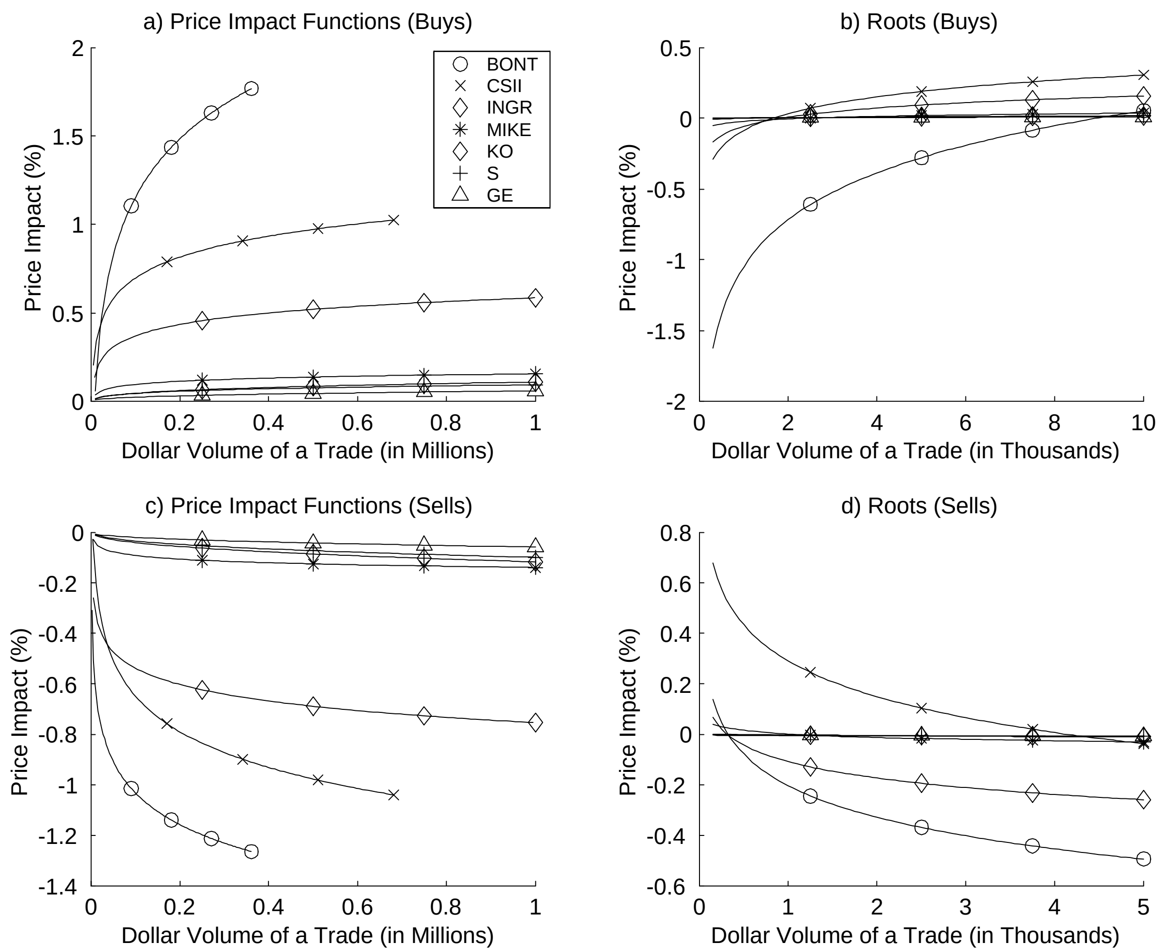

Figure 2: The estimated price-impact functions for the seven representative stocks. The estimated model is described in Section 2.1. Figure a) shows the shapes of the estimated price-impact functions for buy orders. In Figure b), the roots of each curve is shown. Figures c) and d) present the price-impact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

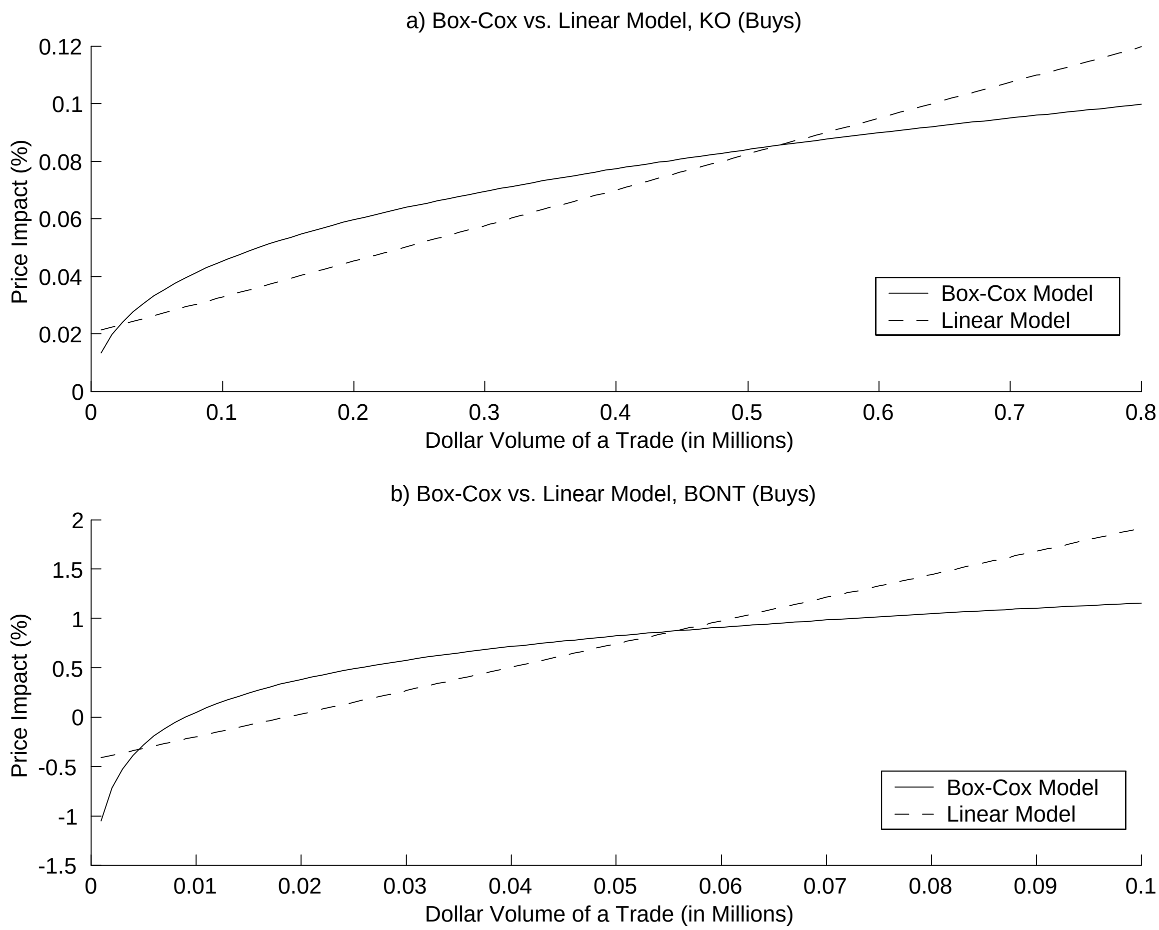

Figure 3: The comparison between the Box-Cox and the linear models. The Box-Cox model is described in Section 2.1 and the linear model in Section 2.4. Figures a) and b) show the estimates for the buy orders of KO and BONT, respectively.

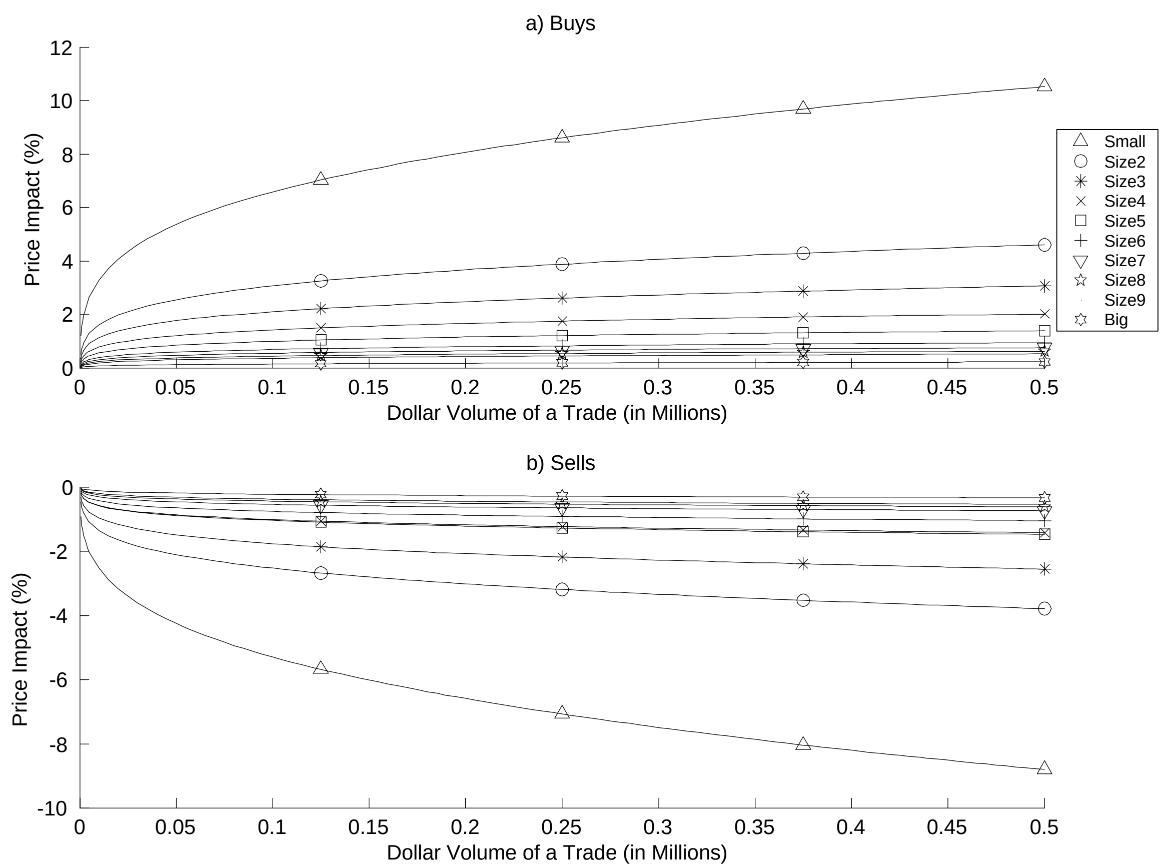

Figure 4: The estimated portfolio price-impact functions by size decile. First, the individual price-impact functions are estimated by the Box-Cox model as described in Section 2.1. The parameter values of a portfolio price-impact function is then computed as the equally weighted average of the parameter values of the individual price-impact functions over the stocks in the corresponding size decile. Figures a) and b) show the price-impact functions for the buy and sell orders, respectively.

