The Illusory Nature of Momentum Profits

David A. Lesmond
Tulane University

Michael J. Schill
University of Virginia

Chunsheng Zhou
University of California, Riverside

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Abstract

In markets with trading friction, the incorporation of information into market prices can be substantially delayed through a weakening of the arbitrage process. We re-examine the profitability of relative strength trading strategies (buying past strong performers and selling past weak performers) by testing the predictions of a friction-based explanation. We provide a model of price friction and then use this model to infer trading costs from investor behavior. We find that the execution of standard relative strength strategies requires large trading costs because of the type and frequency of securities traded such that trading costs prevent profitable relative strength investing. In the cross section, we find evidence that trading costs provide binding constraints to relative strength strategy profits. Relative strength returns are localized among low-price, poor performers and are increasing in investor transaction costs. We conclude that the delay in price adjustment for security returns simply reflects the costs of arbitrage--creating an illusion of anomalous price behavior and momentum trading profit opportunity when, in fact, none exists.

Lesmond can be reached at 504-865-5665 or dlesmond@mailhost.tcs.tulane.edu. Schill can be reached at 909-787-4589 or schillm@darden.virginia.edu. Zhou can be reached at 909-787-6448 or chunsheng.zhou@ucr.edu . We are grateful to David Mayers, Grant McQueen, Jeffrey Pontiff, Sergei Sarkissian, Sheridan Titman, Charles Trzcinka, an anonymous referee and seminar participants at Louisiana State University, Tulane University, the University of California -Riverside, the University of Virginia, and Washington University-St Louis for useful comments and to Ruslana Deykun for clerical assistance. We gratefully acknowledge the support of I/B/E/S for providing data on analyst coverage under their academic research support program.

There is substantial evidence that "relative strength" or "momentum" investment strategies (maintaining a long position in past strong performers and a short position in past weak performers) earn large abnormal returns over a six to twelve month horizon. A growing literature finds this evidence at odds with classical models of rational price formation.[1] Rather, the argument is made that characteristics of investor behavior generate a certain inertia or "momentum" in abnormal returns that creates persistent arbitrage opportunity. Investor attributes which have been found to generate momentum effects include expectation extrapolation (DeLong et al., 1990), conservatism in expectations updating (Barberis et al., 1998), biased self attribution (Daniel et al., 1998), and selective information conditioning (Hong and Stein, 1999).

We make the case for a more traditional explanation for relative strength portfolio returns--friction. It has been argued that trading costs weaken the price discipline of arbitrage in that they prevent arbitrageurs from being fully functional in removing pricing errors.[2] That is, if trading costs are binding, arbitrageurs have no interest in arbitrage positions. The lack of strict arbitrage discipline allows delays or friction in the price adjustment process. Although the notion of price friction is well accepted, the magnitude of the costs of trading and its impact on price behavior is not fully appreciated in some contexts. We find, for example, that relative strength strategies require heavy trading among particularly costly stocks such that the trading costs are much larger than previously acknowledged. Our evidence suggests that stocks that generate momentum returns are precisely those stocks with high trading costs. We propose that the momentum effect observed in security prices is more precisely a friction effect produced by the costs of arbitrage--creating an illusion of trading profit opportunities when, in fact, none exists.

[1] This literature includes Jegadeesh (1990), Cutler et al. (1991), Jegadeesh and Titman (1993, 2001), Chan et al. (1996), and Rouwenhorst (1998). Fama and French (1996) find that momentum patterns are the only CAPM anomaly that is not explained by their three factor model.
[2] See, for example, Rosett (1959), Tobin (1965), and Goldsmith (1976), Cohen et al. (1986).

Trading cost effects have been rejected previously as an explanation for relative strength portfolio performance. Jegadeesh and Titman (JT, 1993) argue that relative strength returns exceed trading costs. Their estimate of trading cost, however, is based on the trade-weighted mean commission and market impact of early 1985 NYSE trades computed by Berkowitz et al. (1988). We find these transaction cost estimates to be unsatisfactory for a number of reasons. First, since trading costs exhibit substantial cross-sectional variation (Keim and Madhavan, 1997), using a NYSE trade-weighted measure is not appropriate as a benchmark for a strategy dominated by small, off-NYSE, extreme performers. We show that the securities used in relative strength strategies are disproportionately drawn from among stocks with large trading costs. Second, a constant or single period measure is unable to capture the substantial time-series variation in trading costs (Lesmond et al., 1999). Third, the Berkowitz et al. measure understates the full trading costs facing investors as it excludes a number of important costs of trading such as bid-ask spread, taxes, short-sale costs, and holding period risk. We conclude that the understatement of the trading costs associated with relative strength strategies has vastly overstated the respective expected profits.[3]

We provide a model of price friction and then use this model to infer trading costs from investor behavior. The estimation procedure is superior to alternative methods because of its grounding in observed investor behavior. Rather than estimate the trading costs from institutional data, we infer the total costs from the distribution of price changes following Lesmond et al. (1999). The approach provides reasonable estimates of transaction costs consistent in magnitude and correlation to other methods and within institutional bid-ask spread quotes. We show that transaction costs are not static, but exhibit substantial cross-sectional and time-series variation over the sample period. We find that the costs of relative strength strategy execution are much larger than those

[3] Transaction costs have been used to explain other well-known asset-pricing anomalies, including filter rules (Fama and Blume, 1966), portfolio upgrading rules (Jensen and Benington, 1970), block-trade returns (Dann et al., 1977), option trading rules (Phillips and Smith, 1980), the January effect (Reinganum, 1983; Bhardwaj and Brooks, 1992), the small-firm effect (Stoll and Whaley, 1983), ex-dividend day returns (Karpoff and Walkling, 1990), switching strategies (Mech, 1993; Knez and Ready, 1996), closed-end fund discounts (Pontiff, 1996), long-run equity offering returns (Pontiff and Schill, 2001), post-earnings price drift (Lesmond, 2000), and analyst recommendation underreaction (Copeland and Mayers, 1982; Barber et al., 2000; Choi, 2000).

