The Cost of Trend Chasing and The Illusion of Momentum Profits

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Abstract

There is a large and growing literature documenting the relation between ex ante observable variables and stock returns. Importantly, much of the evidence on the relation between returns and observable variables like market capitalization, the ratio of price/book, and prior price change has been portrayed in the context of returns to simulated portfolio strategies. Often missing in these analyses is the distinction between realizable returns (i.e., the returns portfolio managers can realistically achieve in practice) and returns to simulated strategies. There is ample evidence that size and value strategies can be successfully implemented in practice; that is not the case for momentum strategies. This paper documents the costs of implementing actual momentum strategies. I examine the trade behavior, and the costs of those trades, for three distinct investor styles (momentum, fundamental/value, and diversified/index) for 33 institutional investment managers executing trades in the U.S. and 36 other equity markets worldwide in both developed and emerging economies. The results show: (1) that momentum traders do indeed condition their trades on prior price movements; and (2) that costs for trades that are made conditional on prior market returns are significantly greater than for unconditional costs, especially for momentum traders. The evidence that we report on the actual costs of momentum-based trades indicates that the returns reported in previous studies of simulated momentum strategies are not sufficient to cover the costs of implementing those strategies.

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1. Introduction

There is a large and growing literature documenting the relation between stock returns and observable variables like market capitalization, the ratio of price to book, and prior price changes. Importantly, much of the evidence on this relation has been portrayed in the context of returns to simulated portfolio strategies. Often missing in the analyses of simulated portfolio strategies is the distinction between simulated "paper" returns and realizable returns (investment strategy returns net of the costs of implementing the strategy). There is ample evidence that size and value strategies can be successfully implemented in practice;[1] that is not obviously the case for momentum strategies. The *paper profits* generated by simulated momentum strategies appear, to many researchers, to be inconsistent with the Efficient Markets Hypothesis.[2] However, to violate the Efficient Markets Hypothesis abnormal returns must exceed the costs of implementing the strategy designed to generate them.

This paper contributes to the growing literature on momentum in stock prices by documenting the costs of implementing actual momentum strategies, and showing that costs for trades that are made conditional on past market movements are significantly greater than unconditional costs. I estimate the implementation costs of momentum strategies directly from the trades of momentum-oriented institutional investors over two different twelve-month periods during 1997-2000. The data include trades not only for momentum managers but also for value and passive managers, and cover more than 1.6 million trades worth $1.1 trillion in the U.S. and 36 other equity markets worldwide in both developed and emerging economies. As such, they permit a more precise focus on the issues than previously possible.

The paper makes three contributions. First, I investigate whether trend chasing is evident in the trading behavior of the three investment styles in the data. The results show that the momentum traders are indeed conditioning their trades on prior price movements. Estimation of

[1] For example, Dimensional Fund Advisors and LSV Asset Management have developed successful mutual funds based on academic research documenting size and value effects.

[2] The evidence has prompted Jegadeesh and Titman (2001) to claim that "the momentum effect represents perhaps the strongest evidence against the Efficient Market Hypothesis." And Johnson (2002, JF) writes "There would appear to be few more flagrant affronts to the idea of rational, efficient markets than the existence of large excess returns to simple momentum strategies in the stock market."

logit models indicate that buys are more likely to be made in rising markets and sells are more likely in falling markets for the momentum traders in my sample. This is in contrast to the index/diversified managers in the sample whose buys and sells are unrelated to recent prior price movements, and for the value managers whose buys (sells) are more likely to follow recent price declines (price increases). The findings show clear evidence of trend chasing (positive feedback trading) by the momentum traders.

Second, I ask whether this trade behavior contributes in an important way to the costs of implementing the strategies. To answer the question, I separately examine the trade costs of the momentum, value and diversified traders – each of whom have different motives for trading – conditional on past market returns to assess how the market environment in which a trade is made affects the cost of execution (and, ultimately, the profitability of the strategy). In previous research, two different approaches have been used to gauge the profitability of momentum strategies: (1) unconditional average cost estimates from prior research are compared to the profits generated by the simulated momentum strategies (e.g., Grinblatt and Moskowitz (2002), Grundy and Martin (2001)); (2) inferences regarding price impacts are drawn from statistical models using transactions-level prices – where the models are simulated without regard to the potential influence on price impacts of either the motivation for trade or the market environment in which the trade takes place – and compared with the profitability of simulated momentum strategies (e.g., Korajczyk and Sadka (2002), Lesmond, Schill and Zhou (2003)). Neither of these approaches accounts for the fact that trade costs are a function of both investment style (see, e.g., Chan and Lakonishok (1995) and Keim and Madhavan (1997)) and the market conditions (e.g., a rising or a falling market) that prevail when the trade is executed. In addition, because traders often break up large trades into smaller individual trades, analysis of the price impacts of individual trades (as is necessary when using transactions-level information like that in the TAQ data base) under-estimates the price impact associated with the total desired order quantity. The price impacts reported here account for all of these important factors by employing the total trade order as the unit of observation and conditioning on trade difficulty (trade size, market cap of the stock), the investment style of the manager, and the direction of the market in which the stock trades.

Conditioning on past market returns is important because momentum traders are buying (selling) when the stock price is rising (falling) and the market for the stock has excess buyers (sellers). Under such conditions, their trade costs (for purchases of stocks on a rising trajectory, for example) are expected to be higher than the unconditional average due to a combination of: (1) increased demand for liquidity on the momentum trader's side of the market due to the existence of other like-minded traders; and/or (2) reduced supply of liquidity due to fewer sellers/owners of recently appreciated stocks who don't wish to realize their capital gains. As it turns out, market environment is an important determinant of price impact. For example, one-way average price impacts for momentum traders in the U.S. are 1.21% when buying stocks in a rising market and 1.37% when selling in a falling market. Adding opportunity costs (of not being able to execute at the price prevailing at the time of the decision to trade) and commissions and other explicit costs of transacting inflates these costs to 1.82% for buys in rising markets and 1.96% for sells in falling markets. The trade costs reported here represent a clearer picture of the costs of implementing momentum strategies than previously reported in the literature and set a very high hurdle rate for the profits implied by the simulated strategies. The reality inevitably falls short of the illusion.

Finally, in addition to documenting momentum trade behavior and its costs in a broad cross section of U.S. and international markets, the results also represent the first detailed analysis of the relative costs of trading equities internationally.

The paper proceeds as follows. Section 2 reviews the previous evidence on momentum profits and section 3 describes the trade data used here to measure price impacts. Section 4 provides an overview of the price impacts for momentum, value and diversified traders in U.S., developed, and emerging stock markets. Section 5 reports the evidence on whether institutional trades are conditioned on prior market movements, and section 6 analyzes the conditional price impacts of momentum trades. Section 7 reports on total trade costs comprising price impacts, opportunity costs and commissions, and discusses the implications of the magnitude of these costs for the profitability of momentum strategies. Section 8 provides some evidence on the short-term performance of the momentum traders in my sample, and section 9 concludes.

2. Prior Evidence on the Profitability of Simulated Momentum Strategies

The research on momentum is in general agreement that intermediate horizon (three to twelve month) stock returns exhibit significant persistence. There is little consensus, however, on the reason for persistence in returns. Some argue that its prevalence over long periods is evidence that the abnormal returns associated with momentum strategies are compensation for some unidentified source of non-diversifiable risk (Carhart (1997), Fama and French (1996)). Other research suggests that the price momentum is related to trading in response to earnings-related news (Boni and Womack (2003), Burch and Swaminathan (2002)).

Still others argue that momentum in stock prices is simply the manifestation of the trade behavior of market participants who condition trades on prior price movements (e.g., positive feedback strategies), behavior that violates the usual norms of rationality necessary for equilibrium asset pricing. Numerous investigators have attempted to model this behavior within well-established psychological paradigms, attributing the investor trading patterns to either under-reaction (Barberis, Schleifer and Vishny (1998), Grinblatt and Han (2002))[3] or over-reaction (Daniel, Hirshleifer and Subramanyam (1998), Hong and Stein (1999)) to the perceived information in prior price movements. Although the evidence is mixed regarding the form of the irrational behavior, this strand of research agrees that the resulting abnormal momentum profits represent a violation of the Efficient Market Hypothesis. (See footnote 2.)

2.1 The Profitability of Simulated Momentum Strategies

Much of the previous research documents profits to momentum strategies simulated with CRSP data for U.S. stocks. This section briefly characterizes the magnitude of the simulated profits by surveying the original results from Jegadeesh and Titman (1993) and three additional recent studies. We also provide a brief description of the experimental strategies used to generate the profits.

Jegadeesh and Titman (1993) form equal-weighted portfolios based on deciles of a ranking of all NYSE and AMEX stocks based on the prior j-month return where j is 3, 6, 9 or 12. Their analysis covers the period 1965 to 1989. The strategy buys decile 10 stocks (winners) and shorts decile 1 stocks (losers), and the profit is the net return to the long-short position, as measured over holding periods of 3, 6, 9 or 12 months. As is common to all the studies discussed below, the portfolio holding period begins one month after the creation of the portfolio to avoid microstructure-related effects in returns. The resulting monthly profits range from 0.69% to 1.49%. Note that although the list of component stocks in a portfolio does not change during the holding period, the equal weighting of the portfolios implicitly imposes a large amount of trading

[3] The explanation for momentum profits in Grinblatt and Han, related to the "disposition effect" in which investors hold losing stocks too long and sell winning stocks too quickly, rests on capital gains and, therefore, tax considerations that apply only to taxable (individual) investors. The evidence presented in this paper indicates that a non-trivial portion of the momentum in stock prices is due to the trades of (tax-exempt) institution investors.

to the strategy as portfolios are rebalanced to equal weights every month. Profits are not adjusted for the costs of trading and portfolio turnover implicit in the strategy.

Grinblatt and Moskowitz (2002) also analyze a strategy that buys decile 10 stocks (winners) and shorts decile 1 stocks (losers). Their analysis covers the period 1966 to 1995 and includes NYSE, AMEX and Nasdaq stocks.. They construct their momentum deciles by ranking stocks based on predicted returns from a multivariate regression employing a variety of lagged returns, measured over intervals of varying lengths, as independent variables (see their table 2). They construct value-weighted portfolios based on those decile breakpoints, and the profit is defined as the difference in monthly return between the top and bottom deciles. Portfolio positions are held for one month. Although their analysis includes a number of strategies resulting from several different combinations of the independent variables used in the multivariate regression, a representative strategy yields a monthly profit of 1.11%. Grinblatt and Moskowitz estimate portfolio turnover implied by this strategy to be 102.6% (monthly), and conclude that trade costs in the neighborhood of 1.0% would be sufficient to eliminate the profitability of the strategy.[4] Relying on previously published studies of trading costs (they do not measure trade costs in their paper) they conclude that the returns to their momentum strategy exceed the costs of implementation.

Grundy and Martin (2001) form equal-weighted portfolios based on deciles of a ranking of all NYSE and AMEX stocks based on the prior 6-month return. Their analysis covers the period 1926 to 1995. The strategy buys decile 10 stocks (winners) and shorts decile 1 stocks (losers), and the profit is the net return to the long-short position measured over a holding period of one month. Grundy and Martin report strategy profits of 0.44% per month, and "risk-adjusted" profits of 1.34% per month in which the strategy's dynamic exposure to size and market factors is hedged out. Given the turnover associated with the strategy, they conclude that round-trip trade costs of 1.5% would render the strategy profits statistically insignificant.