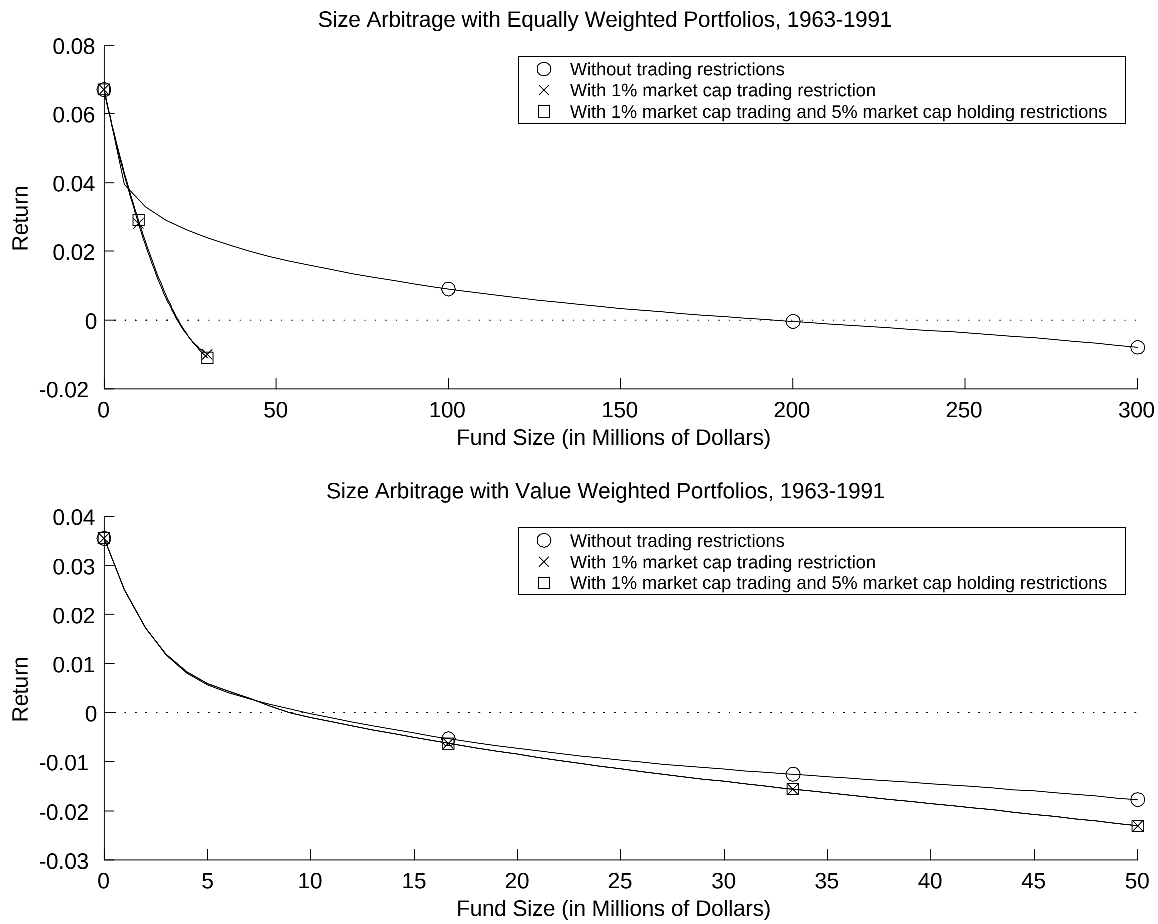

Figure 5: The returns of the size arbitrage are plotted against the arbitrage fund size for various market capital trading restrictions. Figures a) and b) show the returns when equally and value weighted portfolios are used, respectively. The circles denote the returns after both the price-impact costs and transactions fees. The pluses show the returns after costs when the 1% market cap trading restriction is imposed. The squares depict the returns after costs and fees when both the 1% market cap trading and the 5% market cap holding restrictions are invoked.

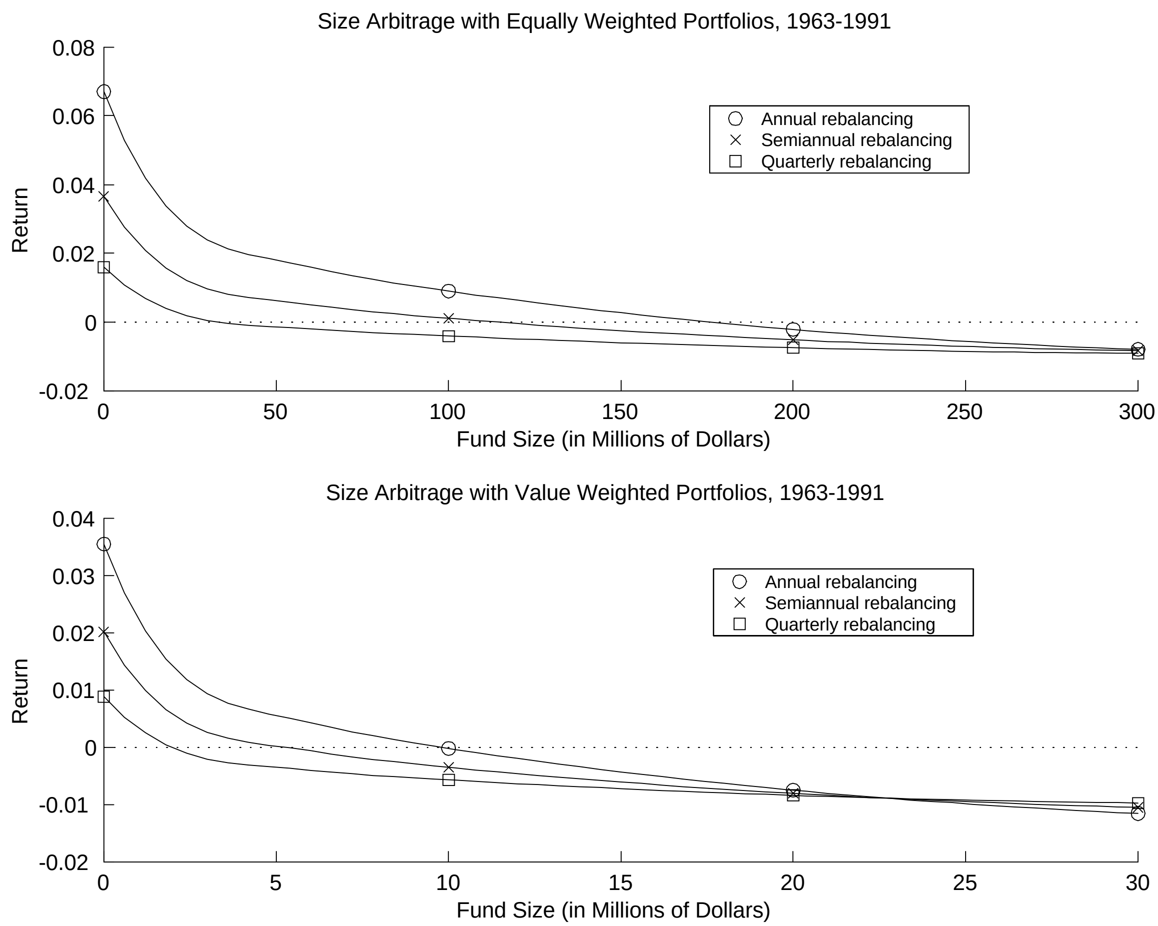

Figure 6: The returns of the size arbitrage with various rebalancing frequencies plotted against the fund size. Figures a) and b) show the returns when equally and value weighted portfolios are employed, respectively. All curves represent returns after both the price-impact costs and the transactions fees; the 1% market cap trading and the 5% market cap holding restrictions are ignored here.

Table 1

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. Number of shares outstanding is 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 the 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	Number of Shares Outstanding	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

The estimated parameter values of the Box-Cox model. The estimated model is $PI_t = a_B + b_B (V_t^{l_B} - 1) / l_B + e_t$ for buys and $PI_t = a_S - b_S (V_t^{l_S} - 1) / l_S + e_t$ for sells with the restriction $0 \leq l_B, l_S \leq 1$ where PI_t (PI_t) is the price impact of a trade measured as the relative quote midpoint change and V_t (V_t) is the trade's dollar volume. The estimation is by nonlinear least squares. t-stats are shown in parentheses.