previously reported, such that the levels of trading costs dominate the returns obtained through relative strength investing. We find that mean trading costs exceed 12 percent for a standard relative strength strategy that generates gross six-month returns of less than six percent. The magnitude of trading costs is explained by both the trading intensity required of relative-strength strategies (the strategy requires four trades for each period) and the illiquidity of the assets traded (the strategy is weighted heavily toward high cost stocks). The trading cost estimates swamp the respective gross strategy profits, implying that trading costs preclude profitable relative-strength strategy execution.[4]

In the cross section, we find that transaction costs are binding to relative strength profits. Relative strength strategies using stocks with high transaction costs generate larger returns than those using stocks with low transaction costs. We find that the bulk of cross-sectional variation occurs across price-level, rather than size class as suggested by Hong et al. (2000). Since trading costs, such as bid-ask spread, are negatively correlated with share price and price is positively correlated with size, we expect that the reported size effect is more appropriately a manifestation of a price effect. We conclude that not only do trading costs prevent profitable relative strength investing, but also that the return patterns are not unexpected given the effect that transaction costs have on arbitrage trading. Relative strength portfolio returns appear to be bound by transaction costs such that the profitability of these strategies is overstated in the literature. We find little evidence to reject rational-based models and argue that the literature has been too hasty in rejecting friction as an explanation for relative strength portfolio returns and too dismissive of the economic significance of trading costs.

This paper is organized as follows. Section I reviews the evidence and behavior of relative strength returns. Section II proposes a simple model of price friction. Section III discusses our estimates of trading costs. Section IV compares the level of gross trading profits with transaction cost estimates. Section V contrasts the existing cross-

[4] This conclusion is not unique to our transaction cost estimation procedure. Other common methods generate the same inferences. We show that the magnitude of the trading cost estimates are sufficiently large as to accommodate substantial error in our trading cost estimates without altering the conclusion.

sectional evidence of relative strength investing returns with that of the friction model. Section VI provides concluding remarks.

I. The Momentum Anomaly

A. *Relative Strength Portfolio Returns*

We examine relative-strength strategies over a period from January 1980 to December 1998. Our classification procedure follows JT (1993) and Hong et al. (HLS, 2000).[5] We construct relative strength portfolios using the Center for Research in Security Prices (CRSP) monthly returns file (ordinary common shares excluding ADRs, REITs, and closed-end funds). Each six months, firms are classified into three portfolios based on gross returns over the past six months: poor performers (P1), moderate performers (P2), and strong performers (P3). Within each portfolio, stocks are initially equally weighted and then held for six months. Since we are less concerned about the statistical magnitude of our estimates, we do not overlap holding periods but rather use calendar periods (January to June and July to December) which would be more operational and cost effective to an investor. Following the notation of Jegadeesh and Titman and Hong et al., the mean returns for each portfolio k are calculated as,

$$Pk = \frac{1}{T}\sum_t r_k(t) = \frac{1}{T}\sum_t \left[\frac{1}{Nk(t)}\sum_{i\in k} r(i,t)\right] \tag{1}$$

[5] We focus on the six-month formation period and six-month holding period to be consistent with the dominant strategies in the literature. If some of the performance of the six-month relative strength strategy is due to dredging the sample-specific best-performing strategy from a multitude of alternative strategies, we are, in a sense, "stacking the deck" against ourselves by testing returns which are not likely to be replicated out of sample. It is worth noting that we repeat our tests for a variety of alternative formation and holding periods and find that our conclusions are unchanged.

where $r(i,t)$ is the holding period return for firm i for period t, $Nk(t)$ is the number of firms in portfolio k for period t, and T is the number of periods in the sample period (38 semi-annual periods).

Summary statistics are presented in Table 1 using all NYSE/AMEX stocks and the 10-90 percentile performance breakpoints of JT. Mean semi-annual returns for the P1, P2, and P3 portfolios are respectively 4.3 percent, 8.7 percent, and 9.8 percent. A trading strategy that maintains a long position in the best performers and a short position in the worst performers (P3-P1) achieves "paper profits" of 5.5 percent per semi-year, significantly positive at the five-percent level. Table 1 also reports statistics for the HLS strategy. Consistent with the HLS study, for these estimates we include NASDAQ stocks and break the performance categories at the 30^{th} and 70^{th} percentiles. For the HLS strategy, the mean performance of the winners and losers is less extreme such that the P3-P1 profits decline to a still highly significant 3.7 percent semi-annual return.

We note that the majority of trading strategy returns is generated by the short position. The P2-P1 position provides 4.4 percentage points of the total 5.5 percent P3-P1 return for the JT strategy. The asymmetry in returns is similar for the HLS strategy. We also note that despite the positive mean performance observed over the sample period, there is considerable variation in abnormal returns for these strategies in any particular period. For the JT strategy the standard deviation for the 5.5 percent P3-P1 return is 15.7 percent with single period returns varying from -55 percent to +29 percent. The evidence suggests that relative strength investors face considerable period-by-period portfolio risk. Arbitrageurs achieve systematic abnormal performance only over extended periods of time.

For the most part, the literature contends that irrational investor behavior leads to "momentum" or sustained abnormal performance in stock returns and affords arbitrage profits through relative strength investing.[6] Models of investor behavior that generate

[6]Conrad and Kaul (1998) and Chordia and Shivakumar (2000) suggest that momentum strategy profitability is due merely to cross-sectional variation in individual mean returns. Martin and Grundy (2001) observe

momentum effects include, DeLong et al. (1990), Barberis et al. (1998), Daniel et al. (1998), and Hong and Stein (1999). JT and HLS suggest that transaction costs are sufficiently small to allow generous profit opportunity for relative strength investors. The estimates of transaction costs used in these studies are based on primarily larger, more liquid stocks. We find that the stocks which comprise relative strength investment portfolios are not of this type. Since there is large cross-sectional variation in stock trading costs, the trading cost estimates used are highly understated.