Hong, Lim and Stein (2000) form equal-weighted portfolios using a ranking of all NYSE and AMEX stocks based on the prior 6-month return. Their analysis covers the period 1980 to 1996. The strategy buys the top third of the stocks (winners) and shorts the bottom third (losers), and the profit is the net return to the long-short position measured over a holding period of six months. The resulting monthly profit from the strategy is 0.52%. The same caveat mentioned with

[4] Grinblatt and Moskowitz (2002) report monthly turnover of 38.86% on the long and 63.75% on the short side of the strategy. This translates to about 450% annually for the long side and 750% on the short side.

regard to Jegadeesh and Titman about equal-weighted portfolios also applies here. Profits are not adjusted for the costs of trading and portfolio turnover implicit in the strategy.

To provide some perspective, Table 1 reports momentum strategy profits as a function of portfolio turnover and total trade costs. The values across a particular row represent net profits associated with a specific level of monthly turnover while varying the level of total trade costs (price impact plus commission). Similarly, the values in a particular column represent net profits associated with a particular level of total trade cost while varying the level of monthly turnover. The values in the table are based on monthly momentum profits reported in Grinblatt and Moskowitz (2002) (GM) of 111 basis points, before adjustment for trade costs. (Although the table could be based on any unadjusted profit value, I chose the 111 basis points associated with the GM strategy because they describe it as a relatively conservative strategy that requires less trading/turnover than other simulated strategies.) Each value is defined as monthly profit (i.e., 111 basis points) minus [(monthly turnover in percent)*(trade costs in basis points)]. Monthly turnover represents roundtrip monthly turnover - for example, if during the month a portfolio manager sells 50% of the value of the positions in her portfolio, then her total trading volume during the month will be 100% of the value of her portfolio: 50% for the securities she sold and 50% for the assets bought to replace the sold positions. (Typically, turnover is stated on a one-way, as opposed to roundtrip, basis; i.e., in this case turnover would be reported as 50%.) Positive profits are in italics, losses are in bold. One could trace the curve that separates the regions of profit and loss and, thereby, identify breakeven levels of trade cost – turnover combinations. For example, the strategy reported in GM has a monthly (roundtrip) turnover of 103%. If one-way total trade costs associated with that strategy were 1.05% or less, the strategy would yield positive monthly profits. It is clear from the table that profitability requires a combination of low turnover and/or low costs, characteristic that are not typical for momentum strategies.

The question is whether the breakeven estimates of total trade costs reported earlier for the simulated momentum strategies are lower than the implementation costs that would be realized by actual momentum traders. Chan and Lakonishok (1995), Edwards and Wagner (1993), Keim and Madhavan (1997, 1998) and others have shown that trade costs of institutional investors vary significantly: (1) across stocks of different market capitalization and share price; (2) across different investing and trading styles; and (3) by quantity of shares traded. It is the case in the empirically simulated momentum strategies that the highest concentration of trading takes place in stocks that are the most difficult and expensive to trade – smaller cap and lower price stocks (see Lesmond, Schill and Zhou (2003)). Keim and Madhavan (1998, table 2) report average one-way total trade costs of 1.78% (2.85%) for buys and 2.03% (2.91%) for sells for the smallest cap quintile of NYSE-AMEX (Nasdaq) stocks for the 1991-93 period, a trading period that lies in the sample periods of the studies referenced above. Further, Keim and Madhavan (1997) show that trade costs for momentum traders in small-cap stocks are higher than for other types of traders, holding other things constant. Trade costs of this magnitude, and in combination with the high turnover rates evident in the simulated strategies (e.g., 103% for the conservative strategy in Grinblatt and Moskowitz), clearly offset the simulated profits (c.f. table 1).

In recent papers, Korajczyk and Sadka (2002) and Lesmond, Schill and Zhou (2003) develop statistical models of price impacts to gauge the profitability of simulated momentum strategies. For example, Lesmond, Schill and Zhou use a variety of models to extract information about (unconditional) costs from transaction-level prices in the TAQ data. Using the resulting security-level cost estimates to calibrate the profitability of simulated momentum strategies from Jegadeesh and Titman (1993, 2001) and Hong, Lim and Stein (2000) (i.e., if the strategy is trading small cap stocks, the simulation adjusts for the costs of trading small cap stocks), they argue that the strategies are not profitable.

There are several shortcomings to the analysis of price impacts in these papers. First, they don't account for the fact that traders often break up a desired order quantity into smaller trades in an attempt to soften the price impact. Thus, by measuring the price impact associated with an individual trade they are providing only a lower bound for the actual price impact associated with the total order quantity. In addition, these papers account for neither the investment style that motivates the trade nor the market environment in which the trade takes place. Momentum strategies, by their very nature, buy stocks that are rising and sell (or short sell) stocks that are dropping. In effect, the momentum trader desires to buy shares during periods of excess demand and sell during periods of excess supply.[5] Thus, to accurately measure the costs of implementing a momentum strategy one has to condition not only on the fact that such trades desire great immediacy in typically less liquid (more expensive) stocks, but also on the fact that momentum traders wish to trade on the side of the market where there is a reduced supply of liquidity (e.g.,

[5] Along these same lines, Kavajecz and Odders-White argue that the trading implicit in technical trading rules (e.g., trading related to "support" and "resistance" levels and to moving average rules) is related to changes in liquidity in the limit order book.

buying when there is a relative increase in the supply of buyers and a relative decrease in the supply of sellers). In such environments, the trading associated with momentum strategies exerts pressure on prices (price impact) that will certainly be greater than the price impact implicit in unconditional costs.

3. Data

The data used in this study contain information on the equity transactions of 33 institutions in the U.S. and 36 other equity markets worldwide during two different time periods – April 1996 to March 1997, and the calendar year 2000. The data were provided by the Plexus Group and are similar to those previously used in Keim and Madhavan (1995, 1997) (for the period Jan 1991 to Mar 1993), Barber and Odean (2002) (Jan 1993 to Mar 1996), and Conrad, Johnson and Wahal (2001) (Oct 1994 to June 1996). The main differences from those used in the earlier papers are that the data used here are from a more recent time period and include international stock transactions (the Plexus data in the previous papers contained only U.S. stock trades.)

The data identify key characteristics – price, number of shares traded, and date of trade – of the individual trades that comprise an expressed intention to buy or sell. Thus, individual trade prices can be aggregated to a volume-weighted price associated with the total desired order quantity. As such, the unit of observation for the analysis in this paper is the trade order, which is composed of one or (typically) more transactions. To be more specific, for each order the data include the following information:

(i) the identity of the stock to be traded and the date when the trading decision was made;
(ii) an indication as to whether the trade is a buy or a sell;
(iii) the closing stock prices (expressed in U.S. dollars) for the fifteen trade days before the decision to trade is made, and for fifteen trade days after the order is completed;
(iv) the dates and the individual components of the order released to the broker;
(v) the volume-weighted average trade price, number of shares traded, and date(s) associated with the trade(s) executed by the broker within a specific order; and
(vi) commissions, stamp duties, and other explicit trade fees.

The database contains almost 607,000 orders (more than 1.6 million individual trades) across 37 international equity markets with a total trade value of $1.1 trillion.

Importantly, for our purposes, the data indicate the institution's investment strategy or style and, thereby, provide information regarding the motivation for the trade. Plexus identifies three types of institutional investment strategies among the traders represented in the data (the identities of the traders are not revealed). Momentum traders employ a strategy that is based primarily on capturing short-term price movements. The investment strategy associated with the Value/Fundamental traders is based on assessment of fundamental value with a decidedly longer-term perspective. Index/Diversified traders seek to mimic the returns of a particular stock index or passive strategy. Thus, the underlying investment strategy dictates the trading strategy and, thereby, motivates the classification used by Plexus. The above characteristics of the data – total desired trade quantity and trade style – are critical for purposes of measuring and analyzing the effects of price impact on the profitability of trading strategies.

4. The Relative Price Impacts of Trading Strategies: A First Look

This section provides a first look at the level of price impacts for the three types of traders included in the sample. In addition to providing summary statistics separately for each of the trader types, I also separate the sample into three market categories: U.S. markets; Developed Markets excluding the U.S.; and Emerging Markets. The countries within each category are listed in the Appendix. Finally, because the data contain two twelve-month sample periods that are separated by 33 months, and represent two very distinct market environments, I also report results separately for the two time periods – April 1996 to March 1997 (96-97) and January 2000 to December 2000 (2000). The 96-97 period was characterized by generally positive returns in most of the markets contained in the sample. For example, for the March 1996-April 1997 period, the average monthly returns for the value-weighted CRSP Index, the EAFE Index and the IFC Emerging Market Index are 1.27%, 0.17% and 0.96% respectively. In contrast, world equity markets were generally down during the calendar year 2000 – the average monthly returns for the same three indexes for 2000 are -0.86%, -1.17% and -3.02% respectively.[6] As described in the next subsection, the analysis in this paper abstracts from the overall market environment by subtracting the local market returns from the price impacts associated with individual institutional trades.

[6] These two time periods also reflect the change in minimum tick size in U.S. markets from eighths (96-97) to pennies (2000). Although such a change in the minimum tick size has clear implications for the costs of retail trades that occur at bid or ask prices, the effect on institutional trade costs (and, particularly, price impacts) in U.S. markets is less clear. See Goldstein and Kavajecz (2000), Jones and Lipson (2001) and Werner (2002) for discussion and evidence.

4.1 Definition of Price Impact

The unit of observation here is an order, which is an aggregated expression of the trader's desired quantity of shares to be traded. Each order is composed of one or more individual trades. For a buyer-initiated order, the price impact is given by the ratio of the volume-weighted average price of the component trades in the order to the closing price on the day before trading of the order is initiated, less one. The total price impact for a seller-initiated trade is measured as the negative value of this quantity. Finally, market-adjusted price impact is computed by deducting the local market return (measured over the trading interval) from the total price impact. The analysis in this paper, spanning numerous international stock exchanges, argues for the reporting of price impacts net of the local market return. Differences in market returns across countries (and across subperiods) produce additional variation in price impacts, when computed inclusive of the local market returns, that is unrelated to the institutions' trade behavior specific to the individual stock. Thus, deducting the local market return from the stock price movement during the trade interval isolates variation in idiosyncratic price movements specific to the institution's trades in those shares.

4.2 Variation in (Unconditional) Price Impacts across Time Periods

Table 2 reports means and standard errors for price impacts adjusted for local market returns. The table is divided into three panels, moving from left to right, corresponding to the trades of Diversified, Value, and Momentum institutions respectively. The table is further divided, from top to bottom, into four additional panels corresponding to U.S. equity market trades, trades in developed markets excluding the U.S., emerging equity market trades, and market impacts averaged over all the markets in the data. Within each of the sub panels, mean price impacts are reported separately for the 96-97 and 2000 time periods.