	Ticker Symbol						
	GE	KO	BONT	CSII	S	INGR	MIKE
Buys							
Number of observations	23183	23041	332	762	10687	1376	4183
a_B	-2.00E-05	-1.10E-04	-4.35E-02	-1.26E-02	-2.30E-04	-7.00E-03	-2.01E-03
	(-0.99)	(-2.89)	(-5.66)	(-4.67)	(-2.63)	(-4.09)	(-6.31)
b_B	1.20E-06	4.68E-06	4.78E-03	1.70E-03	1.30E-05	9.30E-04	2.57E-04
	(2.32)	(3.17)	(5.52)	(5.62)	(2.17)	(4.80)	(7.86)
l_B	0.380	0.319	0.000	0.000	0.218	0.000	0.000
	(10.28)	(11.40)	(-)	(-)	(5.44)	(-)	(-)
Sells							
Number of observations	25453	24904	341	460	16187	974	3816
a_S	-1.70E-05	3.00E-05	1.04E-02	1.70E-02	4.00E-05	5.36E-03	1.44E-03
	(-1.14)	(1.05)	(1.59)	(4.70)	(1.29)	(2.71)	(4.10)
b_S	3.68E-07	1.33E-06	1.80E-03	2.04E-03	1.27E-06	9.33E-04	2.05E-04
	(2.10)	(2.90)	(2.56)	(5.30)	(2.09)	(4.33)	(5.78)
l_S	0.478	0.432	0.000	0.000	0.423	0.000	0.000
	(11.69)	(14.35)	(-)	(-)	(10.08)	(-)	(-)

Table 3

This table shows the estimated parameter values of the linear model and the comparison between the linear and the Box-Cox models for buy orders. The estimated linear model is $PI_t = a_B + b_B V_t + e_t$, where PI_t is the price impact of a trade measured as the relative quote midpoint change and V_t is the trade's 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
Buys							
Number of observations	23183	23041	332	762	10687	1376	4183
a_B	1.29E-04	2.05E-04	-4.33E-03	1.59E-03	2.64E-04	6.61E-04	4.00E-04
	(36.11)	(34.03)	(-3.42)	(4.03)	(31.79)	(2.31)	(8.31)
b_B	6.21E-10	1.24E-09	2.35E-07	7.35E-08	7.71E-10	3.12E-08	2.05E-09
	(35.77)	(39.64)	(3.89)	(3.47)	(24.52)	(3.25)	(2.99)
Price impact of a $50,000 trade							
Linear	0.016%	0.027%	0.742%	0.527%	0.030%	0.222%	0.050%
Box-Cox	0.017%	0.034%	0.824%	0.580%	0.034%	0.306%	0.077%
Difference	-0.001%	-0.007%	-0.082%	-0.054%	-0.004%	-0.084%	-0.027%
Price impact of a $100,000 trade							
Linear	0.019%	0.033%	1.916%	0.894%	0.034%	0.378%	0.061%
Box-Cox	0.023%	0.045%	1.155%	0.698%	0.045%	0.371%	0.095%
Difference	-0.004%	-0.013%	0.761%	0.196%	-0.011%	0.007%	-0.034%

Table 4

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

		a_B (x10^{-3})	b_B (x10^{-4})	l_B	a_S (x10^{-3})	b_S (x10^{-4})	l_S
	Small	-1.24	8.01	0.28	-0.44	4.70	0.31
	2	-4.31	7.38	0.21	2.30	5.36	0.22
	3	-3.85	6.32	0.18	2.65	5.02	0.19
	4	-3.40	5.44	0.16	1.97	3.90	0.15
Size	5	-2.85	4.66	0.13	1.97	3.74	0.16
Rank	6	-2.54	3.95	0.11	1.95	3.49	0.13
	7	-2.36	3.48	0.11	1.86	3.08	0.11
	8	-1.66	2.33	0.13	1.64	2.40	0.12
	9	-1.33	1.65	0.15	1.20	1.69	0.14
	Big	-0.20	0.32	0.22	0.32	0.57	0.20

Table 5

This table shows the returns of the size arbitrage. The arbitarge buys the smallest size decile and sells short the biggest size decile in each June during 1963 and 1991. The corresponding numbers for the same strategy over the period between 1963 to 2000 are shown in square brackets. The short position is assumed to be financed by a cash position with a margin rate of 80% of the Federal Fund rate. Panel (a) shows the statistics for the excess returns (relative to the Federal Fund rates) of both the size arbitrage and the CRSP market portfolio without the price-impact and transactions costs, when equally weighted portfolios are used. Panel (b) accounts for both of these costs. Panels (c) and (d) are based on the size arbitrage which uses value weighted portfolios, without and with costs, respectively. The Mean excess return is the mean of the annual excess returns between 1963 and 1991 [2000]. The Mean Price-Impact Costs are defined as the mean of the ratios (dollar price-impact costs)/(dollar amount invested), and the Mean Turnover is calculated as the mean of the ratios (dollar amount rebalanced)/(dollar amount invested). The ratios are computed in the beginning of each year between 1963 and 1991 [2000].

(a) Equally Weighted, without Costs

Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio
Size Arbitrage	0.067	(1.36)	0.265	0.733 / -0.369	0.252
	[0.056]	[(1.36)]	[0.250]	[0.733 / -0.369]	[0.224]
CRSP	0.092	(1.68)	0.295	0.971 / -0.473	0.311
Equally Weighted	[0.091]	[(2.12)]	[0.265]	[0.971 / -0.473]	[0.344]

(b) Equally Weighted, with Costs

						Long Portfolio		Short Portfolio	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio	Mean Price-Impact Costs	Mean Turnover	Mean Price-Impact Costs	Mean Turnover
100K	0.057	(1.18)	0.263	0.721 / -0.373	0.218	0.006	0.639	0.001	0.521
	[0.046]	[(1.13)]	[0.248]	[0.721 / -0.373]	[0.186]	[0.006]	[0.631]	[0.001]	[0.512]
500K	0.052	(1.07)	0.262	0.715 / -0.376	0.199	0.010	0.641	0.001	0.523
	[0.041]	[(1.01)]	[0.246]	[0.715 / -0.376]	[0.165]	[0.010]	[0.633]	[0.001]	[0.514]
1M	0.049	(1.01)	0.261	0.711 / -0.377	0.188	0.012	0.642	0.001	0.525
	[0.038]	[(0.93)]	[0.246]	[0.711 / -0.377]	[0.153]	[0.013]	[0.634]	[0.001]	[0.516]
5M	0.040	(0.82)	0.259	0.698 / -0.382	0.153	0.020	0.645	0.002	0.529
	[0.028]	[(0.70)]	[0.244]	[0.698 / -0.382]	[0.116]	[0.021]	[0.637]	[0.001]	[0.520]
10M	0.034	(0.72)	0.257	0.690 / -0.384	0.133	0.025	0.647	0.002	0.531
	[0.023]	[(0.58)]	[0.243]	[0.690 / -0.384]	[0.095]	[0.025]	[0.639]	[0.002]	[0.522]
50M	0.018	(0.38)	0.254	0.666 / -0.392	0.071	0.038	0.653	0.003	0.538
	[0.007]	[(0.18)]	[0.239]	[0.666 / -0.392]	[0.030]	[0.038]	[0.645]	[0.002]	[0.530]
100M	0.009	(0.19)	0.251	0.651 / -0.396	0.035	0.045	0.656	0.003	0.542
	[-0.001]	[(-0.03)]	[0.237]	[0.651 / -0.396]	[-0.005]	[0.045]	[0.648]	[0.003]	[0.534]
200M	-0.001	(-0.03)	0.249	0.633 / -0.400	-0.006	0.054	0.660	0.003	0.546
	[-0.011]	[(-0.28)]	[0.234]	[0.633 / -0.400]	[-0.046]	[0.053]	[0.652]	[0.003]	[0.538]
300M	-0.008	(-0.18)	0.247	0.621 / -0.403	-0.033	0.059	0.663	0.004	0.549
	[-0.017]	[(-0.44)]	[0.232]	[0.621 / -0.403]	[-0.073]	[0.058]	[0.654]	[0.003]	[0.541]

Table 5 - Continued

(c) Value Weighted, without Costs

Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio
Size Arbitrage	0.035	(0.78)	0.244	0.607 / -0.409	0.145
	[0.018]	[(0.47)]	[0.235]	[0.607 / -0.409]	[0.078]
CRSP	0.040	(1.14)	0.191	0.570 / -0.344	0.212
Value Weighted	[0.057]	[(1.98)]	[0.178]	[0.570 / -0.344]	[0.321]

(d) Value Weighted, with Costs

						Long Portfolio		Short Portfolio	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio	Mean Price-Impact Costs	Mean Turnover	Mean Price-Impact Costs	Mean Turnover
100K	0.025	(0.56)	0.242	0.593 / -0.414	0.104	0.007	0.787	0.000	0.422
	[0.008]	[(0.21)]	[0.233]	[0.593 / -0.414]	[0.034]	[0.007]	[0.798]	[0.000]	[0.425]
500K	0.019	(0.43)	0.241	0.585 / -0.417	0.080	0.012	0.789	0.001	0.424
	[0.002]	[(0.05)]	[0.232]	[0.585 / -0.417]	[0.009]	[0.012]	[0.801]	[0.001]	[0.427]
1M	0.016	(0.36)	0.240	0.580 / -0.418	0.066	0.015	0.791	0.001	0.425
	[-0.001]	[(-0.04)]	[0.231]	[0.580 / -0.418]	[-0.006]	[0.015]	[0.803]	[0.001]	[0.428]
5M	0.005	(0.12)	0.238	0.565 / -0.423	0.023	0.024	0.795	0.001	0.429
	[-0.012]	[(-0.31)]	[0.229]	[0.565 / -0.423]	[-0.050]	[0.024]	[0.807]	[0.001]	[0.433]
9M	0.001	(0.01)	0.237	0.557 / -0.426	0.003	0.028	0.798	0.001	0.431
	[-0.016]	[(-0.43)]	[0.228]	[0.557 / -0.426]	[-0.071]	[0.028]	[0.810]	[0.001]	[0.435]
10M	0.000	(-0.01)	0.237	0.555 / -0.426	-0.001	0.029	0.798	0.001	0.431
	[-0.017]	[(-0.46)]	[0.227]	[0.555 / -0.426]	[-0.076]	[0.029]	[0.810]	[0.001]	[0.435]
20M	-0.007	(-0.16)	0.235	0.544 / -0.430	-0.030	0.035	0.801	0.002	0.434
	[-0.024]	[(-0.64)]	[0.226]	[0.544 / -0.430]	[-0.105]	[0.034]	[0.813]	[0.001]	[0.438]
50M	-0.018	(-0.41)	0.233	0.526 / -0.435	-0.077	0.044	0.806	0.002	0.438
	[-0.034]	[(-0.92)]	[0.223]	[0.526 / -0.435]	[-0.151]	[0.043]	[0.818]	[0.002]	[0.443]
100M	-0.027	(-0.64)	0.230	0.508 / -0.439	-0.119	0.052	0.811	0.002	0.442
	[-0.043]	[(-1.18)]	[0.221]	[0.508 / -0.439]	[-0.193]	[0.051]	[0.823]	[0.002]	[0.447]

Table 6

The break-even fund sizes for the size-, B/M-, and momentum arbitrage without the 1% market cap trading and the 5% market cap holding restrictions. The break-even fund size is defined as the initial dollar investment that makes the mean excess return zero over the period between 1963 and 1991. The corresponding numbers for the period between 1963 and 2000 are shown in the square brackets. The break-even fund sizes are calculated for three different rebalancing frequencies: annually, semiannually, and quarterly.