Table 1 provides some statistics on the composition of the relative strength portfolios. We find that the extreme performing stocks which comprise the securities traded in relative strength portfolios are unique. For the JT strategy, the portfolio beta estimated over the sample period is largest for portfolios P1 and P3 with P1, P2, P3 estimates of 1.19, 1.02, and 1.25, respectively. We report the mean share price and market capitalization of stocks within each portfolio and find that the share price of stocks within portfolio P1 are much lower than those in the other portfolios. The mean share price for stocks in portfolios P1, P2, and P3 is respectively, \$9.19, \$30.31, and \$34.51. We find that the size of the firms in the three portfolios is much smaller for the relative strength portfolios P1 and P3. The mean market capitalization for stocks in portfolios P1, P2, and P3 is respectively, \$0.4 billion, \$1.7 billion, and \$1.0 billion. We also find that the P1 and P3 stocks are less likely to be traded on the NYSE. Of our NYSE/AMEX sample the proportion of portfolio P1, P2, and P3 stocks which are traded

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that standard risk measures do not explain relative-strength portfolio performance. JT find that momentum returns do not increase standard risk measures. We perform a similar test estimating CAPM and Fama-French model loadings for each of the strategies in Table 4. If risk explains the observed patterns, the loadings should be decreasing in price and abnormal returns should exhibit little monotonic pattern. The results suggest that this is not so. CAPM beta estimates range from -0.34 to 0.22. Those with significant positive beta estimates are among the portfolios with small size and high price. The opposite is true for those with negative betas. This finding suggests that among these portfolios the best and worst performer positions are not perfect risk hedges. In contrast to the risk-based explanation, the portfolios with positive betas tend to be those containing firms with high prices and those with negative betas tend to be those containing firms with low prices. This finding is opposite that expected of a risk-based explanation. The momentum strategies for the low price portfolios achieve higher returns with lower betas. For the Fama-French model, the loadings on the SMB factor increase across the size groups, but show little variation across price level. There is no consistent patterns across the HML loadings. The abnormal returns estimates are similar to those of Table 4. Adjusting for risk has little impact on abnormal performance. It appears unlikely that standard risk measures explain the relationships observed in Table 4. Given the possibility of a bad-model problem, the rejection of standard risk measures does not imply rejection of on the NYSE is 53 percent, 73 percent, and 59 percent, respectively. The composition pattern for the HLS portfolios is similar. In summary, the relative strength portfolios, and particularly portfolio P1 which generates the majority of the total strategy abnormal return, can be characterized as small, high beta, off-NYSE stocks.

The Table 1 characterization of the relative strength portfolios suggests that the assets which generate the abnormal returns may be relatively illiquid. We investigate the relative liquidity of the portfolios by examining the aggregate distribution of CRSP daily returns for the stocks which comprise the three JT portfolios. Figure 1 summarizes the results. First, we note that daily returns of exactly zero percent is quite common among NYSE/AMEX stocks. Over the sample period, zero return days occur on more than 20 percent of the trading days. Although not reported in the figure, we observe that zero return days are rare for large capitalization firms yet commonly occur for more than 50 percent of the days for small capitalization firms. Figure 1 shows that the number of zero return days is particularly large for the P1 portfolio with 30 percent of the daily return values at exactly zero.

Second, we find that the variation of non-zero returns is much greater among the P1 and P3 portfolio stocks than among the P2 portfolio stocks. Daily returns occur within the slightly positive 0 percent to 1 percent range at a rate of only nine percent for portfolio P1, 29 percent for portfolio P2, and 23 percent for portfolio P3. In general the frequency of small, but non-zero daily returns is relatively smaller and the frequency of large magnitude daily returns is much larger for the P1 and P3 portfolios. For example, daily returns occur within the 10 percent to 20 percent range at a rate of 5.2 percent for portfolio P1, 1.7 percent for portfolio P2, and 2.8 percent for portfolio P3. The pattern is similar for other large magnitude ranges. For the -10 percent to -20 percent range the pattern is similar with P1, P2, and P3 daily return frequencies of 5.3 percent, 1.3 percent, and 2.3 percent, respectively.

Conrad and Kaul's hypothesis. It may be that other better specified risk pricing models fully explain the observed patterns.

The pattern of high frequency zero returns, low frequency small-magnitude returns and high frequency large-magnitude returns is characteristic of market friction. With large trading costs, prices are sticky over time since trading friction prevents price updating. The delayed updating of such securities generates an illusion of abnormal return momentum which is fully explained by the costs of trading. We more formally motivate a friction-based explanation of relative strength returns in Section II.

II. A Model of Price Friction

In a market without friction, value-relevant information is instantaneously incorporated into market prices. The mechanism that disciplines market prices is arbitrage. Without trading frictions, costless arbitrage prevents market prices from straying from "fundamental values." The introduction of trading friction reduces the discipline of the arbitrage function, hampering the market's ability to process information. With constrained arbitrage pressure, the incorporation of information into market prices can be substantially delayed.

We motivate the effect of friction on price adjustment delay with a simple model. Consider a market with two sets of traders: arbitrageurs and liquidity traders. Liquidity traders have incomplete information and trade for liquidity needs and on noise, in the spirit of Black (1986). Arbitrageurs trade on informed signals of mispricing, yet only if the value of the accumulated information exceeds the transaction costs (Kyle, 1985; Amihud and Mendelson, 1986). Arbitrageurs have access to enough capital to dominate the price impact of liquidity traders.