Comparing the local-market-adjusted price impacts across time periods, holding trader style and market categories constant, the results in Table 2 do not reveal any clear-cut patterns in price impacts. For example, when averaged over all market categories (panel D), price impacts for buys of the Diversified and Value traders are larger in the 2000 period than in the 96-97 period. However, the price impacts for the sells of the Value and Diversified traders do not exhibit systematic differences across the two time periods – the 2000 sell impacts are higher (lower) than the 96-97 price impacts for the Diversified (Value) traders. In contrast, both the buy and the sell average price impacts for the Momentum traders, when averaged over all markets, are larger in the

96-97 period than in the 2000 period. However, this pattern for the momentum trades does not hold across all market categories. Because price impacts across time periods do not display consistent patterns in Table 2, and because the results of tests in the following subsections are similar when estimated separately in the two subperiods, the analysis in subsequent sections pools the results from the two periods.

One final point regarding subperiod differences: some variation in the (unconditional) average price impacts across sample periods may occur because of differences in trade difficulty (i.e., small-cap vs. large-cap stocks, large trades vs. small trades, etc.) across the sample periods. Section 6 estimates price impact models in which appropriate controls are applied for factors relating to trade difficulty, so those influences will be accounted for explicitly.[7]

4.3 Variation in (Unconditional) Price Impacts across Market Categories

Moving from top to bottom in table 2, the separate panels report price impacts for market categories that are roughly decreasing in liquidity: U.S.; Developed Markets excluding the U.S.; and Emerging Markets. The general impression from the table is that market-adjusted price impacts for buys are increasing with decreasing market liquidity, other things equal. For example, average price impacts for trades executed by the diversified and value traders tend to be the highest in emerging market stocks (buy impacts range from 0.52% to 1.15%) and are often two to four times the average for their trades in the U.S. markets. The price impacts of the buys of momentum traders deviate from this pattern. While the mean price impacts for trades in developed markets (excluding U.S.) are lower than the mean impacts for emerging market trades for the momentum traders, the average price impacts for the U.S. momentum trades are higher than for trades in emerging markets. In contrast, price impacts for sells by diversified, value and momentum traders in U.S. stocks tend to be larger than price impacts for sells in (non-U.S.) developed markets and emerging markets. However, differences in trade difficulty and manager ability – which are not accounted for in these unconditional price impacts – may well contribute to these differences.

[7] Differences in mean price impacts across the two time periods might also reflect differences in the composition of the traders represented in the sample in the two periods, and/or differences in the quantity of trading by the same traders in the two subperiods. That is, different managers might reflect different skill levels, and those different skill levels might translate into significant differences in price impacts (Keim and Madhavan (1997)).

4.4 Variation in (Unconditional) Price Impacts across Trader Types

Inspection of price impacts across trader types in Table 2 clearly shows (as in Keim and Madhavan (1997)) that Momentum traders have higher average price impacts than Value and Diversified traders. For example, in the bottom panel for all markets, the mean price impact for buys for the Momentum traders in 96-97 (0.91%) is about three times larger than the corresponding mean price impacts for the Diversified (0.36%) and the Value traders (0.24%). In the 2000 subperiod the mean price impact of 0.64% for the Momentum trader buys is larger (though not by much) than the mean for the Diversified traders (0.60%) and the Value traders (0.57%). The difference in mean price impacts for sells between the Momentum traders and the other two trader types is even larger – ranging from two to four times larger – in both subperiods.

4.4.1 Motivation for Trade and Trader Behavior

It is interesting that the significant differential in price impact between the momentum traders and the other traders is more pronounced for the sells than for the buys. This is related to asymmetries (or lack thereof) in the kinds of information motivating trade. Previous research finds that buys are more expensive than sells (Chan and Lakonishok (1995), Keim and Madhavan (1997)) and that traders are more patient (e.g., take longer to get into a position, break large trades into smaller pieces, use less aggressive orders, etc.) when buying than when selling (Keim and Madhavan (1995)). Keim and Madhavan (1997) argue that this difference between buys and sells is due to asymmetries in the informational motives between buying and selling – there is a greater likelihood that buys are informationally motivated than sells because "there are many possibly non-informational motives for selling, but there are fewer plausible liquidity motives for buying." This previously-observed difference in price impacts between buys and sells is evident for both the Diversified and the Value traders in table 2, in both subperiods.

In contrast, momentum traders are conditioning both their buys and sells on the same kind of information – past price behavior – and, therefore, their buying and selling behavior and, consequently, the price impacts associated with that behavior are more symmetric. This is evident in the approximate equivalence of momentum price impacts for buys and sells in table 2 for trades executed in the U.S. markets, in other developed markets, and in emerging markets.

5. Are Institutional Trades Conditioned on Prior Price Movements?

That the trade behavior of momentum institutions is linked to past price patterns distinguishes them from other traders whose strategies are more flexible and can be modified in response to changing market conditions. This section documents the relation between momentum trade behavior and market conditions by examining the pre-trade price behavior of the institutional trades in my sample. Specifically, I examine the pre-trade price behavior for three weeks (15 trade days) before the day of the first trade in an order. I subtract the local market return from the individual stock return to arrive at a market-adjusted or excess price change for the three weeks prior to the trade – I call this *PriorXRet*. The results for the pre-trade price patterns are reported in Table 3 for the combined 96-97 and 2000 time periods.[8]

The first two columns of Table 3 report average values of *PriorXRet* separately for buyer- and for seller-initiated trades. Note that these are averages of 15-day price changes and not average daily price changes within the 15-day window. Averaged over the entire sample (top row), *PriorXRet* is 0.83% before buy trades and 0.66% before sell trades. The third column reports a t-test of the difference between the two means to assess whether the idiosyncratic trading environment preceding buys differs from that for sells. Averaged over all institutions and markets, *PriorXRet* for both buy and sell trades is positive (but remember that we've removed the overall market return from these means) but the t-value of 6.21 indicates that excess price changes preceding buys are significantly larger than those preceding sells.

Of course, more interesting is the potential difference in the pre-trade market-adjusted price behavior across the different institutions with their correspondingly different motivations for trading. Thus, the remaining panels in Table 3 report mean values for *PriorXRet* separately for the diversified, value and momentum managers. Within each panel, I further separate the results by the market category within which the trade took place. The disaggregation by trade style reveals an interesting pattern of prior excess price changes. First, for the diversified/index institutions, whose trade are motivated more for liquidity and/or portfolio rebalancing consideration, the expectation is that their trades will not be predicated on pre-trade price behavior. The results confirm this prediction: when measured across all markets, the t-test of the difference in mean *PriorXRet* between buys and sells is -1.42 indicating no significant difference. The results across

[8] As for all the remaining tables in the paper, I have also computed results separately for the 96-97 and 2000 periods. In all cases, the results across subperiods are not materially different so I report only aggregated results in the paper. Subperiod results are available on request.

markets tells essentially the same story: the t-value is insignificant for U.S. trades (1.29) and significant but with different signs for the other developed markets (t = -3.37) and emerging markets (t = 2.20).

Second, the typical perception of a value or fundamentals-based trader is that she buys stocks whose prices are "low relative to fundamentals" (e.g., low Price to Book ratio) and sells when prices are high relative to the fundamentals. Although such trades are not explicitly conditioned on prior price movement, the buying and selling motives just described are indeed consistent with buying after prices have fallen and selling after prices have risen if "fundamentals" (e.g., Book Value) evolve more slowly over time than do prices. The pattern in pre-trade market-adjusted price movements for the Value managers in the sample is consistent with this prediction. Averaged over all markets, the mean *PriorXRet* of 0.17% for buys is significantly smaller than the mean of 0.94% for sells (t = -17.00). This pattern is repeated for trades in both the U.S. exchanges (t = -10.99), where the Value managers are indeed buying after (market-adjusted) price declines and selling after price increases, and in the other developed markets excluding the U.S. (t = -14.49). For trades in emerging market exchanges, the difference in *PriorXRet* between buys and sells is also significant for the value managers.

Finally, the objective of the momentum trader is to capture (short-term) persistence in return. As such, the momentum trader is explicitly conditioning her trades on prior price movements – buying stocks that are on an upward trajectory and selling (or shorting) those on a downward trajectory. Thus, we expect *PriorXRet* for buys to be significantly larger than for sells for the momentum traders. This is precisely what we find, over all markets (t = 24.05) and in each of the separate market categories. Indeed, for the trades in the U.S. and emerging market exchanges, buys follow large market-adjusted price run-ups (e.g., *PriorXRet* = 2.33% for the U.S. trades) and sells follow market-adjusted price declines (*PriorXRet* = -0.31% for U.S. trades).

Based on the results for mean pre-trade excess returns in the first three columns in Table 3 it is evident that the value and momentum manages are conditioning their trades, either implicitly or explicitly, on prior share price movements. To reinforce these inferences, I also estimate a logit model to accompany the t-tests in each of the separate rows in Table 3. The dependent variable in the logit model is an indicator variable that takes the value one if the order *i* is a buy and zero if it is a sell. The independent variable in the model is $PriorXRet_i$, the three-week market-adjusted price change for the stock prior to order *i*. The estimated coefficients of the model are reported in the middle two columns of Table 3, and are reported in bold if they are significant at the 5% level. The results of the logit estimation are consistent with the t-tests of the difference in means. For example, the significant slope coefficient of -0.0081 for the trades of the value institutions across all markets indicates that the higher the pre-trade market-adjusted price change, the more likely it is that a value manager's trade will be a sell. The significant slope coefficient of 0.0092 for the trades of the momentum traders across all markets indicates that the higher the pre-trade excess return, the more likely it is that a momentum trade will be a buy.

6. The Price Impact of Momentum Trading

The previous section demonstrates that the momentum trader's raison d'être – chasing price trends – distinguishes the behavior of momentum traders from the diversified and value traders. That their motivation for trade is indelibly linked to the trajectory of the market has two effects on the relative costs of momentum versus other types of trading. First, the momentum trader is typically chasing short-term price movements, so she demands a great deal of immediacy when trading – she wants the trade executed now. Previous research has shown that increased demand for immediacy (e.g., using more aggressive market orders than more passive limit orders) results in higher trade costs (Keim and Madhavan (1997)). Second, she tends to buy in rising markets and sell in falling markets. Whereas value traders, whose objective is to buy stocks that have been depressed to price levels at or below fundamentals, are effectively paddling with the current, momentum traders are paddling against the current. It is this second effect – the market environment in which the trade takes place – that can result in large differences in the price impacts between the momentum traders and the others.

Given that momentum traders condition their trades on prior price movements, this section examines price impacts of trades conditional on the direction of the local market in which the stock trades. We predict buys in rising markets to be more expensive (have larger price impacts) than buys in falling markets. This is because, information considerations aside, there is excess demand for the stock in rising markets due to a combination of (1) increased demand for liquidity on the momentum trader's side of the market due to the existence of other like-minded traders, and/or (2) reduced supply of liquidity due to fewer sellers/owners of recently appreciated stocks who don't wish to realize their capital gains. Thus, buyers demanding immediacy in rising markets should expect to pay a larger price concession than in falling markets, where the buyer is effectively supplying liquidity to the market. Similar reasoning predicts that sells in falling markets will be more expensive (have larger price impacts) than sells in rising markets.

To this end, Table 4 reports mean price impacts separately for buys and sells for each of the three institutional classifications and for each of the three market categories, but also reports results separately for trades occurring in rising and falling markets. A rising or falling market is determined by the three-week pre-trade return on the local stock market index being greater than zero or less than or equal to zero. Panel A contains summary statistics related to buy transactions. The first column contains information for buys executed in a falling market and the second column for buy trades executed in a rising market. Each triad contains the mean price impact (as defined in section 4.1) of the orders, the total value of the orders in billions of dollars, and the number of orders for that particular category of trade. For example, the mean price impact for buys in a rising market, across all institutions and market categories, is 0.61% based on 161,707 orders valued at $273.0 billion. The corresponding mean price impact for buys in a falling market is 0.48% (n = 166,119; $293.5 billion) which is economically and statistically significantly lower than the price impact for buys in rising markets (difference = 0.13%, t = 10.30), consistent with the above prediction.