		(in millions of dollars)	
		Equally Weighted	Value Weighted
Size Arbitrage	Annually	186.1	9.80
		[93.3]	[0.750]
	Semiannually	119.1	5.22
		[31.0]	[0.277]
	Quarterly	34.8	1.34
		[4.88]	[<0.1]
B/M Arbitrage	Annually	2.38	<0.1
		[1.83]	[<0.1]
	Semiannually	0.987	<0.1
		[1.09]	[<0.1]
	Quarterly	0.367	<0.1
		[0.400]	[<0.1]
Size&B/M Arbitrage	Annually	13.3	12.8
		[11.7]	[3.32]
	Semiannually	8.77	5.68
		[6.38]	[1.39]
	Quarterly	2.00	0.750
		[1.00]	[0.200]
Momentum Arbitrage	Annually	0.141	44.2
		[<0.1]	[56.7]
	Semiannually	<0.1	26.5
		[0.163]	[66.3]
	Quarterly	<0.1	<0.1
		[<0.1]	[1.04]

Table 7

This table shows the returns of the B/M arbitrage. The arbitrage buys the highest B/M decile and sells short the lowest B/M decile in each June during 1963 and 1991. The numbers for the same strategy over the period between 1963 and 2000 are shown in square brackets. The short position is assumed to be financed by a cash position with a margin rate of 80% of the Federal Fund rate. Panel (a) shows the statistics for the excess returns (relative to the Federal Fund rates) of both the B/M arbitrage and the CRSP market portfolio without the price-impact and transactions costs, when equally weighted portfolios are used. Panel (b) accounts for both of these costs. Panels (c) and (d) are based on the B/M arbitrage which uses value weighted portfolios, without and with costs, respectively. The Mean excess return is the mean of the annual excess returns between 1963 and 1991 [2000]. The Mean Price-Impact Costs are defined as the mean of the ratios (dollar price-impact costs)/(dollar amount invested), and the Mean Turnover is calculated as the mean of the ratios (dollar amount rebalanced)/(dollar amount invested). The ratios are computed in the beginning of each year between 1963 and 1991 [2000].

(a) Equally Weighted, without Costs

Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio
B/M Arbitrage	0.092	(3.56)	0.140	0.320 / -0.235	0.661
	[0.087]	[(3.51)]	[0.151]	[0.320 / -0.278]	[0.576]
CRSP	0.092	(1.68)	0.295	0.971 / -0.473	0.311
Equally Weighted	[0.091]	[(2.12)]	[0.265]	[0.971 / -0.473]	[0.344]

(b) Equally Weighted, with Costs

						Long Portfolio		Short Portfolio	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio	Mean Price-Impact Costs	Mean Turnover	Mean Price-Impact Costs	Mean Turnover
10K	0.070	(2.67)	0.140	0.306 / -0.249	0.497	0.009	0.991	0.008	0.951
	[0.062]	[(2.50)]	[0.152]	[0.306 / -0.311]	[0.412]	[0.009]	[0.939]	[0.009]	[0.956]
50K	0.057	(2.16)	0.141	0.298 / -0.257	0.402	0.015	0.998	0.013	0.957
	[0.049]	[(1.96)]	[0.152]	[0.298 / -0.326]	[0.323]	[0.015]	[0.946]	[0.014]	[0.962]
100K	0.049	(1.88)	0.142	0.293 / -0.261	0.349	0.018	1.002	0.016	0.961
	[0.042]	[(1.67)]	[0.153]	[0.293 / -0.333]	[0.274]	[0.019]	[0.950]	[0.017]	[0.966]
500K	0.028	(1.03)	0.145	0.281 / -0.273	0.192	0.028	1.016	0.025	0.973
	[0.021]	[(0.82)]	[0.154]	[0.281 / -0.351]	[0.135]	[0.028]	[0.962]	[0.026]	[0.977]
1M	0.016	(0.59)	0.147	0.274 / -0.279	0.110	0.033	1.025	0.030	0.981
	[0.010]	[(0.39)]	[0.156]	[0.274 / -0.358]	[0.064]	[0.033]	[0.969]	[0.031]	[0.983]
2M	0.003	(0.11)	0.151	0.267 / -0.286	0.021	0.039	1.036	0.035	0.991
	[-0.002]	[(-0.08)]	[0.158]	[0.267 / -0.366]	[-0.013]	[0.038]	[0.978]	[0.036]	[0.992]
3M	-0.005	(-0.18)	0.154	0.264 / -0.308	-0.034	0.043	1.044	0.039	0.998
	[-0.009]	[(-0.36)]	[0.160]	[0.264 / -0.369]	[-0.059]	[0.041]	[0.985]	[0.039]	[0.998]
5M	-0.016	(-0.55)	0.159	0.259 / -0.356	-0.103	0.048	1.056	0.044	1.009
	[-0.019]	[(-0.71)]	[0.164]	[0.259 / -0.374]	[-0.117]	[0.046]	[0.995]	[0.043]	[1.007]
10M	-0.033	(-1.03)	0.170	0.254 / -0.439	-0.192	0.055	1.079	0.051	1.030
	[-0.033]	[(-1.16)]	[0.172]	[0.254 / -0.439]	[-0.191]	[0.052]	[1.013]	[0.049]	[1.023]

Table 7 - Continued

(c) Value Weighted, without Costs

Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio
B/M Arbitrage	0.027	(0.86)	0.172	0.275 / -0.319	0.160
	[0.009]	[(0.31)]	[0.175]	[0.275 / -0.319]	[0.051]
CRSP	0.040	(1.14)	0.191	0.570 / -0.344	0.212
Value Weighted	[0.057]	[(1.98)]	[0.178]	[0.570 / -0.344]	[0.321]

(d) Value Weighted, with Costs

						Long Portfolio		Short Portfolio	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio	Mean Price-Impact Costs	Mean Turnover	Mean Price-Impact Costs	Mean Turnover
10K	0.005	(0.16)	0.172	0.262 / -0.343	0.030	0.011	0.947	0.007	0.678
	[-0.015]	[(-0.51)]	[0.176]	[0.262 / -0.343]	[-0.084]	[0.012]	[0.940]	[0.008]	[0.706]
20K	0.000	(0.01)	0.172	0.259 / -0.347	0.002	0.013	0.949	0.009	0.680
	[-0.020]	[(-0.68)]	[0.176]	[0.259 / -0.347]	[-0.113]	[0.014]	[0.943]	[0.010]	[0.709]
30K	-0.003	(-0.09)	0.172	0.257 / -0.350	-0.017	0.015	0.951	0.010	0.682
	[-0.023]	[(-0.80)]	[0.176]	[0.257 / -0.350]	[-0.131]	[0.016]	[0.945]	[0.011]	[0.711]
50K	-0.007	(-0.23)	0.172	0.255 / -0.355	-0.044	0.018	0.954	0.012	0.685
	[-0.028]	[(-0.95)]	[0.177]	[0.255 / -0.355]	[-0.157]	[0.019]	[0.947]	[0.013]	[0.714]
100K	-0.015	(-0.45)	0.173	0.251 / -0.361	-0.084	0.022	0.958	0.015	0.689
	[-0.035]	[(-1.19)]	[0.177]	[0.251 / -0.361]	[-0.196]	[0.023]	[0.952]	[0.016]	[0.719]
500K	-0.036	(-1.08)	0.177	0.239 / -0.378	-0.201	0.033	0.973	0.023	0.704
	[-0.055]	[(-1.85)]	[0.180]	[0.239 / -0.378]	[-0.305]	[0.033]	[0.966]	[0.024]	[0.734]
1M	-0.047	(-1.39)	0.181	0.233 / -0.385	-0.259	0.039	0.984	0.028	0.713
	[-0.065]	[(-2.17)]	[0.183]	[0.233 / -0.385]	[-0.357]	[0.039]	[0.976]	[0.028]	[0.743]

Table 8

This table shows the returns of the momentum arbitrage. The arbitrage buys the winner decile and sells short the loser decile based on the past 12-month returns in each June during 1963 and 1991. The numbers for the same strategy over the period between 1963 to 2000 are shown in square brackets. The short position is assumed to be financed by a cash position with a margin rate of 80% of the Federal Fund rate. Panel (a) shows the statistics for the excess returns (relative to the Federal Fund rates) of both the momentum arbitrage and the CRSP market portfolio without the price-impact and transactions costs, when equally weighted portfolios are used. Panel (b) accounts for both of these costs. Panels (c) and (d) are based on the momentum arbitrage which uses value weighted portfolios, without and with costs, respectively. The Mean excess return is the mean of the annual excess returns between 1963 and 1991 [2000]. The Mean Price-Impact Costs are defined as the mean of the ratios (dollar price-impact costs)/(dollar amount invested), and the Mean Turnover is calculated as the mean of the ratios (dollar amount rebalanced)/(dollar amount invested). The ratios are computed in the beginning of each year between 1963 and 1991 [2000].