In a frictionless market, the arbitrageur's model of expected trading returns is given as

$$\bar{r}(i,t) = \bar{r}^*(i,t) + e(i,t) \tag{2}$$

where $\bar{r}^*(i,t)$ is the expected return for asset i at time t based on the appropriate asset pricing model and $e(i,t)$ is a mean zero term that captures the information not yet revealed in the liquidity trader pricing sequence. The $e(i,t)$ term may also be interpreted as the expected gains from arbitrage. In a frictionless market, the no-arbitrage rule is stated as $e(i,t)=0$.

We now introduce trading friction into the market, defining $\alpha_1<0$ as the sell-side trading cost for asset i, $\alpha_2>0$ as the purchase side cost. We define $\bar{r}^A(i,t)$ as the after trading-cost arbitrage return to the informed arbitrageur, such that

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\begin{aligned}
&\bar{r}^A(i,t) = -e(i,t) + a_1(i) && \text{if } \varepsilon(i,t)<\alpha_1(i) \\
&\bar{r}^A(i,t) = 0 && \text{if } \alpha_1(i)<\varepsilon(i,t)<\alpha_2(i) \qquad (3)\\
&\bar{r}^A(i,t) = e(i,t) - a_2(i) && \text{if } \varepsilon(i,t)>\alpha_2(i).
\end{aligned}
$$

For each asset, the threshold for arbitrage on negative information is $\alpha_1(i)$ and the threshold for arbitrage on positive information is $\alpha_2(i)$. The arbitrageur makes trading decisions on the basis of the observable contemporaneous market-wide information and all "other "information. The "other" information may contain accumulated past market-wide and firm-specific information that has not yet been incorporated into the price. We assume that all information not contained in the contemporaneous market return is captured by the $\varepsilon(i,t)$ term.

With trading friction, the no arbitrage condition is adjusted to $\left|\bar{r}^A(i,t)\right| \le 0$.
Since arbitrageurs face transaction costs, this condition differs from classical models. The trading costs faced by arbitrageurs allow for assets to trade among liquidity traders across a valid range of prices. With large trading costs, price updating to ongoing news events may be substantially delayed as arbitrageurs are discouraged from moving prices.

The behavioral explanation of relative strength portfolio returns is that noise-trader capital dominates arbitrageur capital, such that abnormal performance can persist. The insufficiency of arbitrage capital provides the opportunity for systematic profit making through buying past winners and selling past losers. The alternative friction-based explanation is that transaction costs and other barriers[7] make arbitrage positions costly. The resulting friction in price adjustment produces the illusion of performance persistence when paper profits are bound by trading costs. We assert that the friction hypothesis merits greater attention. Proponents of momentum trading argue that such strategies produce abnormal profit opportunities for informed investors. Yet, claiming the existence of profit opportunity requires rejecting the friction hypothesis. We re-examine the friction explanation by considering whether trading costs are absolutely and cross-sectionally binding to relative strength investing returns. Specifically, we test firstly, whether trading costs exceed relative strength trading profits, and secondly, whether relative strength trading profits are increasing in trading costs. We begin with a discussion of an appropriate method for estimating trading costs.

III. Trading Cost Estimation

The literature provides a menu of trading cost estimation procedures for consideration. The first class of estimators measure the components of trading cost by examining transaction cost data directly. Stoll and Whaley (1983) and Bhardwaj and Brooks (1992) produce estimates of "spread plus commission" (S+C) costs by directly examining quoted market bid-ask spread data and prevailing commission schedules. Since trades frequently occur off the quoted prices and with variation in commissions charged, quoted measures are likely to be inaccurate (Lee, 1993; Peterson and Fialkowski, 1994; Seppi, 1997). As an alternative, a number of techniques produce "effective" or "realized" trading cost estimates by matching the quotes to the transaction

[7] Shleifer and Vishny (1997) argue that holding costs such as hedging costs and tracking error risk provide important barriers to arbitrage. Pontiff and Schill (2001) find empirical support for such holding risk barriers among new equity offerings.

record. Although these estimates may be in many ways superior to the quoted S+C approach, they are problematic for our purposes because (1) they still ignore substantial components of the total trading costs, such as price impact, commission, or short-sale constraints[8] and (2) current data limitations do not allow estimation of effective trading costs for the entire CRSP universe over our 1980 to 1998 sample period.

The second class of estimators indirectly infer trading costs based on price behavior. Roll (1984) proposes an estimator of implied bid-ask spread based on measuring the negative autocorrelation produced by bounces between the bid and ask prices. Although the Roll technique produces reasonable estimates using intra-day data for samples of large capitalization Nasdaq stocks (Schultz, 2000), the measure is again unsuitable for our purposes because the over 60% of large capitalization NYSE/AMEX stocks and over 35% of small NSYE/AMEX capitalization stocks experience positive serial correlation returns in violation of Roll's conjecture. This result is exacerbated for NASDAQ listed securities where over 65% of large capitalization stocks and over 40% of small capitalization stocks experience positive serial autocovariance. The disparity in the rejection rate of Roll's conjecture of negative serial covariance is largely due to the strong tendency for zero return days we observed among small stocks. Paradoxically, the lack of zero returns produces invalid Roll estimates for more liquid stocks.