Although this pattern of buys being more expensive in rising than in falling markets holds uniformly across all institutions and market categories (the t-values in the third column reject a difference of zero in all cases), it is especially pronounced for the momentum traders. Averaged across all markets, the difference in price impacts between rising and falling markets for the momentum traders is 0.20%; the average price impact for the buys executed in rising markets is 0.84%. In comparison, the difference in price impacts between rising and falling markets for the diversified and value managers is on the order of 0.10% (averaged over all markets); and the average price impact for buys in rising markets ranges from 0.47% to 0.55% for those traders.

A similar pattern emerges for the price impacts for the sell transactions in Panel B in Table 4. For example, the average price impact for sells in a falling market is 0.46%;[9] in contrast, the mean price impact for sells in a rising market is 0.22% which is economically and statistically lower than the price impact for sells in falling markets (difference = 0.24%; t = -15.48). This significant difference is consistent with our earlier prediction. Analogous to the results for buys in Panel A, the pattern of sells being more expensive in falling than in rising markets holds

[9] Recall that the price impacts for sells are multiplied by -1.0 so they can be interpreted as costs and, thereby, directly compared to impacts estimated for buys.

consistently across all institutions and markets. Once again, the difference is large for the momentum managers. Averaged over all markets, the difference in price impacts between falling and rising markets for the momentum traders is 0.19%; the average price impacts for sells executed in falling markets is 0.78%. The corresponding difference for the diversified and value traders ranges from 0.16% to 0.34%. These differences are not dramatically different from the momentum traders. The reason is that even though the mean price impact for their sells in falling markets is half the magnitude of that for the momentum traders (ranging from 0.27% to 0.39%), their price impacts for selling in a rising market are only 10 – 20% of the magnitude of those costs for the momentum traders. Indeed, in two instances the diversified and value traders have "negative costs" when selling in rising markets. The "negative costs" associated with the sells in rising markets can be attributed to traders acting as liquidity suppliers. Liquidity demanders pay a price concession for demanding immediacy, whereas liquidity suppliers (e.g., market makers) are paid to provide liquidity or transaction immediacy, thereby enjoying "negative" costs of transacting. Indeed, such negative price impacts are associated with the trades of the diversified and the value traders whose investment strategies do not require the degree of trade immediacy that is characteristic of a momentum strategy. Diversified and value strategies permit a more patient approach to trading in which liquidity provision is possible.

6.1 A Model of Price Impacts

The average price impacts in table 4 do not control for differences in trade characteristics (that proxy for trade difficulty) that have been shown in previous research to affect trade costs. Thus, in this section I estimate a model of price impacts that controls explicitly for trade difficulty (e.g., trade size, market liquidity) as well as market conditions (as captured by prior price movement of the stock being traded.) The objective is to assess whether the estimated price impact function is significantly different in rising and falling markets, as might be expected given the results presented above on mean price impacts. Specifically, I estimate a variant of the model used by Keim and Madhavan (1997) in their analysis of total trade costs. For *buy* transactions I estimate:

$$PI_i = \beta_0 + \beta_1\, TradeSize_i + \beta_2\, (1/P_i) + \beta_3\, ln(Mcap_i) + \delta_0\, D_i^B + \delta_1\, TradeSize_i * D_i^B + \delta_2\, (1/P_i) * D_i^B + \delta_3\, ln(Mcap_i) * D_i^B$$

where PI_i is the price impact for order i, $TradeSize_i$ is the number of shares traded in order i as a percent of the total shares outstanding, P_i is the price of the stock in order i, $Mcap_i$ is the market capitalization of the stock traded in order i in billions of dollars, D_i^B equals one if $R_M \leq 0$, zero otherwise, and R_M is the three-week pre-trade return on the local stock market index. Larger orders should result in higher costs, so β_1 is expected to be positive. The proportional bid-ask spread decreases with price so that β_2 is expected to be greater than zero. Market capitalization of the stock being traded is included as a proxy for liquidity, so that β_3 is expected to be less than zero.

Note that for buys, the coefficients β_0 to β_3 measure the price impact function in rising markets. The coefficients δ_0 to δ_3 measure the difference in the marginal effect of the independent variables on price impact (or on the level of the intercept) between falling and rising markets. A negative value for δ_1, for example, indicates that the estimated relation (slope) between price impact and trade size is lower in falling markets than in rising markets. To maintain symmetry in interpretation of the estimated coefficients for buys and sells, when estimating the model for *sells* the value of D_i^S equals one if $R_M > 0$, and zero otherwise. Therefore, for sells the coefficients β_0 to β_3 measure the price impact function in falling markets; and the coefficients δ_0 to δ_3 measure the difference in the marginal effects of the independent variables (or in the level of the intercept) between rising and falling markets. Thus, in both models the estimated coefficients on the non-dummied variables measure the impact function for trades made in the same direction as the local market movement (i.e., buys in rising markets and sells in falling markets).

Turn first to the models estimated for buys in Panel A in Table 5. The estimated coefficients are generally significant and have the expected signs: price impacts are increasing in trade size, decreasing with increasing market liquidity (as proxied by market cap), and increasing with the proportional bid-ask spread (as proxied by price inverse). Comparing across trade styles, the estimated intercepts (the unconditional base-level price impact) are clearly larger for trades by momentum traders than for diversified and value traders. And controlling for bid-ask spread and market liquidity effects, the relation between price impact and trade size for momentum trades ranges from three to four times the magnitude for trades by the other institutions.

The estimated coefficients on the interacted variables for buy trades are less clear regarding differences in price impacts between rising and falling markets. The estimates reveal several interesting patterns. First, the estimates of δ_0 for the different trade styles are all negative and significant, indicating that the intercepts estimated in falling markets are smaller than those in rising markets. The estimates for δ_1 indicate that the influence of trade size on price impact is significantly dampened in falling markets for value traders. However, the significant positive coefficient for the buys of momentum traders indicate a steeper slope for the price impact–trade size relation in falling than in rising markets (contrary to expectations). Finally, the estimates of δ_2 and δ_3 are insignificant in most cases, suggesting there is not much difference in the effects of proportional bid-ask spread and market cap on the price impacts of buy trades between rising and falling markets.

The models estimated for the sell transactions reveal a more unified picture to that described above for the buys. Briefly, the coefficient estimates are generally of the expected sign and are significant. Both the estimated intercepts and the estimated relation between price impact and trade size are (1) significantly larger in falling markets than in rising markets, and (2) much larger for the momentum trades than for the trades of the diversified and value institutions.

The results in Table 5 show for both buys and, especially, sells that momentum trading exacerbates the adverse effects on price impacts associated with trade size and, thereby, significantly magnifies its effect on total trade cost. Figure 1 presents a visual representation of this relation between predicted price impact and trade size separately for the three institutional types, and illustrates how the relation differs in rising and falling markets. The price impact functions are shown separately for buys (Panel A) and sells (Panel B); and note that, unlike the results in Table 5, the price impact functions for sells are not multiplied by negative one. The figure plots the estimated relation over the range of trade size in our sample, and uses values for market cap of $1 billion and share price of $15 U.S.[10] The plots clearly illustrate several patterns in the price impacts. First, the price impact functions are generally steeper with larger intercepts when trades are executed in the direction of the market (i.e., trend chasing). The main exception is the steeper slope for the impact function of the momentum buy trades in falling markets. Although the slope of the price impact function for momentum buys is flatter in rising than in falling markets, the intercept in rising markets is much higher than in falling markets. Indeed, this latter effect is large enough to offset the flatter slope in rising markets so that expected price impacts for momentum traders are higher in rising than in falling markets over a wide range of trade size (specifically, for all trades less than 0.6% of total shares outstanding for the traded stock.) Second, across the entire range of trade size, the price impacts of the momentum traders are larger than the

[10] Lesmond, Schill and Zhou (2003) replicate the simulated strategies of Jegadeesh and Titman (1993) and Hong, Lim and Stein (2000) and report that the winner and loser portfolios in those simulations are concentrated in small cap, low price stocks. For example, the median market cap (share price) for the stocks in the decile of winners is $210.3 million ($19.36). The corresponding median values for the stocks in the decile of losers are $55.4 million and $6.32. These values motivate my choice of $1billion and $15 for the plots in Figure 1.

price impacts of the diversified and value traders in both rising and falling markets and for both buys and sells. At the low end of the trade size spectrum, predicted one-way price impacts for momentum trades range from 0.5% to 1.0% for both buys and sells. In the upper ranges of trade size predicted one-way price impacts reach levels of 1.9% to 2.5% for both buys and sells. These results for price impacts cast doubt on the likelihood of successfully implementing momentum strategies, suggesting that committing institutional-scale assets to such strategies may be futile.[11] Before any final assessment, however, we have to examine total trading costs.

7. Total Trade Costs and the Profitability of Momentum Strategies

The evidence on price impacts in section 6 casts considerable doubt on the feasibility of momentum strategies. The prospect of successfully implementing such strategies becomes even bleaker with the recognition that price impacts are only one component of the total costs of implementing an investment strategy. Total trade costs include explicit costs and opportunity costs in addition to price impacts (see Keim and Madhavan (1998) for an overview). Explicit costs include commissions, custodial fees and, in the context of trades outside domestic markets, stamp duties (transactions taxes levied on non-resident traders). Opportunity costs reflect the inability to actually execute at the price prevailing when the decision to trade is made. The idea is that the trader has (monopolistic) access to information regarding the future value of the stock, but the value of that information will decay over time as others traders acquire that information and make trades based on it. Thus, the longer the lag between the decision to trade and the actual commencement of trading, the greater is the possibility of not capturing that value. Opportunity costs are particularly relevant for momentum traders who attempt to buy (sell) a stock on an upward (downward) trajectory. A lag between the decision to trade and the actual trade results in the possibility of missing part (or all) of the prospective price movement. The longer the lag, the greater is the possible opportunity loss.

Table 6 reports average total trade costs separately for the three investment styles, the three market categories, and buys and sells. Total costs are decomposed into explicit and implicit costs. Explicit costs include commissions, custodial fees and stamp duties. Following Keim and Madhavan (1997), implicit costs are defined as the ratio of the volume-weighted average trade price of the individual trades within an order to the closing stock price on the day before the

[11] See also Korajczyk and Sadka (2002) who reach similar conclusions using a simulation approach to estimating price impacts.

decision to trade, minus 1.0, in excess of the market return over the interval of the order. As such, the implicit cost measure incorporates both price impact and opportunity cost. Several aspects of the average trade costs are worth pointing out. First, implicit costs tend to be larger than explicit costs, especially for buys. For the momentum traders, implicit costs are much larger than explicit costs for both buys and sells. Second, explicit costs are smallest for trades executed in the U.S. markets (ranging from 0.107% to 0.190%) and are largest in emerging markets (0.438% to 0.499%). Finally, total trade costs (implicit plus explicit costs) are lowest for the value traders (0.77% for buys, 0.392% for sells, across all markets) and highest for momentum traders (1.307% for buys, 1.131% for sells, across all markets).