(a) Equally Weighted, without Costs

Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio
Momentum	0.042	(1.47)	0.152	0.344 / -0.241	0.277
Arbitrage	[0.036]	[(1.52)]	[0.142]	[0.344 / -0.241]	[0.253]
CRSP	0.092	(1.62)	0.300	0.971 / -0.473	0.306
Equally Weighted	[0.091]	[(2.06)]	[0.269]	[0.971 / -0.473]	[0.339]

(b) Equally Weighted, with Costs

						Long Portfolio		Short Portfolio	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio	Mean Price-Impact Costs	Mean Turnover	Mean Price-Impact Costs	Mean Turnover
10K	0.022	(0.78)	0.150	0.317 / -0.263	0.147	0.005	1.681	0.007	1.559
	[0.015]	[(0.63)]	[0.140]	[0.317 / -0.263]	[0.106]	[0.005]	[1.673]	[0.008]	[1.553]
50K	0.010	(0.35)	0.149	0.301 / -0.273	0.066	0.010	1.690	0.013	1.567
	[0.003]	[(0.11)]	[0.139]	[0.301 / -0.273]	[0.019]	[0.010]	[1.681]	[0.014]	[1.561]
100K	0.003	(0.11)	0.148	0.292 / -0.279	0.022	0.013	1.694	0.016	1.571
	[-0.004]	[(-0.17)]	[0.138]	[0.292 / -0.279]	[-0.029]	[0.013]	[1.686]	[0.017]	[1.565]
200K	-0.005	(-0.16)	0.148	0.282 / -0.285	-0.031	0.016	1.700	0.020	1.576
	[-0.012]	[(-0.50)]	[0.138]	[0.282 / -0.285]	[-0.084]	[0.016]	[1.692]	[0.021]	[1.570]
500K	-0.017	(-0.60)	0.147	0.266 / -0.294	-0.113	0.021	1.709	0.026	1.584
	[-0.023]	[(-1.01)]	[0.137]	[0.266 / -0.294]	[-0.169]	[0.020]	[1.701]	[0.027]	[1.578]
1M	-0.027	(-0.99)	0.146	0.252 / -0.302	-0.186	0.025	1.717	0.032	1.591
	[-0.033]	[(-1.45)]	[0.136]	[0.252 / -0.302]	[-0.242]	[0.024]	[1.709]	[0.032]	[1.585]
5M	-0.057	(-2.10)	0.143	0.214 / -0.319	-0.397	0.036	1.741	0.047	1.614
	[-0.060]	[(-2.70)]	[0.133]	[0.214 / -0.319]	[-0.449]	[0.034]	[1.731]	[0.045]	[1.605]

Table 8 - Continued

(c) Value Weighted, without Costs

Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio
Momentum	0.090	(1.83)	0.259	0.588 / -0.488	0.347
Arbitrage	[0.094]	[(2.36)]	[0.237]	[0.588 / -0.488]	[0.394]
CRSP	0.036	(0.99)	0.193	0.570 / -0.344	0.187
Value Weighted	[0.055]	[(1.84)]	[0.180]	[0.570 / -0.344]	[0.303]

(d) Value Weighted, with Costs

						Long Portfolio		Short Portfolio	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio	Mean Price-Impact Costs	Mean Turnover	Mean Price-Impact Costs	Mean Turnover
100K	0.064	(1.34)	0.252	0.551 / -0.509	0.253	0.005	1.772	0.011	1.759
	[0.066]	[(1.72)]	[0.231]	[0.551 / -0.509]	[0.286]	[0.005]	[1.735]	[0.012]	[1.774]
500K	0.053	(1.12)	0.250	0.536 / -0.517	0.213	0.008	1.779	0.017	1.767
	[0.055]	[(1.45)]	[0.229]	[0.536 / -0.517]	[0.242]	[0.008]	[1.742]	[0.018]	[1.782]
1M	0.047	(1.01)	0.248	0.529 / -0.521	0.191	0.009	1.783	0.021	1.771
	[0.050]	[(1.31)]	[0.228]	[0.529 / -0.521]	[0.218]	[0.009]	[1.746]	[0.021]	[1.786]
5M	0.031	(0.67)	0.245	0.507 / -0.534	0.126	0.014	1.795	0.030	1.783
	[0.034]	[(0.90)]	[0.225]	[0.507 / -0.534]	[0.149]	[0.013]	[1.758]	[0.031]	[1.799]
10M	0.022	(0.48)	0.243	0.496 / -0.540	0.092	0.016	1.801	0.035	1.789
	[0.025]	[(0.68)]	[0.223]	[0.496 / -0.540]	[0.113]	[0.015]	[1.765]	[0.036]	[1.805]
40M	0.002	(0.04)	0.239	0.468 / -0.555	0.007	0.021	1.817	0.048	1.805
	[0.006]	[(0.16)]	[0.219]	[0.468 / -0.555]	[0.027]	[0.020]	[1.780]	[0.047]	[1.821]
50M	-0.002	(-0.05)	0.238	0.463 / -0.558	-0.009	0.022	1.820	0.050	1.808
	[0.002]	[(0.07)]	[0.219]	[0.463 / -0.558]	[0.011]	[0.021]	[1.782]	[0.049]	[1.824]

Table 9

The break-even fund sizes (in the upper rows, in millions of dollars) and the mean excess returns (in the lower rows) for the various momentum arbitrages without the 1% market cap trading and the 5% market cap holding restrictions. The break-even fund size is defined as the initial dollar investment that makes the mean excess return zero. The mean excees return is the mean of the annual excess returns (relative to the Federal Fund rates) between 1963 and 1991 [2000]. The momentum arbitrages are based on the past J-month returns and held for K months, J in {1,3,6,9,12} and K in {1,3,6,12}, with rebalancing occurring every K months. All returns are

(a) 1963-1991

Equally Weighted

		K			
		1	3	6	12
	1	<0.1	<0.1	<0.1	<0.1
		-33.19%	-14.79%	-5.90%	1.69%
	3	<0.1	<0.1	<0.1	0.7
		-21.68%	-4.45%	1.09%	7.07%
J	6	<0.1	<0.1	<0.1	2.5
		-11.33%	1.63%	3.90%	11.14%
	9	<0.1	<0.1	0.3	1.4
		-5.51%	4.49%	7.35%	8.73%
	12	<0.1	0.2	0.3	0.1
		0.62%	8.73%	7.75%	4.20%

Value Weighted

		K			
		1	3	6	12
	1	<0.1	<0.1	<0.1	1.2
		-12.23%	-2.96%	1.70%	2.99%
	3	<0.1	<0.1	4.7	132.2
		-4.97%	5.58%	9.51%	10.70%
J	6	<0.1	3.9	26.5	285.5
		3.17%	13.35%	14.33%	12.14%
	9	<0.1	13.8	107.4	136.3
		7.93%	15.85%	17.09%	11.12%
	12	2.3	62.1	107.3	44.2
		17.14%	21.05%	17.12%	8.97%

(b) 1963-2000

Equally Weighted

		K			
		1	3	6	12
	1	<0.1	<0.1	<0.1	<0.1
		-30.90%	-11.14%	-5.49%	2.62%
	3	<0.1	<0.1	<0.1	0.9
		-18.34%	-0.95%	3.41%	7.62%
J	6	<0.1	<0.1	0.2	3.7
		-8.54%	4.79%	6.40%	12.23%
	9	<0.1	0.1	0.7	1.2
		-2.62%	7.42%	8.91%	8.70%
	12	<0.1	0.4	0.5	<0.1
		2.02%	10.32%	8.38%	3.58%

Value Weighted

		K			
		1	3	6	12
	1	<0.1	<0.1	0.2	93.2
		-8.72%	1.95%	3.36%	7.04%
	3	<0.1	1.0	35.5	241.3
		-0.27%	9.86%	12.67%	11.40%
J	6	<0.1	17.5	66.3	1,483.3
		6.82%	15.85%	15.87%	15.24%
	9	0.6	51.4	184.2	310.4
		11.52%	18.42%	18.00%	12.79%
	12	4.1	81.4	103.5	58.3
		18.04%	20.85%	16.62%	9.35%

Table 10

This table shows the returns of the size&B/M arbitrage. The arbitrage buys the smallest size, highest B/M quintile and sells short the biggest size, lowest B/M quintile in each June during 1963 and 1991. The numbers for the same strategy over the period between 1963 to 2000 are shown in square brackets. The short position is assumed to be financed by a cash position with a margin rate of 80% of the Federal Fund rate. Panel (a) shows the statistics for the excess returns (relative to the Federal Fund rates) of both the size&B/M arbitrage and the CRSP market portfolio without the price-impact and transactions costs, when equally weighted portfolios are used. Panel (b) accounts for both of these costs. Panels (c) and (d) are based on the size&B/M arbitrage which uses value weighted portfolios, without and with costs, respectively. The Mean excess return is the mean of the annual excess returns between 1963 and 1991 [2000]. The Mean Price-Impact Costs are defined as the mean of the ratios (dollar price-impact costs)/(dollar amount invested), and the Mean Turnover is calculated as the mean of the ratios (dollar amount rebalanced)/(dollar amount invested). The ratios are computed in the beginning of each year between 1963 and 1991 [2000].