Lesmond et al. (1999) provide an alternative indirect method for estimating trading costs based on earlier limited dependent variable (LDV) procedures by Tobin (1958), Rosett (1959), and Maddala (1983). The Lesmond et al. method is appealing for three reasons, (1) the estimator is consistent with the model of price friction presented in Section II, (2) it avoids the data limitations of the other approaches since it relies exclusively on daily return data which is readily available from CRSP, and (3) it generates as estimator which includes <u>all</u> relevant components of total trading costs. Although the LDV estimate (like the Roll method) uses an entirely different set of data

[8] Omitted trading cost components, such as price impact and short sale constraints, are particularly important for the small, off-NYSE type of securities involved in relative strength investing strategies. Knez and Ready (1996) find that because of the poor depth of small firm quotes, effective spread are actually generally wider for trades of any significance on small stocks.

and approach than the direct methods, Lesmond et al. find that their estimates are highly correlated with and of reasonable magnitude when compared with estimates using other approaches. Because of the noteworthy advantages of the LDV trading cost estimate, we focus on this approach and further discuss the estimation procedure in the next section.

A. *The LDV Estimate*

The maintained hypothesis is that arbitrageurs trade only if the value of the accumulated information exceeds trading costs. If trading costs are sizeable, then Lesmond et al. argue that zero return days occur more frequently since new information must accumulate longer on average before arbitrage capital affects prices. The higher the level of transaction costs the more zero return days are likely to occur.[9]

As a simple specification of the return-generating process, r*, they use the common "market model" regression of the raw daily return on security i and time t, r(i,t), on the return of market index, $r_M(t)$,

$$r^*(i,t) = b(i)\, r_M(t) + e(i,t)\,. \tag{4}$$

We follow the same approach. In equation 4, the stock's return is assumed to be generated by price responses to market-wide and new firm-specific information through the terms $b(i)r_M(t)$ and e(i,t), respectively. In a frictionless market, either index-wide or firm-specific information is immediately reflected in asset prices, regardless of the magnitude of the impact of the information.[10] As in equation 3, the transaction costs are

[9] This observation is consistent with that of Easley, Kiefer, O'Hara, and Paperman (1996) who observe that "on the NYSE it is common for individual stocks not to trade for days or even weeks at a time, while one stock in London never traded in an eleven-year period. One characteristic of such infrequently-traded stocks is their large bid-ask spreads."

[10] Cohen et al. (1983) and Amihud and Mendelson (1986) assume that actual returns are determined from "expected" returns by adjusting for the bid-ask spread. The market model is still valid, but only after transaction costs are exceeded.

modeled as α_1 for sell side and as α_2 buy side purchases. Otherwise, the actual return is modeled as zero.

We can use equation 3 and 4 to form an econometric model. Assuming that returns are normally distributed, estimates of α_1 and α_2 are obtained by maximizing the following log-likelihood function,

$$\begin{aligned}\ln L = \quad & \sum_{R_1} \ln \frac{1}{\left(2\pi\sigma(i)^2\right)^{1/2}} - \sum_{1} \frac{1}{2\sigma(i)^2}\left(r(i,t) + \alpha_1(i) - b(i)r_M(t)\right)^2 \\ & + \sum_{R_2} \ln \frac{1}{\left(2\pi\sigma(i)^2\right)^{1/2}} - \sum_{2} \frac{1}{2\sigma(i)^2}\left(r(i,t) + \alpha_2(i) - b(i)r_M(t)\right)^2 \\ & + \sum_{R_0} \ln\left(\Phi_2(i) - \Phi_1(i)\right)\end{aligned} \tag{5}$$

where R_1 and R_2 denote the region where the measured return r(i,t) in the non-zero negative and positive regions, respectively, and $r_M(t)$ is the return to market portfolio on day t. The other parameters b(i) and $\sigma(i)^2$ represent the respective market risk beta estimate and the variance of the non-zero measured returns. The first term corresponds to the negative market returns and second term corresponds to the positive market returns of equation 3. The third term corresponds to the zero-return region that spans both positive and negative market returns.

The sensitivity of the asset's dollar value to the general information environment is $b(i)r_M(t)$. If $\alpha_1 < br_M < \alpha_2$ then the observed dollar value of the security trading volume represents noise trading where the positive and negative market returns that span this liquidity trading region are consequently defined as $\frac{\alpha_1}{b} < r_M < \frac{\alpha_2}{b}$. The estimate of interest is the difference between $\alpha_2(i)$ and $\alpha_1(i)$, which represents the implied round trip trading costs for asset i. We denote this estimate as, α_2-α_1. Since this difference is an estimate of investors' reservation returns, it includes all explicit and implicit trading costs (Keim and Madhavan, 1998).[11]

Using the maximum likelihood formulation of equation 5 we estimate parameters, $\alpha_1(i)$, $\alpha_2(i)$, b(i), and $\sigma(i)$, simultaneously following Lesmond et al. with a Marquardt-Lavenberg iteration procedure and a finite difference approximation for the Jacobian. This requires using one year of daily returns for each stock that comprise our portfolio. Returns are obtained from the CRSP daily master file. For each semi-annual period we estimate the transaction costs using the returns up to one week before the portfolio performance period so as not to contaminate the estimation results with performance results. Thus, for a portfolio performance period that began on January 1, we estimate the trading costs for each firm individually from January 1 to December 24 of the prior year. For a portfolio performance period that began on July 1, we estimate the trading costs from June 30 of the prior year to June 24 of the year of the performance evaluation again maintaining a separation of one week between the estimation and performance periods.[12] We use the equally weighted market return to measure market-wide