The total trade costs reported in table 6 for momentum traders serve to amplify the previous discussion (in the context of price impacts) regarding the profitable implementation of momentum strategies. The one-way total trade costs of 1.13 to 1.31% for the momentum traders in our sample are sufficient to offset the abnormal returns of simulated momentum strategies. But remember that such unconditional costs represent lower bounds on the costs for momentum traders. To help illustrate the potential magnitude of the conditional total trade costs for momentum traders, Figure 2 plots the relation between predicted *total* trade costs and trade size for the three investment styles, separately in rising and falling markets and separately for buys and sells. Figure 2 is the total trade cost analog to Figure 1, and is based on the same model described in section 6.1 with one exception: the dependent variable in the model is total trade cost as defined above (price impact plus opportunity cost plus commission).[12] At the low end of the trade size range, predicted one-way total trade costs for momentum buys (sells) in rising (falling) markets is approximately 1.9% (1.7%); in the upper range of trade size, these values are about 2.9% and 3.4%. Referring to Table 1, the combination of 110% turnover implied in the Grinblatt-Moskowitz strategy and average one-way price impacts in the range of 1.7% to 3.4% yields an implied strategy profit that is deep in the net loss region of the matrix. To turn a profit with such high trading costs would require levels of portfolio turnover that are lower than is typical for the simulated momentum strategies. For example, with one-way costs of 1.90%, positive profits are possible only for

[12] The estimated model coefficients for total trade costs display similar patterns across investment styles and across buy and sell trades as those reported in Table 5 for price impacts. Indeed, there are no major exceptions to the description of the patterns and significance levels provided for the price impact coefficients in section 6.1. The main difference, as expected, are larger estimated intercepts for the regressions estimated for total trade costs. Estimation results for the total trade cost models are available on request.

turnover levels less than 60% per month. Such high costs make successful implementation of simulated strategies unlikely.

8. Some (Modest) Evidence on the (Short-Term) Performance of Momentum Strategies

So, a relevant question remains: Are *actual* momentum strategies – as opposed to simulated strategies – profitable? More specifically, do the strategies of the momentum funds in my sample generate returns that sufficiently offset their high trade costs, thereby resulting in positive profits? If so, it would be interesting to know more about the design of the strategies. If not, how long does it take for the momentum funds to either (1) modify their investment and/or trading strategy in the attempt to become profitable, or (2) go out of business. Unfortunately, I don't know the identities of the funds, and have only a short window into their trading activities. Thus, I can say little about either the performance or the longevity of the funds. (Because of poor performance it is indeed possible that the funds don't exist for very long after their appearance in the Plexus data.) Nevertheless, in this section I offer some insights into the answer by examining the short-term performance of the momentum traders in my sample for the two years of trades available. In contrast to the simulated strategies that examine 3 to 12 month post-trade performance, the three weeks of post-trade share price data provided by Plexus permit only a short-term glimpse (a peek behind the curtain) of post-trade performance.[13]

My performance measure is simply the average (local) market-adjusted price change for the momentum traders for the three weeks after the trade (from the trade price to the closing price on day $t+16$).[14] Based on this measure, the performance of the momentum traders is not good. The post-trade performance of the buys is uniformly flat – the excess three-week price changes are not significantly different from zero when averaged over all markets (0.052%) or if measured in each of the markets separately: 0.003% (U.S.); 0.107% (other developed markets); -0.144% (emerging markets). And the post-trade excess price behavior of the sells is significantly positive (0.327%) when averaged over all markets. Thus, although the momentum traders are indeed buying (selling) stocks that exhibit a rising (falling) trajectory, their presence in the market for

[13] For the U.S. trades, the Plexus data could be merged with the CRSP daily stock price data to lengthen this post-trade window. For the non-U.S. trades, however, such a merge is not feasible because of the lack of readily available and reliable individual stock price data for most of the markets in the sample. Therefore, to maintain consistency in the results for both the U.S. and other market, I report performance only for this three-week post-trade period.

[14] There is no explicit risk adjustment to the price changes reported here. Given the short post-trade time interval, formal risk adjustment would add little to the analysis.

these stocks merely serves to exacerbate that trajectory. However, the post-trade price trajectory is either not in the desired direction or of an insignificant magnitude. This is an admittedly short window of post-trade performance. However, the picture that emerges contains no indication that the profitability of these trades would improve if the window were lengthened. After all, these traders appear to be pursuing short-term price trends that simply fail to materialize in the short period following the trade.

9. Conclusions

The objective of this paper is to help clarify the claims of profitability of *simulated* momentum strategies by documenting the costs of implementing *actual* momentum strategies. To properly gauge the profitability of momentum strategies requires the distinction between unconditional implementation costs and implementation costs that are conditioned on trading style and market conditions prevailing at the time of the trade. I examine the trade behavior, and the costs of those trades, for three distinct investor styles (momentum, fundamental/value, and diversified/index) for 33 institutional investment managers executing trades in the U.S. and 36 other equity markets worldwide in both developed and emerging economies. The results show: (1) that momentum traders do indeed condition their trades on prior price movements; and (2) that costs for trades conditional on past price movements are significantly greater than unconditional costs, and this difference is amplified for momentum traders who typically demand more trade immediacy than other traders.

The evidence that we report on the costs of *actual* momentum-based trades indicates that the returns reported in previous studies of *simulated* momentum strategies are not sufficient to cover the costs of implementing those strategies. This of course leaves the question of whether momentum traders in practice can generate returns that exceed actual implementation costs. The data used here, unfortunately, are unable to adequately address the issue of performance of actual momentum managers. The limited evidence we can offer reveals that the short-term (3-week) post-trade performance of the momentum managers in our sample is flat. Nevertheless, the continued proliferation of momentum managers suggests an affirmative answer. But this in turn raises another question: if their strategies are profitable, then exactly how do those strategies differ from the simulated strategies that appear to be unprofitable?

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Appendix

Trade Activity by Investment Style

33 Institutional Traders, reported separately for 37 International Stock Markets.
(Averaged over April 1996 - March 1997 and January 2000 - December 2000 subperiods)

Country	Local Market Index*	Diversified # orders	Diversified $ Billions	Value # orders	Value $ Billions	Momentum # orders	Momentum $ Billions
Developed Markets							
United States	S&P 500	43,882	38.3	51,584	114.9	57,893	85.3
Australia	FW	7,610	6.3	4,135	6.3	3,759	7.6
Austria	FW	766	0.6	232	0.2	124	0.1
Belgium	FW	698	0.5	358	0.4	337	0.4
Canada	FW	1,398	0.8	1,234	1.8	1,751	2.6
Denmark	FW	1,269	1.5	666	1.1	647	1.0
Finland	CI	1,663	5.1	1,258	4.0	2,030	6.4
France	FW	14,147	29.0	9,918	20.9	9,279	25.8
Germany	FW	11,864	22.8	7,278	20.7	6,798	15.4
Hong Kong	FW	8,466	11.9	5,234	10.5	5,527	8.7
Ireland	FW	1,014	0.7	433	0.9	1,036	1.1
Italy	FW	6,040	11.1	3,204	9.0	4,689	12.1
Japan	FW	54,813	77.4	33,505	52.2	18,409	44.6
Netherlands	FW	7,594	16.4	4,989	15.7	6,190	14.1
New Zealand	FW	944	0.7	716	0.9	180	0.1
Norway	FW	1,167	0.6	694	1.1	508	0.5
Singapore	FW	3,961	4.2	2,215	2.7	2,371	2.8
Spain	FW	5,207	9.7	2,829	6.9	2,570	5.5
Sweden	FW	3,553	7.9	2,150	6.0	3,863	8.6
Switzerland	FW	4,478	13.4	2,934	8.7	3,027	10.6
United Kingdom	FW	41,634	120.4	37,720	65.3	29,328	56.7
Emerging Markets							
Argentina	CI	196	0.1	124	0.2	201	0.0
Brazil	CI	1,738	1.5	1,206	2.0	1,258	0.8
Czech Republic	FW	755	0.5	281	0.3	263	0.1
Greece	CI	513	0.4	391	0.4	458	0.3
India	CI	787	0.9	568	1.3	1,240	0.8
Indonesia	CI	472	0.3	331	0.5	256	0.1
Korea	CI	2,701	2.6	1,190	6.1	2,013	3.1
Malaysia	FW	5,147	3.7	2,654	1.6	2,417	1.8
Mexico	FW	1,506	1.1	1,250	1.7	1,231	0.9
Philippines	CI	924	0.4	423	0.5	280	0.1
Poland	CI	654	0.3	214	0.2	429	0.2
Portugal	CI	511	0.8	369	1.1	357	0.5
South Africa	FW	2,612	1.9	1,623	2.0	1,534	0.7
Taiwan	CI	1,945	2.1	925	4.5	1,841	2.4
Thailand	CI	1,704	1.6	835	0.9	884	0.5
Turkey	CI	668	0.6	645	0.5	459	0.2
Overall		245,001	398.3	186,315	373.9	175,437	322.7
Developed		222,168	379.5	173,286	350.3	160,316	310.2
Emerging		22,833	18.8	13,029	23.7	15,121	12.5

*CI indicates Morgan Stanley Capital International local market index; FW indicates FTSE World local market index

Table 1

The sensitivity of momentum profits to trade costs and portfolio turnover.

The table reports profits to momentum trading after adjustment for transaction costs. The values in the table are based on monthly momentum profits reported in Grinblatt and Moskowitz (2002) of 1.11% that are unadjusted for trading costs. Each cell in the table is defined as monthly profit (i.e., 111 basis points) minus (monthly turnover in percent)*(trade costs in basis points). Monthly turnover represents roundtrip monthly turnover - for example, if during the month a portfolio manager sells 50% of the value of the positions in her portfolio, then her total trading volume during the month will be 100% of the value of her portfolio: 50% for the securities she sold and 50% for the assets bought to replace the sold positions. Trade costs (at the top of the columns) are one-way costs. Profits are in italics, losses are in bold. For example, the strategy reported in Grinblatt and Moskowitz reports an unadjusted monthly profit of 111 basis points and a monthly turnover of 103%. If the trade costs associated with that strategy were 1.0% on average, the strategy would yield an average monthly profit of 8 basis points.