(a) Equally Weighted, without Costs

Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio
Size&B/M	0.089	(2.22)	0.216	0.512 / -0.325	0.412
Arbitrage	[0.081]	[(2.42)]	[0.203]	[0.512 / -0.325]	[0.398]
CRSP	0.092	(1.68)	0.295	0.971 / -0.473	0.311
Equally Weighted	[0.091]	[(2.12)]	[0.265]	[0.971 / -0.473]	[0.344]

(b) Equally Weighted, with Costs

						Long Portfolio		Short Portfolio	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio	Mean Price-Impact Costs	Mean Turnover	Mean Price-Impact Costs	Mean Turnover
100K	0.061	(1.59)	0.208	0.434 / -0.341	0.296	0.018	0.837	0.003	0.489
	[0.054]	[(1.67)]	[0.196]	[0.434 / -0.341]	[0.275]	[0.017]	[0.806]	[0.003]	[0.483]
500K	0.047	(1.25)	0.204	0.394 / -0.347	0.233	0.028	0.843	0.005	0.490
	[0.041]	[(1.29)]	[0.192]	[0.394 / -0.347]	[0.212]	[0.027]	[0.812]	[0.005]	[0.484]
1M	0.040	(1.06)	0.201	0.387 / -0.351	0.197	0.034	0.846	0.005	0.491
	[0.034]	[(1.07)]	[0.190]	[0.387 / -0.351]	[0.176]	[0.032]	[0.815]	[0.005]	[0.484]
5M	0.017	(0.46)	0.194	0.373 / -0.360	0.086	0.051	0.857	0.007	0.493
	[0.013]	[(0.42)]	[0.184]	[0.373 / -0.360]	[0.069]	[0.048]	[0.824]	[0.007]	[0.486]
10M	0.004	(0.13)	0.190	0.367 / -0.364	0.024	0.060	0.863	0.008	0.495
	[0.002]	[(0.07)]	[0.181]	[0.367 / -0.364]	[0.011]	[0.056]	[0.829]	[0.008]	[0.487]
20M	-0.009	(-0.27)	0.186	0.360 / -0.368	-0.050	0.071	0.870	0.009	0.497
	[-0.010]	[(-0.34)]	[0.177]	[0.360 / -0.368]	[-0.056]	[0.065]	[0.835]	[0.008]	[0.489]
50M	-0.030	(-0.88)	0.182	0.350 / -0.373	-0.164	0.086	0.882	0.010	0.501
	[-0.027]	[(-0.96)]	[0.174]	[0.350 / -0.373]	[-0.158]	[0.078]	[0.845]	[0.009]	[0.492]

Table 10 - Continued

(c) Value Weighted, without Costs

Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio
Size&B/M	0.061	(1.63)	0.201	0.412 / -0.360	0.303
Arbitrage	[0.042]	[(1.28)]	[0.201]	[0.412 / -0.360]	[0.211]
CRSP	0.040	(1.14)	0.191	0.570 / -0.344	0.212
Value Weighted	[0.057]	[(1.98)]	[0.178]	[0.570 / -0.344]	[0.321]

(d) Value Weighted, with Costs

						Long Portfolio		Short Portfolio	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio	Mean Price-Impact Costs	Mean Turnover	Mean Price-Impact Costs	Mean Turnover
100K	0.043	(1.17)	0.197	0.400 / -0.370	0.217	0.012	0.632	0.002	0.406
	[0.025]	[(0.76)]	[0.197]	[0.400 / -0.370]	[0.125]	[0.011]	[0.625]	[0.002]	[0.398]
500K	0.033	(0.92)	0.195	0.393 / -0.375	0.170	0.019	0.636	0.004	0.407
	[0.016]	[(0.49)]	[0.195]	[0.393 / -0.375]	[0.080]	[0.018]	[0.628]	[0.003]	[0.398]
1M	0.028	(0.77)	0.193	0.390 / -0.377	0.144	0.023	0.638	0.004	0.407
	[0.011]	[(0.33)]	[0.193]	[0.390 / -0.377]	[0.054]	[0.022]	[0.630]	[0.004]	[0.399]
5M	0.012	(0.33)	0.189	0.379 / -0.385	0.062	0.035	0.643	0.006	0.408
	[-0.004]	[(-0.14)]	[0.190]	[0.379 / -0.385]	[-0.023]	[0.033]	[0.635]	[0.005]	[0.400]
10M	0.003	(0.08)	0.187	0.373 / -0.388	0.015	0.042	0.647	0.006	0.409
	[-0.012]	[(-0.40)]	[0.187]	[0.373 / -0.388]	[-0.065]	[0.040]	[0.638]	[0.006]	[0.400]
20M	-0.007	(-0.21)	0.184	0.367 / -0.392	-0.039	0.050	0.651	0.007	0.410
	[-0.021]	[(-0.70)]	[0.185]	[0.367 / -0.392]	[-0.115]	[0.047]	[0.641]	[0.007]	[0.401]
30M	-0.014	(-0.41)	0.182	0.363 / -0.394	-0.075	0.055	0.653	0.008	0.411
	[-0.027]	[(-0.90)]	[0.183]	[0.363 / -0.394]	[-0.148]	[0.051]	[0.644]	[0.007]	[0.402]
50M	-0.023	(-0.68)	0.180	0.357 / -0.397	-0.126	0.062	0.657	0.008	0.413
	[-0.035]	[(-1.17)]	[0.181]	[0.357 / -0.397]	[-0.193]	[0.057]	[0.647]	[0.008]	[0.403]
100M	-0.036	(-1.10)	0.177	0.350 / -0.401	-0.204	0.072	0.663	0.009	0.415
	[-0.046]	[(-1.59)]	[0.178]	[0.350 / -0.401]	[-0.262]	[0.066]	[0.652]	[0.008]	[0.405]

Table 11

This table shows the returns of the B/M arbitrage which uses only those stocks in the biggest five size deciles (the stocks in the biggest five size deciles are sorted by the B/M into deciles). The arbitrage buys the highest B/M decile and sells short the lowest B/M decile in each June during 1963 and 1991. The numbers for the same strategy over the period between 1963 to 2000 are shown in square brackets. The short position is assumed to be financed by a cash position with a margin rate of 80% of the Federal Fund rate.Panel (a) shows the statistics for the excess returns (relative to the Federal Fund rates) of both the B/M arbitrage and the CRSP market portfolio without the price-impact and transactions costs, when equally weighted portfolios are used. Panel (b) accounts for both of these costs. Panels (c) and (d) are based on the B/M arbitrage which uses value weighted portfolios, without and with costs, respectively. The Mean excess return is the mean of the annual excess returns between 1963 and 1991 [2000]. The Mean Price-Impact Costs are defined as the mean of the ratios (dollar price-impact costs)/(dollar amount invested), and the Mean Turnover is calculated as the mean of the ratios (dollar amount rebalanced)/(dollar amount invested). The ratios are computed in the beginning of each year between 1963 and 1991 [2000].

(a) Equally Weighted, without Costs

Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio
B/M Arbitrage	0.047	(1.39)	0.180	0.330 / -0.301	0.259
	[0.025]	[(0.80)]	[0.190]	[0.330 / -0.432]	[0.132]
CRSP	0.092	(1.68)	0.295	0.971 / -0.473	0.311
Equally Weighted	[0.091]	[(2.12)]	[0.265]	[0.971 / -0.473]	[0.344]

(b) Equally Weighted, with Costs

						Long Portfolio		Short Portfolio	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio	Mean Price-Impact Costs	Mean Turnover	Mean Price-Impact Costs	Mean Turnover
10K	0.022	(0.67)	0.180	0.311 / -0.322	0.124	0.010	0.937	0.009	0.885
	[0.000]	[(0.01)]	[0.189]	[0.311 / -0.456]	[0.001]	[0.010]	[0.909]	[0.010]	[0.912]
50K	0.009	(0.26)	0.180	0.301 / -0.334	0.049	0.016	0.945	0.015	0.893
	[-0.013]	[(-0.42)]	[0.189]	[0.301 / -0.466]	[-0.070]	[0.016]	[0.918]	[0.016]	[0.920]
100K	0.001	(0.03)	0.181	0.295 / -0.340	0.006	0.020	0.951	0.018	0.897
	[-0.020]	[(-0.66)]	[0.189]	[0.295 / -0.471]	[-0.108]	[0.019]	[0.923]	[0.019]	[0.924]
200K	-0.008	(-0.23)	0.181	0.289 / -0.346	-0.042	0.024	0.957	0.022	0.903
	[-0.029]	[(-0.92)]	[0.189]	[0.289 / -0.477]	[-0.152]	[0.023]	[0.929]	[0.023]	[0.929]
300K	-0.013	(-0.40)	0.182	0.285 / -0.351	-0.073	0.027	0.961	0.025	0.907
	[-0.034]	[(-1.09)]	[0.189]	[0.285 / -0.480]	[-0.180]	[0.026]	[0.933]	[0.026]	[0.933]
400K	-0.018	(-0.52)	0.182	0.282 / -0.354	-0.097	0.029	0.964	0.027	0.910
	[-0.038]	[(-1.22)]	[0.189]	[0.282 / -0.482]	[-0.201]	[0.027]	[0.936]	[0.027]	[0.936]
500K	-0.021	(-0.62)	0.183	0.279 / -0.356	-0.116	0.030	0.967	0.029	0.913
	[-0.041]	[(-1.32)]	[0.189]	[0.279 / -0.484]	[-0.218]	[0.029]	[0.938]	[0.029]	[0.938]

Table 11 - Continued

(c) Value Weighted, without Costs

Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio
B/M Arbitrage	-0.001	(-0.04)	0.189	0.270 / -0.421	-0.007
	[0.025]	[(0.80)]	[0.190]	[0.330 / -0.432]	[0.132]
CRSP	0.040	(1.14)	0.191	0.570 / -0.344	0.212
Value Weighted	[0.091]	[(2.12)]	[0.265]	[0.971 / -0.473]	[0.344]