[11]Lesmond et al. (1999) argue that any bias due to misspecification of the return generating model is netted out in the LDV estimate. "The intercept term usually included in the market model is now subsumed by transaction cost intercept terms. The intercept in the market model normally captures any misspecification in the market index that may not be mean-variance efficient. Thus any difference in the alphas across assets may simply be due to an inefficient mean-variance market index and not transactions costs. Since we are interested in the difference of the α_2-α_1 to determine the round-trip transaction costs, any effect of model specification on the transaction costs is very small. We verified this by running a simulation using a benchmark that was likely to be inefficient. We constructed a benchmark portfolio that was composed of securities based on size decile. For securities in each decile we used a mismatched benchmark that was composed solely of stocks in another decile at the opposite extreme. For example, decile 10 securities were grouped in decile 1, size decile 9 securities were grouped into decile 2, etc. We then estimated the transaction costs with the LDV model using this misspecified benchmark. For comparison purposes, we used the equally weighted index as a more "proper" benchmark. We found that the LDV estimates of α_2-α_1 were different in the third decimal place regardless of size decile. Thus we do not believe the results are sensitive to the choice of a broad market index" (p. 1120). We have further tested this claim and found that the $\alpha_2-\alpha_1$ estimates also appear to be immune to the addition of alternative factors. For example, the addition of a daily Fama and French (1993) SMB factor in the LDV model has a negligible effect on the $\alpha_2-\alpha_1$ estimates. We solved algebraically for the LDV model omitted factor bias in the $\alpha_2-\alpha_1$ estimate and found that it is offset by two countervailing terms. A detailed discussion of our analytical and empirical testing of the LDV model is available by request.

[12] Since the returns used to generate the relative strength portfolios (months t-6 to t-1) overlap with those used to estimate the $\alpha_2-\alpha_1$ values (months t-12 to t-1), the LDV estimates of the respective portfolios may be biased in some way. To test for any bias, we estimate the LDV model using returns for the year prior to the measurement period (months t-18 to t-6). The estimates are virtually unchanged. Using the lagged estimation period appears to make little difference on the LDV estimates.

information because of the equal weight each firm receives in our portfolio formation procedure.

Figure 2 provides a histogram of the α_2-α_1 estimates of round-trip trading costs for each firm period. The frequency distribution is highly skewed with estimates most commonly found between two and four percent, but with almost eight percent of the estimates greater than 20 percent. The sample mean α_2-α_1 is 8.1 percent while the median is 5.1 percent. Stated otherwise, arbitrageurs are not willing to take positions on most stocks unless the expected abnormal returns are greater than five percent. Our estimates appear to be consistent with the magnitude and distributions characteristics of Lesmond et al. estimates. We compare our findings to that of other studies in the next section.

B. Other Trading Cost Estimates

Traditional trading cost estimates are associated with large cross-sectional variation (Bessembinder, 1999). For large capitalization stocks, round-trip trading cost estimates are generally between one and two percent over our sample period; however, for small capitalization stocks, the estimates are much larger at five to nine percent (see Stoll and Whaley, 1983; Kothare and Laux, 1995; Knez and Ready, 1996; Chan and Lakonishok, 1997; and Keim and Madhavan, 1998). Jones and Seguin (1997) find that the mean bid-ask spread for all Nasdaq stocks is 12 percent and 18 percent for small Nasdaq stocks. As a point of reference, we compare the $\alpha_2 - \alpha_1$ estimates to those of other standard trading cost estimation procedures: the quoted spread-plus-commission estimate, the Roll estimate, and the effective spread estimate.

We obtain quoted spread-plus-commission estimates similar to those used by Stoll and Whaley (1983) and Bhardwaj and Brooks (1992). To obtain these estimates, we use the NYSE's Trades and Quotes (TAQ) database to provide quoted spread estimates for the 1994 to 1998 sample period.[13] The end-of-month bid-ask quote is tabulated for each firm over each annual trading period to produce 12 bid-ask quotes that are averaged to produce an annual spread measure. This annual spread measure is tabulated on proportional basis and is defined as,

$$Spread(i,t) = \frac{1}{12}\sum_{t=1}^{12}\left\{\left(Ask(i,t) - Bid(i,t)\right)/\tfrac{1}{2}\left(Ask(i,t) + Bid(i,t)\right)\right\}. \quad (6)$$

The commission schedule is determined using the discount brokerage schedule from CIGNA financial services that is a standard (broker-assisted) commission schedule and reflects competitive commission rates for our sample period.[14] The principal amount is calculated using information from the NYSE, AMEX, and NASDAQ fact books as to the average trade size (in shares) for each year from 1994 to 1998. TAQ data is unavailable prior to 1994. For comparison purposes the average trade size in 1998 is 1,063 shares, 2,334 shares, and 1,236 shares, respectively for the NYSE, AMEX, Nasdaq. Thus the principal amount is determined using the share price multiplied by the average trade size of the listing market. Summing the spread and commission estimates yields the S+C estimate of representative trading costs experienced by investors in each security for each year.

[13] We choose to compare the LDV estimate to the quoted spread estimate because of the difficulty in estimating spreads for a wide cross-section of stocks. Traditional effective spread estimation techniques are generally applied only to a small sub-sample of more liquid stocks, not the entire CRSP universe.

[14] The commission schedule is as follows:

Transaction Amount	Commission
$0-$2,500	$29 +1.7% of Principal Amount
$2500.01-$6,250	$55 +0.66% of Principal Amount
$6,250.01-$20,000	$75 +0.34% of Principal Amount
$20,000.01-$50,000	$99 +0.22% of Principal Amount
$50,000.01-$500,000	$154 +0.11% of Principal Amount
$500,000+	$254 +0.09% of Principal Amount

For stocks under $1.00 per share the commission rate is $38 plus 4% of principal. The overriding minimum commission is $38 per trade. Although the magnitude of the commissions in this schedule may appear high with respect to the on-line commission rates offered in the later part of the sample period. We use the schedule to be consistent with that of those using this method in the literature by using the average commission rate charged over the sample period. We do find, however, that our conclusions are robust to excluding commission costs entirely. Also, the use of a commission schedule for Nasdaq firms may overstate the true commission costs experienced by trading individuals as the Nasdaq listed firms sometimes lump commissions costs into the spread (Plexus Group). Thus, for some firms we may be overstating the quoted costs for trading in those securities.