Trade Costs (Price Impact + Commissions) in basis points

Monthly Turnover	40	45	50	55	60	65	70	75	80	85	90	95	100	105	110	115	120	125	130
30	99	98	96	95	93	92	90	89	87	86	84	83	81	80	78	77	75	74	72
35	97	95	94	92	90	88	87	85	83	81	80	78	76	74	73	71	69	67	66
40	95	93	91	89	87	85	83	81	79	77	75	73	71	69	67	65	63	61	59
45	93	91	89	86	84	82	80	77	75	73	71	68	66	64	62	59	57	55	53
50	91	89	86	84	81	79	76	74	71	69	66	64	61	59	56	54	51	49	46
55	89	86	84	81	78	75	73	70	67	64	62	59	56	53	51	48	45	42	40
60	87	84	81	78	75	72	69	66	63	60	57	54	51	48	45	42	39	36	33
65	85	82	79	75	72	69	66	62	59	56	53	49	46	43	40	36	33	30	27
70	83	80	76	73	69	66	62	59	55	52	48	45	41	38	34	31	27	24	20
75	81	77	74	70	66	62	59	55	51	47	44	40	36	32	29	25	21	17	14
80	79	75	71	67	63	59	55	51	47	43	39	35	31	27	23	19	15	11	7
85	77	73	69	64	60	56	52	47	43	39	35	30	26	22	18	13	9	5	1
90	75	71	66	62	57	53	48	44	39	35	30	26	21	17	12	8	3	-2	-6
95	73	68	64	59	54	49	45	40	35	30	26	21	16	11	6	2	-3	-8	-13
103	70	65	60	54	49	44	39	34	29	23	18	13	8	3	-2	-7	-13	-18	-23
105	69	64	59	53	48	43	38	32	27	22	17	11	6	1	-5	-10	-15	-20	-26
110	67	62	56	51	45	40	34	29	23	18	12	7	1	-5	-10	-16	-21	-27	-32
115	65	59	54	48	42	36	31	25	19	13	8	2	-4	-10	-16	-21	-27	-33	-39
120	63	57	51	45	39	33	27	21	15	9	3	-3	-9	-15	-21	-27	-33	-39	-45
125	61	55	49	42	36	30	24	17	11	5	-2	-8	-14	-20	-27	-33	-39	-45	-52
130	59	53	46	40	33	27	20	14	7	1	-6	-13	-19	-26	-32	-39	-45	-52	-58
135	57	50	44	37	30	23	17	10	3	-4	-11	-17	-24	-31	-38	-44	-51	-58	-65
140	55	48	41	34	27	20	13	6	-1	-8	-15	-22	-29	-36	-43	-50	-57	-64	-71
145	53	46	39	31	24	17	10	2	-5	-12	-20	-27	-34	-41	-49	-56	-63	-70	-78
150	51	44	36	29	21	14	6	-2	-9	-17	-24	-32	-39	-47	-54	-62	-69	-77	-84
155	49	41	34	26	18	10	3	-5	-13	-21	-29	-36	-44	-52	-60	-67	-75	-83	-91
160	47	39	31	23	15	7	-1	-9	-17	-25	-33	-41	-49	-57	-65	-73	-81	-89	-97
165	45	37	29	20	12	4	-4	-13	-21	-29	-38	-46	-54	-62	-71	-79	-87	-95	-104
170	43	35	26	18	9	1	-8	-17	-25	-34	-42	-51	-59	-68	-76	-85	-93	-102	-110
175	41	32	24	15	6	-3	-12	-20	-29	-38	-47	-55	-64	-73	-82	-90	-99	-108	-117
180	39	30	21	12	3	-6	-15	-24	-33	-42	-51	-60	-69	-78	-87	-96	-105	-114	-123
185	37	28	19	9	0	-9	-19	-28	-37	-46	-56	-65	-74	-83	-93	-102	-111	-120	-130
190	35	26	16	6	-3	-13	-22	-32	-41	-51	-60	-70	-79	-89	-98	-108	-117	-127	-136
195	33	23	14	4	-6	-16	-26	-35	-45	-55	-65	-74	-84	-94	-104	-113	-123	-133	-143
200	31	21	11	1	-9	-19	-29	-39	-49	-59	-69	-79	-89	-99	-109	-119	-129	-139	-149

Monthly Turnover	135	140	145	150	155	160	165	170	175	180	185	***190***	195	200	205	210	215	220
30	71	69	68	66	65	63	62	60	59	57	56	54	53	51	50	48	47	45
35	64	62	60	59	57	55	53	52	50	48	46	45	43	41	39	38	36	34
40	57	55	53	51	49	47	45	43	41	39	37	35	33	31	29	27	25	23
45	50	48	46	44	41	39	37	35	32	30	28	26	23	21	19	17	14	12
50	44	41	39	36	34	31	29	26	24	21	19	16	14	11	9	6	4	1
55	37	34	31	29	26	23	20	18	15	12	9	7	4	1	-2	-5	-7	-10
60	30	27	24	21	18	15	12	9	6	3	0	-3	-6	-9	-12	-15	-18	-21
65	23	20	17	14	10	7	4	1	-3	-6	-9	-13	-16	-19	-22	-26	-29	-32
70	17	13	10	6	3	-1	-5	-8	-12	-15	-19	-22	-26	-29	-33	-36	-40	-43
75	10	6	2	-2	-5	-9	-13	-17	-20	-24	-28	-32	-35	-39	-43	-47	-50	-54
80	3	-1	-5	-9	-13	-17	-21	-25	-29	-33	-37	-41	-45	-49	-53	-57	-61	-65
85	-4	-8	-12	-17	-21	-25	-29	-34	-38	-42	-46	-51	-55	-59	-63	-68	-72	-76
90	-11	-15	-20	-24	-29	-33	-38	-42	-47	-51	-56	-60	-65	-69	-74	-78	-83	-87
95	-17	-22	-27	-32	-36	-41	-46	-51	-55	-60	-65	-70	-74	-79	-84	-89	-93	-98
103	-28	-33	-38	-44	-49	-54	-59	-64	-69	-74	-80	-85	-90	-95	-100	-105	-110	-116
105	-31	-36	-41	-47	-52	-57	-62	-68	-73	-78	-83	-89	-94	-99	-104	-110	-115	-120
110	-38	-43	-49	-54	-60	-65	-71	-76	-82	-87	-93	-98	-104	-109	-115	-120	-126	-131
115	-44	-50	-56	-62	-67	-73	-79	-85	-90	-96	-102	-108	-113	-119	-125	-131	-136	-142
120	-51	-57	-63	-69	-75	-81	-87	-93	-99	-105	-111	-117	-123	-129	-135	-141	-147	-153
125	-58	-64	-70	-77	-83	-89	-95	-102	-108	-114	-120	-127	-133	-139	-145	-152	-158	-164
130	-65	-71	-78	-84	-91	-97	-104	-110	-117	-123	-130	-136	-143	-149	-156	-162	-169	-175
135	-71	-78	-85	-92	-98	-105	-112	-119	-125	-132	-139	-146	-152	-159	-166	-173	-179	-186
140	-78	-85	-92	-99	-106	-113	-120	-127	-134	-141	-148	-155	-162	-169	-176	-183	-190	-197
145	-85	-92	-99	-107	-114	-121	-128	-136	-143	-150	-157	-165	-172	-179	-186	-194	-201	-208
150	-92	-99	-107	-114	-122	-129	-137	-144	-152	-159	-167	-174	-182	-189	-197	-204	-212	-219
155	-98	-106	-114	-122	-129	-137	-145	-153	-160	-168	-176	-184	-191	-199	-207	-215	-222	-230
160	-105	-113	-121	-129	-137	-145	-153	-161	-169	-177	-185	-193	-201	-209	-217	-225	-233	-241
165	-112	-120	-128	-137	-145	-153	-161	-170	-178	-186	-194	-203	-211	-219	-227	-236	-244	-252
170	-119	-127	-136	-144	-153	-161	-170	-178	-187	-195	-204	-212	-221	-229	-238	-246	-255	-263
175	-125	-134	-143	-152	-160	-169	-178	-187	-195	-204	-213	-222	-230	-239	-248	-257	-265	-274
180	-132	-141	-150	-159	-168	-177	-186	-195	-204	-213	-222	-231	-240	-249	-258	-267	-276	-285
185	-139	-148	-157	-167	-176	-185	-194	-204	-213	-222	-231	-241	-250	-259	-268	-278	-287	-296
190	-146	-155	-165	-174	-184	-193	-203	-212	-222	-231	-241	-250	-260	-269	-279	-288	-298	-307
195	-152	-162	-172	-182	-191	-201	-211	-221	-230	-240	-250	-260	-269	-279	-289	-299	-308	-318
200	-159	-169	-179	-189	-199	-209	-219	-229	-239	-249	-259	-269	-279	-289	-299	-309	-319	-329

Table 2

Average Price Impacts (%) and Other Characteristics for Institutional Equity Trades

Average price impacts are based on trades in 37 international stock markets and are reported separately for: three investment styles; U.S., other developed, and emerging markets; and buy and sell trades. Price impact is the ratio of the average trade price of the individual trades within an order to the closing stock price on the day before the order was initiated, minus 1.0, in excess of the market return over the interval of the order. Price impacts for sells are multiplied by negative one so they can be interpreted as costs and easily compared to impacts for buys. Results are shown separately for the periods April 1996 - March 1997 (for 26 institutions) and January 2000 - December 2000 (for 33 institutions).

	Diversified Institutions				**Value Institutions**				**Momentum Institutions**			
	1996-1997		**2000**		**1996-1997**		**2000**		**1996-1997**		**2000**	
	Buys	**Sells**	**Buys**	**Sells**	**Buys**	**Sells**	**Buys**	**Sells**	**Buys**	**Sells**	**Buys**	**Sells**
A. U.S. Equity Markets												
Mean Price Impact	0.077	0.787	0.468	0.391	0.006	0.303	0.482	0.336	1.134	1.291	0.810	0.746
(Standard Error)	(0.056)	(0.078)	(0.023)	(0.029)	(0.025)	(0.021)	(0.041)	(0.042)	(0.029)	(0.035)	(0.045)	(0.060)
# obs	3,387	2,686	21,259	16,552	10,269	11,339	15,267	14,719	23,099	19,200	9,022	6,578
B. Developed Markets (not U.S.)												
Mean Price Impact	0.358	0.144	0.647	0.198	0.284	0.161	0.538	0.130	0.406	0.169	0.615	0.499
(Standard Error)	(0.010)	(0.015)	(0.020)	(0.019)	(0.011)	(0.013)	(0.025)	(0.023)	(0.027)	(0.032)	(0.018)	(0.021)
# obs	49,060	26,637	48,810	53,783	32,396	23,340	29,709	36,259	10,087	7,456	48,137	36,770
C. Emerging Equity Markets												
Mean Price Impact	0.515	0.222	0.773	0.217	0.551	0.284	1.151	0.058	0.910	0.014	0.624	0.682
(Standard Error)	(0.041)	(0.071)	(0.081)	(0.071)	(0.064)	(0.080)	(0.100)	(0.083)	(0.115)	(0.116)	(0.055)	(0.062)
# obs	7,702	3,756	4,836	6,541	2,976	1,653	3,843	4,557	1,809	1,770	6,199	5,349
D. All Markets												
Mean Price Impact	0.362	0.206	0.604	0.241	0.239	0.211	0.569	0.179	0.912	0.917	0.643	0.553
(Standard Error)	(0.010)	(0.016)	(0.016)	(0.016)	(0.011)	(0.011)	(0.021)	(0.020)	(0.022)	(0.026)	(0.016)	(0.019)
# obs	60,149	33,079	74,905	76,876	45,641	36,332	48,819	55,535	34,995	28,426	63,358	48,697
mktcap ($bill)	7.882	8.145	33.704	28.951	10.783	11.730	30.264	24.475	6.417	5.440	26.470	27.331
trsize (% of Shr Outst)	0.043	0.073	0.050	0.056	0.056	0.053	0.093	0.082	0.129	0.155	0.043	0.053
$ Value of Trades ($ bill)	50.20	34.34	160.20	153.63	41.39	35.33	147.99	149.23	38.63	37.24	128.12	118.87

Table 3

Are Institutional Investors' Trades Conditioned on Prior Price Movements?