(d) Value Weighted, with Costs

						Long Portfolio		Short Portfolio	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio	Mean Price-Impact Costs	Mean Turnover	Mean Price-Impact Costs	Mean Turnover
10K	-0.026	(-0.78)	0.184	0.235 / -0.443	-0.144	0.011	1.011	0.009	0.757
	[0.000]	[(0.01)]	[0.189]	[0.311 / -0.456]	[0.001]	[0.010]	[0.909]	[0.010]	[0.912]
50K	-0.041	(-1.20)	0.182	0.224 / -0.454	-0.223	0.019	1.021	0.015	0.765
	[-0.013]	[(-0.42)]	[0.189]	[0.301 / -0.466]	[-0.070]	[0.016]	[0.918]	[0.016]	[0.920]
100K	-0.048	(-1.44)	0.181	0.218 / -0.461	-0.267	0.023	1.027	0.018	0.771
	[-0.020]	[(-0.66)]	[0.189]	[0.295 / -0.471]	[-0.108]	[0.019]	[0.923]	[0.019]	[0.924]
200K	-0.057	(-1.71)	0.181	0.210 / -0.468	-0.317	0.027	1.035	0.022	0.777
	[-0.029]	[(-0.92)]	[0.189]	[0.289 / -0.477]	[-0.152]	[0.023]	[0.929]	[0.023]	[0.929]

Table 12

This table shows the returns of the momentum arbitrage which uses only those stocks in the biggest five size deciles. In each June, stocks in the biggest five size deciles are sorted by the past 12-month returns into deciles. The arbitrage buys the winner decile and sells short the loser decile during 1963 and 1991. The numbers for the same strategy over the period between 1963 to 2000 are shown in square brackets. The short position is assumed to be financed by a cash position with a margin rate of 80% of the Federal Fund rate. Panel (a) shows the statistics for the excess returns (relative to the Federal Fund rates) of both the momentum arbitrage and the CRSP market portfolio without the price-impact and transactions costs, when equally weighted portfolios are used. Panel (b) accounts for both of these costs. Panels (c) and (d) are based on the momentum arbitrage which uses value weighted portfolios, without and with costs, respectively. Panels (e) and (f) reproduce panels (b) and (d), respectively, when in addition the 1% market cap trading restriction is imposed. The Mean excess return is the mean of the annual excess returns between 1963 and 1991 [2000]. The Mean Price-Impact Costs are defined as the mean of the ratios (dollar price-impact costs)/(dollar amount invested), and the Mean Turnover is calculated as the mean of the ratios (dollar amount rebalanced)/(dollar amount invested). The ratios are computed in the beginning of each year between 1963 and 1991 [2000].

(a) Equally Weighted, without Costs

Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio
Momentum	0.070	(1.80)	0.204	0.577 / -0.315	0.341
Arbitrage	[0.090]	[(2.28)]	[0.236]	[0.906 / -0.315]	[0.381]
CRSP	0.092	(1.62)	0.300	0.971 / -0.473	0.306
Equally Weighted	[0.091]	[(2.06)]	[0.269]	[0.971 / -0.473]	[0.339]

(b) Equally Weighted, with Costs

						Long Portfolio		Short Portfolio	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio	Mean Price-Impact Costs	Mean Turnover	Mean Price-Impact Costs	Mean Turnover
100K	0.054	(1.43)	0.201	0.553 / -0.326	0.271	0.004	1.620	0.004	1.616
	[0.073]	[(1.89)]	[0.232]	[0.874 / -0.326]	[0.316]	[0.004]	[1.617]	[0.004]	[1.612]
500K	0.050	(1.31)	0.200	0.546 / -0.330	0.248	0.006	1.623	0.006	1.620
	[0.068]	[(1.77)]	[0.230]	[0.865 / -0.330]	[0.295]	[0.006]	[1.620]	[0.006]	[1.615]
1M	0.047	(1.25)	0.199	0.542 / -0.331	0.236	0.007	1.624	0.007	1.621
	[0.065]	[(1.71)]	[0.230]	[0.860 / -0.331]	[0.285]	[0.007]	[1.622]	[0.007]	[1.617]
5M	0.041	(1.09)	0.198	0.532 / -0.336	0.205	0.010	1.628	0.010	1.625
	[0.059]	[(1.54)]	[0.228]	[0.849 / -0.336]	[0.257]	[0.010]	[1.626]	[0.010]	[1.621]
10M	0.037	(1.01)	0.197	0.527 / -0.339	0.190	0.011	1.630	0.011	1.627
	[0.055]	[(1.46)]	[0.227]	[0.844 / -0.339]	[0.244]	[0.012]	[1.628]	[0.012]	[1.623]
50M	0.029	(0.79)	0.195	0.514 / -0.345	0.148	0.015	1.636	0.015	1.633
	[0.047]	[(1.24)]	[0.225]	[0.830 / -0.345]	[0.207]	[0.015]	[1.634]	[0.015]	[1.629]
100M	0.025	(0.68)	0.194	0.507 / -0.348	0.128	0.017	1.638	0.016	1.635
	[0.042]	[(1.13)]	[0.225]	[0.823 / -0.348]	[0.189]	[0.017]	[1.636]	[0.017]	[1.632]
500M	0.014	(0.38)	0.192	0.490 / -0.357	0.072	0.021	1.645	0.021	1.643
	[0.031]	[(0.84)]	[0.222]	[0.806 / -0.357]	[0.141]	[0.022]	[1.644]	[0.022]	[1.639]
1B	0.008	(0.23)	0.190	0.481 / -0.361	0.043	0.024	1.649	0.024	1.646
	[0.026]	[(0.70)]	[0.221]	[0.798 / -0.361]	[0.117]	[0.024]	[1.647]	[0.024]	[1.643]
2B	0.002	(0.07)	0.189	0.472 / -0.366	0.013	0.026	1.653	0.026	1.651
	[0.020]	[(0.54)]	[0.220]	[0.790 / -0.366]	[0.090]	[0.027]	[1.651]	[0.027]	[1.647]
3B	-0.001	(-0.04)	0.188	0.466 / -0.369	-0.007	0.028	1.655	0.028	1.653
	[0.016]	[(0.44)]	[0.219]	[0.785 / -0.369]	[0.074]	[0.028]	[1.654]	[0.028]	[1.650]
5B	-0.006	(-0.17)	0.187	0.458 / -0.373	-0.033	0.030	1.659	0.030	1.656
	[0.011]	[(0.31)]	[0.218]	[0.778 / -0.373]	[0.052]	[0.030]	[1.657]	[0.030]	[1.653]
10B	-0.013	(-0.38)	0.185	0.447 / -0.379	-0.071	0.033	1.664	0.033	1.662
	[0.005]	[(0.13)]	[0.216]	[0.769 / -0.379]	[0.021]	[0.033]	[1.662]	[0.033]	[1.658]
20B	-0.021	(-0.60)	0.184	0.435 / -0.385	-0.113	0.036	1.669	0.036	1.667
	[-0.003]	[(-0.08)]	[0.215]	[0.759 / -0.385]	[-0.013]	[0.036]	[1.667]	[0.036]	[1.663]

Table 12 - Continued

(c) Value Weighted, without Costs

Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio
Momentum	0.058	(1.47)	0.207	0.522 / -0.368	0.277
Arbitrage	[0.082]	[(2.10)]	[0.234]	[0.845 / -0.368]	[0.349]
CRSP	0.036	(0.99)	0.193	0.570 / -0.344	0.187
Value Weighted	[0.055]	[(1.84)]	[0.180]	[0.570 / -0.344]	[0.303]

(d) Value Weighted, with Costs

						Long Portfolio		Short Portfolio	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max / Min	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
100K	0.044	(1.13)	0.205	0.500 / -0.377	0.214	0.003	1.748	0.003	1.731
	[0.067]	[(1.75)]	[0.230]	[0.820 / -0.377]	[0.291]	[0.003]	[1.724]	[0.003]	[1.737]
500K	0.040	(1.04)	0.204	0.494 / -0.380	0.196	0.005	1.751	0.005	1.734
	[0.063]	[(1.64)]	[0.230]	[0.814 / -0.380]	[0.274]	[0.005]	[1.727]	[0.005]	[1.740]
1M	0.038	(0.99)	0.203	0.491 / -0.381	0.186	0.006	1.752	0.006	1.735
	[0.061]	[(1.59)]	[0.229]	[0.810 / -0.381]	[0.265]	[0.006]	[1.728]	[0.006]	[1.742]
5M	0.032	(0.84)	0.202	0.482 / -0.385	0.160	0.008	1.756	0.008	1.739
	[0.055]	[(1.45)]	[0.228]	[0.801 / -0.385]	[0.241]	[0.008]	[1.732]	[0.008]	[1.746]
10M	0.029	(0.77)	0.202	0.477 / -0.387	0.146	0.009	1.758	0.009	1.742
	[0.052]	[(1.37)]	[0.227]	[0.797 / -0.387]	[0.229]	[0.009]	[1.734]	[0.010]	[1.748]
50M	0.022	(0.57)	0.200	0.465 / -0.393	0.108	0.013	1.763	0.013	1.748
	[0.044]	[(1.17)]	[0.226]	[0.784 / -0.393]	[0.194]	[0.013]	[1.740]	[0.013]	[1.755]
100M	0.018	(0.47)	0.199	0.458 / -0.396	0.088	0.014	1.766	0.014	1.751
	[0.040]	[(1.06)]	[0.225]	[0.778 / -0.396]	[0.177]	[0.015]	[1.743]	[0.015]	[1.758]
500M	0.006	(0.17)	0.197	0.440 / -0.404	0.033	0.019	1.774	0.019	1.760
	[0.028]	[(0.77)]	[0.223]	[0.762 / -0.404]	[0.128]	[0.019]	[1.751]	[0.020]	[1.767]
1B	0.001	(0.02)	0.196	0.431 / -0.408	0.004	0.022	1.779	0.022	1.764
	[0.023]	[(0.62)]	[0.221]	[0.755 / -0.408]	[0.103]	[0.022]	[1.755]	[0.022]	[1.772]
2B	-0.005	(-0.15)	0.194	0.420 / -0.413	-0.028	0.025	1.783	0.024	1.769
	[0.017]	[(0.45)]	[0.220]	[0.747 / -0.413]	[0.075]	[0.025]	[1.760]	[0.025]	[1.777]
5B	-0.015	(-0.40)	0.192	0.405 / -0.420	-0.076	0.029	1.790	0.028	1.777
	[0.008]	[(0.21)]	[0.219]	[0.735 / -0.420]	[0.035]	[0.028]	[1.767]	[0.028]	[1.784]
9B	-0.021	(-0.58)	0.191	0.394 / -0.425	-0.110	0.032	1.795	0.031	1.782
	[0.001]	[(0.03)]	[0.217]	[0.727 / -0.425]	[0.005]	[0.031]	[1.772]	[0.031]	[1.790]
10B	-0.022	(-0.62)	0.191	0.392 / -0.426	-0.117	0.032	1.796	0.031	1.783
	[-0.000]	[(0.00)]	[0.217]	[0.726 / -0.426]	[0.000]	[0.032]	[1.773]	[0.032]	[1.791]