To provide a comparison with other commonly used transaction costs measures, we provide estimates using the Roll (1984) methodology. To implement this approach, we use one year of daily security returns identical to that used to estimate the LDV model's estimate of transaction costs. All Roll estimates from a return series with positive serial autocovariance are ignored. Ignoring those stocks that violate Roll's conjecture does not bias our findings as we primarily retain the less liquid stocks.[15] Using only these cases provides the best estimates for the Roll model and a convenient comparison with the LDV model's results consistent with our primary hypothesis of a friction effect centered on small stocks.

To complete the alternative transaction cost comparison, we examine the "effective spread" defined as twice the absolute value price deviation from the bid-ask midpoint. The effective spread is estimated for the closing trade price and last quote of the day. We infer the trade direction using the following algorithm roughly based on the Lee and Ready (1991) procedure. If the trade price is greater than the midpoint of the quote then the trade is classified as a buy. If the trade price is less than the midpoint of the quote then the trade is classified as a sell. If the trade is at the midpoint then the effective spread becomes zero. Due to the sheer enormity of processing intra-day data over such a large cross-section and times-series, this is accomplished for the entire sample period using only the last day in December for each year.

The correlation between the LDV estimate and the other trading cost estimates is relatively high. For the NYSE/AMEX stocks, correlation coefficients between the LDV estimates and the quoted S+C measure, the Roll spread measure, and the effective spread measure are respectively, 0.88, 0.78, and 0.51. The correlation is even higher when NASDAQ stocks are included with respective correlations of 0.90, 0.73, and 0.60. The high correlation between the two very different approaches is consistent with Lesmond's (1995) findings.

[15] However, Lesmond (1995) shows that using only those firms with negative serial autocovariance (i.e. obeys Roll's conjecture), the LDV model's estimates are still more highly correlated with the quoted bid-ask spread than the Roll model estimates.

In Figure 3, we compare the annual mean round-trip trading cost estimates over the sample period for all NYSE/AMEX/NASDAQ stocks in size class 2 and 5. Both the LDV measure and the S+C quotes are similar in pattern and magnitude. The figure illustrates both the time-series and cross-sectional variation in trading costs. For size class 2, the α_2- α_1 estimate remains between eight and 16 percent while the S+C estimates are consistently slightly larger. For the larger firms, the mean α_2-α_1 estimate declines from six percent to almost two percent. Again the S+C estimate is slightly greater. The expected relationship between the LDV and S+C estimates is unclear. The S+C estimate certainly overstates the effective spread and commission facing marginal arbitrageurs, but omits other important costs such as taxes, price impact, and short-sale constraints. The Roll spread and effective spread measures are, as predicted, well below (about half) the LDV and S+C estimates. The cross-sectional and time-series variation in trading costs emphasizes the importance of matching the trading strategy's asset specific characteristics when estimating the appropriate trading costs. We turn to this process in the next section.

IV. Do Relative Strength Portfolio Returns Exceed Trading Costs?

We test the magnitude of our trading-cost estimates by comparing the average gross P3-P1 returns for various momentum strategies to the respective transaction cost estimates. By the friction hypothesis, relative strength returns must not exceed the respective expected transaction costs. In Panel A of Table 2, we report the mean α_2-α_1 trading cost estimate for the semi-annual holding period. We repeat the P1, P2, P3, and P3-P1 estimates from Table 1 for reference ease. For the JT strategy, investors in the long position face 5.9 percent of cost from P3 to generate six-month returns of 9.8 percent. For the short position, investor face 7.7 percent of cost from P1 to generate six-month returns of 4.3 percent. In aggregate, the strategy generates net P3-P1 profits of 5.5 percent at a considerable estimated combined α_2-α_1 cost of 13.6 percent. As a point of comparison, we provide the mean S+C estimate for the semi-annual strategy. The S+C approach generates a mean direct trading cost estimate of 16.3 percent for implementing the momentum strategy. Since the S+C source data is limited, the 16 percent S+C estimate is based only on the latter part of the sample period and so is not directly comparable to the 14 percent α_2-α_1 estimate. To provide a comparable statistic, we also report the mean α_2-α_1 estimate for the same period (1994-1998). The α_2-α_1 estimate for the P3-P1 strategy is 12.2 percent. Given the trends observed in Figure 3, the decline of the α_2-α_1 estimate in the later period is expected. We observe that the α_2-α_1 estimate is consistently below the S+C estimates. All four α_2-α_1 trading cost estimates are below the respective S+C estimates when compared with the same sample period. As an additional reference estimate we provide the mean Roll spread and effective spread estimates for portfolios P1, P2, and P3. We find that mean 5.5 percent P3-P1 returns are approximately the same as the total Roll spread and effective spread costs of 6.3 percent and 4.9 percent, respectively. Because of the relatively large spreads associated with the P1 portfolio, relative strength strategy returns do not appear to even exceed bid-ask spread costs. The pattern is even more extreme for the HLS strategy. Trading profit returns of 3.7 percent are associated with an α_2-α_1 cost of 18.8 percent. The trading cost estimate rises substantially due to the inclusion of less liquid NASDAQ stocks. Again, trading costs swamp the relative strength returns. Even the Roll spread and effective spread estimates of 7.0 and 8.3 percent, respectively, exceed the anticipated trading profits.