The table reports average 3-week excess returns prior to institutional trade packages and estimates of a logistic regression model for these buy and sell packages. The average excess returns are measured over the 15 trading days prior to the commencement of a trade. The 3-week pre-trade excess return for security *i* , $PriorXRet_i$, is defined as the return for security *i* for the 15 trading days preceding the trade minus the return (for the same period) for the market in which the stock is traded. The dependent variable in the logit model is a dummy variable that takes the value 1 if the package is a buy, and 0 otherwise. $PriorXRet_i$ is the independent variable in the model. Maximum liklihood estimates of the model are reported, with asymptotic standard errors in parentheses. Results are reported for the 33 institutions in the U.S. and 36 other international equity markets for the pooled 96-97 and 2000 sample periods.

	Mean 3-week excess price change (%) (*PriorXRet*) prior to:			Logit Model Coefficient Estimates		Frequency Counts for	
	Buys	**Sells**	**t(Buys-Sells)**	**intercept**	***PriorXRet***	**Buys**	**Sells**
Overall	0.833	0.658	6.21	**-0.1607**	**0.0015**	327,615	278,677
				(0.0025)	(0.0002)		
A. Diversified Institutions							
All Markets	0.662	0.721	-1.42	**-0.2062**	-0.0006	134,992	109,884
				(0.0041)	(0.0004)		
U.S.	0.474	0.313	1.29	**-0.2478**	0.0010	24,635	19,221
				(0.0096)	(0.0007)		
Other Developed	0.713	0.867	-3.37	**-0.1978**	**-0.0017**	97,822	80,372
				(0.0048)	(0.0005)		
Emerging	0.631	0.347	2.20	**-0.1958**	**0.0030**	12,535	10,291
				(0.0132)	(0.0014)		
B. Value Institutions							
All Markets	0.170	0.941	-17.00	**-0.0328**	**-0.0081**	94,412	91,776
				(0.0046)	(0.0005)		
U.S.	-0.305	0.783	-10.99	**0.0176**	**-0.0087**	25,507	26,013
				(0.0088)	(0.0008)		
Other Developed	0.302	1.059	-14.49	**-0.0478**	**-0.0092**	62,087	59,558
				(0.0058)	(0.0006)		
Emerging	0.751	0.471	1.67	**-0.0923**	0.0031	6,818	6,205
				(0.0176)	(0.0018)		
C. Momentum Institutions							
All Markets	1.741	0.232	24.05	**-0.2342**	**0.0092**	98,211	77,017
				(0.0048)	(0.0004)		
U.S.	2.334	-0.306	23.89	**-0.2045**	**0.0154**	32,083	25,753
				(0.0084)	(0.0007)		
Other Developed	1.434	0.629	10.06	**-0.2698**	**0.0050**	58,125	44,152
				(0.0063)	(0.0005)		
Emerging	1.146	-0.287	8.06	**-0.1129**	**0.0122**	8,003	7,112
				(0.0163)	(0.0015)		

Bold indicates significance at the 5% level.

Table 4

Trend Chasing, Investment Flows, and Price Impacts

Agregate investment flows and average price impacts conditioned on pre-trade local market return being greater than zero or less than or equal to zero. Market return (R_M) is the three-week pre-trade local market return. Price impact is the ratio of the average trade price to the closing stock price on the day before the order was initiated, minus 1.0, in excess of the market return over the interval of the trade. Price impacts for sells are multiplied by negative one so that they can be interpreted as costs and easily compared to the impacts for buys. T-values of the difference in average impact in upward- and downward-trending markets is to the right of these values. Agregate investment flow is the sum of the dollar value of all trades in the respective category, reported in billions of dollars. Number of orders is in parentheses. Results are reported for the 1996-97 and 2000 periods.

	A. Buys			B. Sells		
	(A) $R_M \le 0$	(B) $R_M > 0$	t (B-A)	(C) $R_M \le 0$	(D) $R_M > 0$	t (D-C)
Overall	0.478	0.613	10.30	0.457	0.220	-15.48
	$293.49	$272.95		$280.58	$247.83	
	(166,119)	(161,707)		(143,928)	(134,970)	
Diversified Institutions						
All Markets	0.448	0.548	5.13	0.390	0.048	-14.13
	$105.95	$104.43		$98.10	$89.77	
	(69,384)	(65,662)		(58,261)	(51,683)	
U.S.	0.360	0.486	2.92	0.570	0.303	-4.91
	$11.47	$8.88		$10.02	$7.97	
	(13,991)	(10,654)		(10,374)	(8,863)	
Other Developed	0.454	0.551	4.32	0.351	-0.012	-13.32
	$89.99	$90.64		$83.72	$76.65	
	(49,195)	(48,668)		(42,318)	(38,094)	
Emerging	0.597	0.631	0.42	0.353	0.061	-2.80
	$4.49	$4.91		$4.36	$5.05	
	(6,198)	(6,340)		(5,569)	(4,726)	
Value Institutions						
All Markets	0.353	0.467	4.70	0.269	0.110	-6.24
	$103.05	$86.31		$98.05	$86.50	
	(47,191)	(47,262)		(46,285)	(45,570)	
U.S.	0.212	0.373	3.01	0.364	0.279	-1.66
	$33.18	$23.90		$31.91	$25.94	
	(12,867)	(12,665)		(13,130)	(12,921)	
Other Developed	0.350	0.460	4.21	0.234	0.047	-6.34
	$63.82	$56.07		$59.76	$55.67	
	(30,773)	(31,329)		(29,730)	(29,864)	
Emerging	0.885	0.893	0.06	0.215	-0.001	-1.64
	$6.05	$6.34		$6.39	$4.89	
	(3,551)	(3,268)		(3,425)	(2,785)	
Momentum Institutions						
All Markets	0.639	0.842	7.94	0.778	0.589	-6.13
	$84.50	$82.21		$84.43	$71.56	
	(49,544)	(48,783)		(39,382)	(37,717)	
U.S.	0.864	1.208	7.06	1.368	0.975	-6.55
	$20.51	$23.76		$18.97	$22.06	
	(15,234)	(16,881)		(11,509)	(14,263)	
Other Developed	0.528	0.632	3.35	0.496	0.376	-3.25
	$60.78	$55.38		$62.07	$46.61	
	(30,153)	(28,054)		(24,222)	(19,989)	
Emerging	0.614	0.769	1.57	0.789	0.227	-5.10
	$3.20	$3.07		$3.39	$2.89	
	(4,157)	(3,848)		(3,651)	(3,465)	

Table 5

Regression model of Price Impacts for Trades of 33 Institutions in the U.S. and 36 other International Equity Markets

The table contains results for the following models estimated separately for buys and sells:

Buys: $PI_i = \beta_0 + \beta_1\, TradeSize_i + \beta_2\, (1/P_i) + \beta_3\, ln(Mcap_i) + \delta_0\, D_i^B + \delta_1\, TradeSize_i * D_i^B + \delta_2\, (1/P_i) * D_i^B + \delta_3\, ln(Mcap_i) * D_i^B$

Sells: $PI_i = \beta_0 + \beta_1\, TradeSize_i + \beta_2\, (1/P_i) + \beta_3\, ln(Mcap_i) + \delta_0\, D_i^S + \delta_1\, TradeSize_i * D_i^S + \delta_2\, (1/P_i) * D_i^S + \delta_3\, ln(Mcap_i) * D_i^S$

where: PI_i is the price impact for order i; $TradeSize_i$ is the number of shares traded in order i as a percent of the total shares outstanding; P_i is the price of the stock in order i; $Mcap_i$ is the market capitalization of the stock traded in order i in billions of dollars; D_i^B equals one if $R_M \leq 0$, zero otherwise; D_i^S equals one if $R_M > 0$, zero otherwise; and R_M is the three-week pre-trade return on the local stock market index. The β coefficients measure the price impact function for buys (sells) in rising (falling) markets. The δ coefficients measure the difference in the estimates of the price impact function between rising and falling markets. Standard errors are heteroskedasticity-consistent estimates. The models are estimated over the pooled 96-97 and 2000 sample periods. Coefficient estimates in bold are significant at the 5% level.

	β_0	β_1	β_2	β_3	δ_0	δ_1	δ_2	δ_3	Adj R^2	# Obs
A. Buys										
All Styles	**0.7707**	**0.3485**	**0.0855**	**-0.1307**	**-0.1455**	0.0249	**-0.0125**	**0.0160**	0.017	327,853
	(0.0126)	(0.0175)	(0.0039)	(0.0053)	(0.0181)	(0.0307)	(0.0049)	(0.0074)		
Diversified	**0.6764**	**0.2931**	0.0035	**-0.0870**	**-0.0655**	0.0201	-0.0024	-0.0179	0.004	135,047
	(0.0197)	(0.0287)	(0.0080)	(0.0080)	(0.0274)	(0.0491)	(0.0094)	(0.0111)		
Value	**0.5890**	**0.1591**	**0.1335**	-0.1017	**-0.0929**	**-0.1408**	**-0.0149**	-0.0075	0.018	94,457
	(0.0247)	(0.0274)	(0.0058)	(0.0103)	(0.0352)	(0.0475)	(0.0073)	(0.0144)		
Momentum	**0.9906**	**0.7191**	**0.0813**	**-0.1796**	**-0.2657**	**0.4463**	0.0005	**0.0644**	0.021	98,347
	(0.0224)	(0.0365)	(0.0071)	(0.0096)	(0.0332)	(0.0675)	(0.0095)	(0.0136)		
B. Sells										
All Styles	**0.6811**	**0.5115**	**-0.0737**	**-0.1421**	**-0.2778**	**-0.1259**	-0.0047	**0.0169**	0.011	278,934
	(0.0145)	(0.0246)	(0.0030)	(0.0059)	(0.0208)	(0.0306)	(0.0050)	(0.0084)		
Diversified	**0.6238**	**0.1220**	**-0.0425**	**-0.1347**	**-0.4082**	**-0.1398**	**-0.0325**	**0.0476**	0.007	109,951
	(0.0228)	(0.0376)	(0.0044)	(0.0091)	(0.0333)	(0.0584)	(0.0074)	(0.0132)		
Value	**0.4257**	**0.3589**	**-0.0894**	**-0.0877**	-0.0706	**-0.2131**	0.0068	**-0.0545**	0.010	91,864
	(0.0258)	(0.0418)	(0.0047)	(0.0105)	(0.0363)	(0.0527)	(0.0078)	(0.0148)		
Momentum	**0.9840**	**1.2716**	**-0.1172**	**-0.1817**	**-0.3467**	**-0.1313**	**0.0539**	**0.0644**	0.027	77,117
	(0.0286)	(0.0502)	(0.0082)	(0.0113)	(0.0394)	(0.0638)	(0.0126)	(0.0160)		

Table 6

Average Total Trade Costs (%) for Institutional Equity Trades

Average total trade costs are reported separately for: three investment styles; U.S., other developed, and emerging markets; and buy and sell trades. Implicit cost is the ratio of the average trade price of the individual trades within an order to the closing stock price on the day before the decision to trade, minus 1.0, in excess of the market return over the interval of the order. Implicit costs for sells are multiplied by negative one so they can be interpreted as costs and easily compared to impacts for buys. Explicit costs include commissions, custodial fees, and stamp duties for international trades. Results are reported for 33 institutions in the U.S. and 36 other international equity markets for the pooled 96-97 and 2000 sample periods