Table 12 - Continued

(e) Equally Weighted, with Costs and 1% Market Cap Trading Restriction

						Long Portfolio		Short Portfolio	
Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max/Min	Sharpe Ratio	Mean Price Impact	Mean Turnover	Mean Price Impact	Mean Turnover
100K	0.054	(1.43)	0.201	0.553 / -0.326	0.271	0.004	1.620	0.004	1.616
	[0.073]	[(1.89)]	[0.232]	[0.874 / -0.326]	[0.316]	[0.004]	[1.617]	[0.004]	[1.612]
500K	0.050	(1.31)	0.200	0.546 / -0.330	0.248	0.006	1.623	0.006	1.620
	[0.068]	[(1.77)]	[0.230]	[0.865 / -0.330]	[0.295]	[0.006]	[1.620]	[0.006]	[1.615]
1M	0.047	(1.25)	0.199	0.542 / -0.331	0.236	0.007	1.624	0.007	1.621
	[0.065]	[(1.71)]	[0.230]	[0.860 / -0.331]	[0.285]	[0.007]	[1.622]	[0.007]	[1.617]
5M	0.041	(1.09)	0.198	0.532 / -0.336	0.205	0.010	1.628	0.010	1.625
	[0.059]	[(1.54)]	[0.228]	[0.849 / -0.336]	[0.257]	[0.010]	[1.626]	[0.010]	[1.621]
10M	0.037	(1.01)	0.197	0.527 / -0.339	0.190	0.011	1.630	0.011	1.627
	[0.055]	[(1.46)]	[0.227]	[0.844 / -0.339]	[0.244]	[0.012]	[1.628]	[0.012]	[1.623]
50M	0.029	(0.79)	0.195	0.514 / -0.346	0.148	0.015	1.636	0.015	1.633
	[0.047]	[(1.24)]	[0.226]	[0.829 / -0.346]	[0.207]	[0.015]	[1.634]	[0.015]	[1.629]
100M	0.024	(0.65)	0.196	0.508 / -0.358	0.123	0.017	1.639	0.017	1.636
	[0.042]	[(1.12)]	[0.225]	[0.822 / -0.358]	[0.186]	[0.018]	[1.637]	[0.017]	[1.632]
300M	0.002	(0.07)	0.195	0.482 / -0.409	0.013	0.027	1.656	0.026	1.652
	[0.023]	[(0.61)]	[0.226]	[0.814 / -0.409]	[0.101]	[0.026]	[1.652]	[0.025]	[1.647]
400M	-0.006	(-0.15)	0.194	0.472 / -0.430	-0.029	0.031	1.663	0.029	1.659
	[0.016]	[(0.43)]	[0.225]	[0.811 / -0.430]	[0.071]	[0.029]	[1.657]	[0.028]	[1.652]
500M	-0.012	(-0.34)	0.193	0.468 / -0.450	-0.065	0.034	1.669	0.032	1.665
	[0.010]	[(0.28)]	[0.225]	[0.810 / -0.450]	[0.046]	[0.032]	[1.662]	[0.030]	[1.657]
700M	-0.023	(-0.63)	0.193	0.461 / -0.482	-0.120	0.039	1.679	0.037	1.674
	[0.002]	[(0.05)]	[0.226]	[0.809 / -0.482]	[0.008]	[0.036]	[1.670]	[0.034]	[1.664]
800M	-0.027	(-0.76)	0.193	0.460 / -0.495	-0.143	0.041	1.683	0.039	1.679
	[-0.002]	[(-0.04)]	[0.226]	[0.809 / -0.495]	[-0.007]	[0.037]	[1.673]	[0.035]	[1.668]
1B	-0.035	(-0.96)	0.193	0.458 / -0.513	-0.181	0.044	1.690	0.042	1.686
	[-0.007]	[(-0.20)]	[0.227]	[0.809 / -0.513]	[-0.033]	[0.040]	[1.679]	[0.038]	[1.673]

Table 12 - Continued

(f) Value Weighted, with Costs and 1% Market Cap Trading Restriction

Arbitrage Fund Size	Mean Excess Return	(t-stat)	Standard Deviation	Max/Min	Sharpe Ratio	Long Portfolio Mean Price Impact	Long Portfolio Mean Turnover	Short Portfolio Mean Price Impact	Short Portfolio Mean Turnover
100K	0.044	(1.13)	0.205	0.500 / -0.377	0.214	0.003	1.748	0.003	1.731
	[0.067]	[(1.75)]	[0.230]	[0.820 / -0.377]	[0.291]	[0.003]	[1.724]	[0.003]	[1.737]
500K	0.040	(1.04)	0.204	0.494 / -0.380	0.196	0.005	1.751	0.005	1.734
	[0.063]	[(1.64)]	[0.230]	[0.814 / -0.380]	[0.274]	[0.005]	[1.727]	[0.005]	[1.740]
1M	0.038	(0.99)	0.203	0.491 / -0.381	0.186	0.006	1.752	0.006	1.735
	[0.061]	[(1.59)]	[0.229]	[0.810 / -0.381]	[0.265]	[0.006]	[1.728]	[0.006]	[1.742]
5M	0.032	(0.84)	0.202	0.482 / -0.385	0.160	0.008	1.756	0.008	1.739
	[0.055]	[(1.45)]	[0.228]	[0.801 / -0.385]	[0.241]	[0.008]	[1.732]	[0.008]	[1.746]
10M	0.029	(0.77)	0.202	0.477 / -0.387	0.146	0.009	1.758	0.009	1.742
	[0.052]	[(1.37)]	[0.227]	[0.797 / -0.387]	[0.229]	[0.009]	[1.734]	[0.010]	[1.748]
50M	0.022	(0.57)	0.200	0.465 / -0.393	0.108	0.013	1.763	0.013	1.748
	[0.044]	[(1.17)]	[0.226]	[0.784 / -0.393]	[0.194]	[0.013]	[1.740]	[0.013]	[1.755]
100M	0.017	(0.46)	0.199	0.459 / -0.397	0.087	0.014	1.767	0.015	1.751
	[0.040]	[(1.06)]	[0.225]	[0.778 / -0.397]	[0.176]	[0.015]	[1.743]	[0.015]	[1.758]
400M	0.003	(0.09)	0.201	0.440 / -0.442	0.017	0.021	1.780	0.021	1.764
	[0.027]	[(0.71)]	[0.226]	[0.767 / -0.442]	[0.119]	[0.020]	[1.754]	[0.021]	[1.770]
500M	-0.001	(-0.03)	0.200	0.432 / -0.459	-0.006	0.023	1.784	0.023	1.769
	[0.023]	[(0.62)]	[0.226]	[0.767 / -0.459]	[0.103]	[0.022]	[1.758]	[0.023]	[1.773]
1B	-0.020	(-0.52)	0.200	0.412 / -0.526	-0.098	0.031	1.803	0.032	1.788
	[0.008]	[(0.22)]	[0.227]	[0.766 / -0.526]	[0.037]	[0.028]	[1.773]	[0.029]	[1.789]
2B	-0.041	(-1.08)	0.202	0.409 / -0.623	-0.204	0.040	1.832	0.043	1.816
	[-0.008]	[(-0.22)]	[0.231]	[0.765 / -0.623]	[-0.036]	[0.035]	[1.794]	[0.037]	[1.809]
3B	-0.055	(-1.42)	0.203	0.409 / -0.659	-0.269	0.046	1.849	0.048	1.834
	[-0.019]	[(-0.48)]	[0.233]	[0.765 / -0.659]	[-0.080]	[0.040]	[1.808]	[0.042]	[1.823]

Table 13

Hedge fund size by styles in 2000. The strategies are as defined in the TASS data set and are overlapping.

			Fund size (in millions of dollars)			
Strategy	Number of funds	Percent of total	Mean	Min	Max	Sum
Top down macro	362	27.4%	241.4	0.0147	4,122.0	87,396.0
Bottom up approach	694	52.6%	195.0	0.1898	23,474.4	135,306.2
Short selling	524	39.7%	201.1	0.0147	4,618.1	105,362.6
Long bias	443	33.6%	181.1	0.3780	23,474.4	80,217.2
Market neutral	313	23.7%	152.0	0.0147	4,122.0	47,563.9
Opportunities	498	37.8%	139.0	0.1100	23,474.4	69,206.0
Relative value	360	27.3%	183.0	0.0147	10,194.0	65,862.1
Arbitrage	408	30.9%	137.3	0.0602	23,474.4	56,018.6
Descretionary	275	20.8%	101.1	0.0147	23,474.4	27,803.3
Trend follower	201	15.2%	72.7	0.3384	3,958.9	14,603.4
Technical	401	30.4%	74.9	0.0147	23,474.4	30,036.8
Fundamental	702	53.2%	169.5	0.1898	4,618.1	118,957.1
Systematic	323	24.5%	83.4	0.0602	10,194.0	26,940.0
Diverse	354	26.8%	140.2	0.0147	23,474.4	49,646.3
Other	153	11.6%	98.6	0.0147	23,474.4	15,087.2
Total	1319	100.0%	139.9	0.0147	23474.4	184492.4