	A. Buy Trade Costs			**B. Sell Trade Costs**		
	Implicit	**Explicit**	**# Obs**	**Implicit**	**Explicit**	**# Obs**
Diversified Institutions						
All Markets	0.561	0.284	135,054	0.256	0.232	109,955
U.S.	0.377	0.107	24,646	0.432	0.128	19,238
Other Developed	0.580	0.300	97,870	0.205	0.225	80,420
Emerging	0.772	0.499	12,538	0.327	0.481	10,297
Value Institutions						
All Markets	0.483	0.296	94,460	0.176	0.216	91,867
U.S.	0.328	0.139	25,536	0.248	0.141	26,058
Other Developed	0.480	0.344	62,105	0.135	0.225	59,599
Emerging	1.079	0.442	6,819	0.258	0.443	6,210
Momentum Institutions						
All Markets	1.011	0.296	98,353	0.900	0.231	77,123
U.S.	1.270	0.190	32,121	1.333	0.191	25,778
Other Developed	0.855	0.334	58,224	0.620	0.217	44,226
Emerging	1.101	0.438	8,008	1.066	0.468	7,119

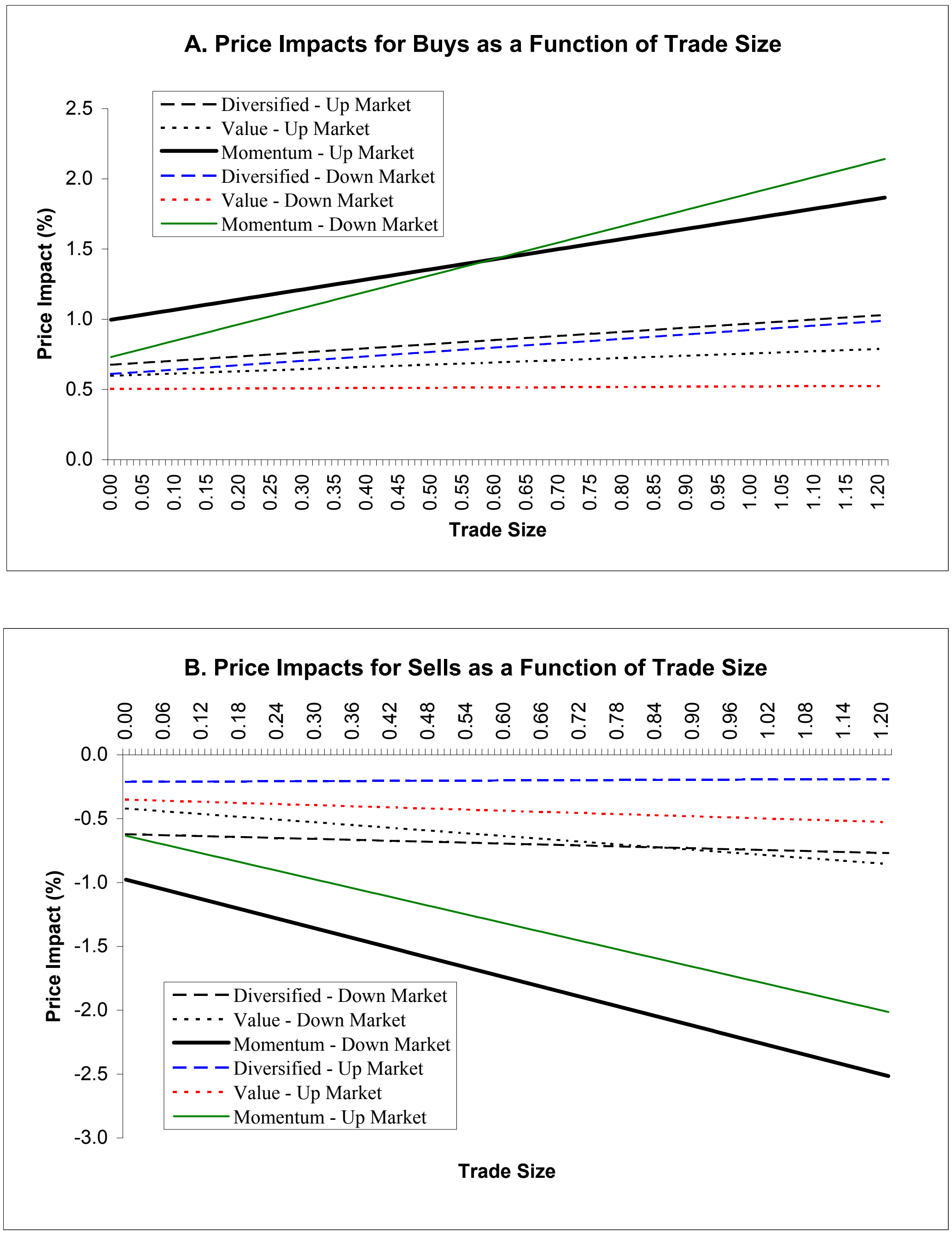

Figure 1. Estimated *Price Impact* Functions

The figure is based on the following models estimated separately for buys (Panel A) and sells (Panel B):

$$\text{Buys:} \quad PI_i = \beta_0 + \beta_1\, TradeSize_i + \beta_2\, (1/P_i) + \beta_3\, \ln(Mcap_i) + \delta_0\, D_i^B + \delta_1\, TradeSize_i * D_i^B + \delta_2\, (1/P_i) * D_i^B + \delta_3\, \ln(Mcap_i) * D_i^B$$

$$\text{Sells:} \quad PI_i = \beta_0 + \beta_1\, TradeSize_i + \beta_2\, (1/P_i) + \beta_3\, \ln(Mcap_i) + \delta_0\, D_i^S + \delta_1\, TradeSize_i * D_i^S + \delta_2\, (1/P_i) * D_i^S + \delta_3\, \ln(Mcap_i) * D_i^S$$

where: PI_i is the price impact for order i; $TradeSize_i$ is the number of shares traded in order i as a percent of the total shares outstanding; P_i is the price of the stock in order i; $Mcap_i$ is the market capitalization of the stock traded in order i in billions of dollars; D_i^B equals one if $R_M \leq 0$ for the stock in buy order i, zero otherwise; and D_i^S equals one if $R_M > 0$, zero otherwise. The models are estimated over the pooled 96-97 and 2000 sample periods.

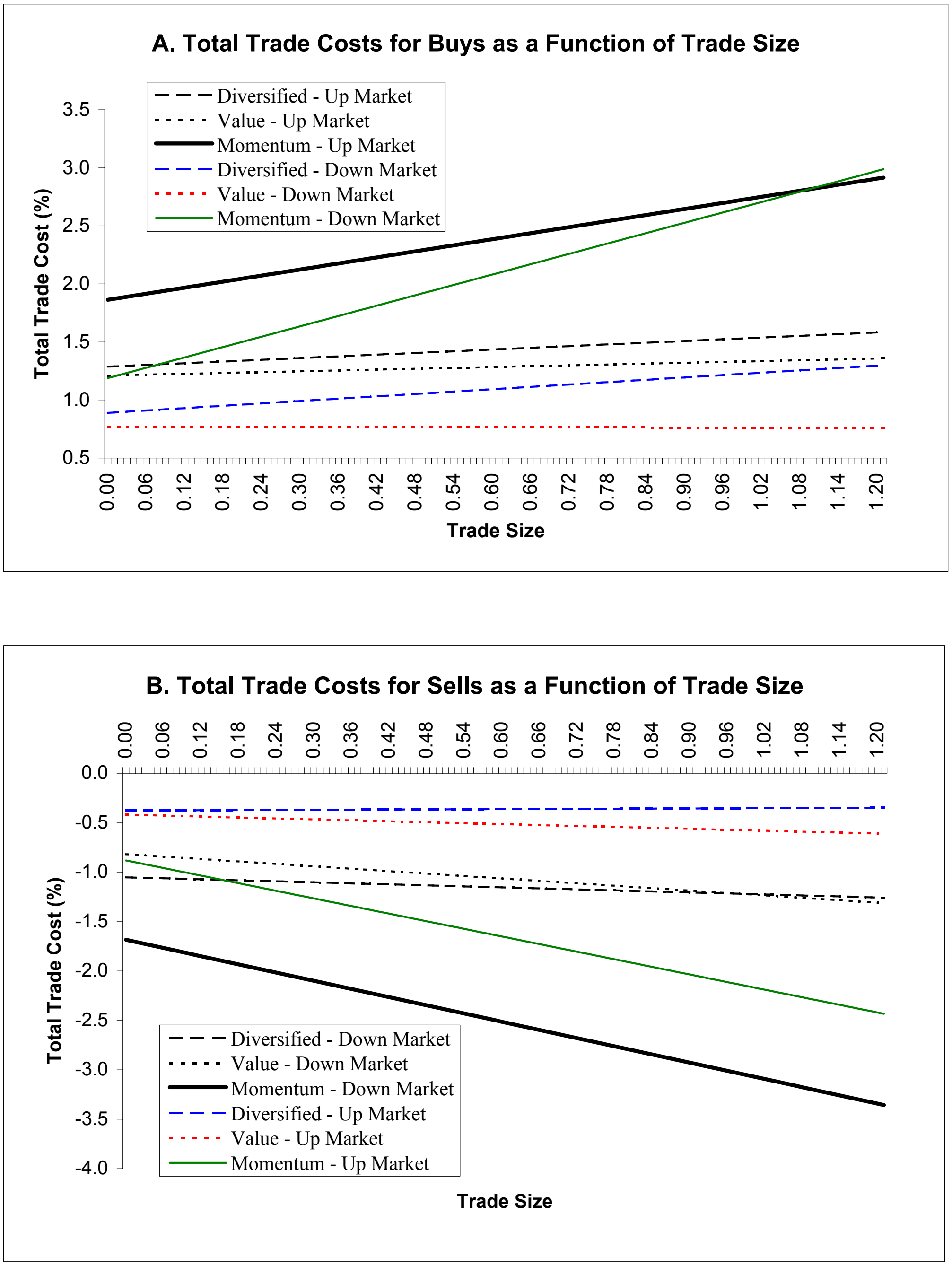

Figure 2. Estimated *Total Trade Cost* Functions

The figure is based on the following models estimated separately for buys (Panel A) and sells (Panel B):

$$\textit{Buys:}\quad TotTrCost_i = \beta_0 + \beta_1\, TradeSize_i + \beta_2\, (1/P_i) + \beta_3\, ln(Mcap_i) + \delta_0\, D_i^B + \delta_1\, TradeSize_i * D_i^B + \delta_2\, (1/P_i) * D_i^B + \delta_3\, ln(Mcap_i) * D_i^B$$

$$\textit{Sells:}\quad TotTrCost_i = \beta_0 + \beta_1\, TradeSize_i + \beta_2\, (1/P_i) + \beta_3\, ln(Mcap_i) + \delta_0\, D_i^S + \delta_1\, TradeSize_i * D_i^S + \delta_2\, (1/P_i) * D_i^S + \delta_3\, ln(Mcap_i) * D_i^S$$

where: $TotTrCost_i$ is the total trade cost for order *i;* $TradeSize_i$ is the number of shares traded in order *i* as a percent of the total shares outstanding; P_i is the price of the stock in order *i;* $Mcap_i$ is the market capitalization of the stock traded in order *i* in billions of dollars; D_i^B equals one if $R_M \leq 0$ for the stock in buy order *i* , zero otherwise; and D_i^S equals one if $R_M > 0$, zero otherwise. The models are estimated over the pooled 96-97 and 2000 sample periods.