Since the standard momentum strategy requires four trades (opening and closing the position in two sets of securities), the average one-way LDV trading cost estimate is 3.4 and 4.7 percent, respectively, for the JT and HLS strategies. The magnitude of this trading cost estimate is much larger than previous estimates of relative strength strategy trading costs. For example, JT base their trading cost estimate of one percent on Berkowitz et al. (1988). We argue that such transaction cost estimates substantially underestimate the true execution costs for a number of reasons. First, the Berkowitz et al. estimate excludes a number of relevant and important trading costs facing investors such as bid-ask spread, taxes, short-sale costs, and holding period risk. By comparing trading profits to commissions and price impact costs only, JT portray a false sense of net profitability. Second, a constant or single period measure is unable to capture the substantial time-series variation in trading costs (Lesmond et al., 1999). The Berkowitz et al. measure is based solely on transaction data from January to March 1985. Third, since trading costs exhibit substantial cross-sectional variation, using a NYSE trade-weighted measure is not appropriate as a benchmark if the securities used in such strategies are disproportionately drawn from among large trading cost stocks as suggested by Table 1 and Figure 1. To investigate the cross-sectional trading cost characteristics of our portfolio composition, we contrast the trading costs of portfolios P1 and P3 with that of P2. We observe large differences in α_2-α_1 trading cost estimates across portfolios. For the JT strategy, portfolios 1 and 3 exhibit mean trading costs estimates of 7.7 and 5.9 percent, respectively. Portfolio 2's mean estimate of 3.5 percent is more representative of stock trading costs since it includes 80 percent of all stocks, yet the costs are significantly lower than that of relative strength portfolio stocks. For the HLS strategy, portfolios 1 and 3 exhibit mean trading costs estimates of 10.6 and 8.2 percent, respectively, where as portfolio 2's mean estimate is just 6.3 percent. The pattern is similar for the quoted S+C, Roll spread, and effective spread measures. The composition of the trading portfolios and particularly portfolio 1 is made up of stocks that are relatively more costly to trade. The extraordinary high trading cost observed for relative strength strategies results from both the high trading frequency of strategy execution as well as the costly nature of the specific securities traded.

Our estimates assume that relative strength traders liquidate their positions in each period. Since next period's strategy may result in the same position for some stocks, the trader can avoid incurring unnecessary trading cost by maintaining the position in those stocks into the next period. To provide some measure of the potential savings, we report the mean fraction of stocks which remain within the same portfolio in sequential periods. If subsequent performance is independent of past performance, we expect the retention proportions to be equal to the breakpoint percentiles, 10 percent or 30 percent. If subsequent performance is correlated with past performance, we expect the retention proportions to be greater than the breakpoint percentiles. We find portfolio persistence to be strongest among the poor performers. For the P1 portfolio, 22 percent of the worst performing 10 percent of NYSE/AMEX stocks continue to be among the worst 10 percent in subsequent periods and 38 percent of the worst 30 percent of NYSE/AMEX/NASDAQ stocks continue to be among the worst 30 percent in subsequent periods. Within the P3 portfolio, the retention proportion is 14 percent and 32 percent, respectively for the JT and HLS strategy, not much greater than through random shuffling. If the arbitrageur can avoid 22 percent of his P1 trading cost and 14 percent of his P3 trading cost, the expected total JT strategy cost falls from 14 to 11 percent, still well above the mean abnormal return of 5.1 percent. The effect of trade conservation is similar for the HLS strategy.

HLS suggest that investors can generate abnormal profits by pursuing relative strength trading among the mid- to small-size firms. We repeat their experiment. At the beginning of each period, we sort all CRSP listed stocks by market capitalization and group them into size-based quintiles based on NYSE/AMEX breakpoints. Market capitalization is measured six months prior to portfolio formation so that the past six months' performance does not affect firm classification. Size class 1 contains the smallest firms and size class 5 contains the largest firms. Within each class, we sort stocks by past period return performance using the 30-70 breakpoints. Within the size sub-samples, we compute the P3-P1 momentum profits. We report our results in Panel B. Consistent with HLS, size class 2 generates P3-P1 returns of five percent and size class 5 generates P3-P1 returns near zero.

The friction-based explanation predicts that strategies which purport larger paper profits are accompanied with larger trading costs. To begin, for each size class we report the mean proportion of zero-return trading days. For the smallest size class, there is no close-to-close price change in 44 percent of the trading days. Among the largest stocks, the zero returns occur on only 13 percent of the trading days. This evidence is consistent with increased trading friction among the smaller stocks. We also report mean trading cost estimates by size class. Trading cost estimates include round trip costs for portfolio P3 plus roundtrip costs for P1, $(\alpha_2\text{-}\alpha_1)_3+(\alpha_2\text{-}\alpha_1)_1$. The total round-trip transaction cost estimates for size classes 1 through 5 are respectively, 30.9, 13.1, 8.6, 6.1, and 4.8

percent. The P3-P1 profits of 1.4, 5.3, 4.2, 2.9, and -0.2 percent, respectively, decrease with the trading cost values, yet remain well below the α_2-α_1 estimates. Strategies which focus on classes of stocks with high expected momentum profits such as size class 2 with P3-P1 of 5.3 percent, also face high trading costs of more than 13 percent. The quoted S+C, Roll spread, and effective spread estimates and the portfolio retention figures are again provided with similar conclusions. The effective spread estimates, for example, decline from 15 percent for the smallest stocks to one percent for the largest stocks.

Lee and Swaminathan (2000) identify a relationship between share turnover and momentum returns. They also reject the friction hypothesis in favor of behavioral models.[16] We follow their approach by sorting stocks into turnover class based on the mean shares traded divided by the number of shares outstanding over the six months prior to the measuring period. Matching their approach we exclude from this analysis stocks not traded on the NYSE or AMEX (due to broker-to-broker trade recording problems with Nasdaq data) or stocks selling at pre-holding period share prices of less than one dollar. Within each size class we form performance portfolios as before and compute mean returns over the six-month holding period. The results are reported in Panel C. Across turnover classes the P3-P1 returns increase from -1.8 percent to 6.1 percent. Yet, the large P3-P1 return for turnover class 5 is still less than the aggregate trading cost estimate of 8.0 percent. Lee and Swaminathan suggest that relative strength returns are greater for a long position in low volume winners and a short position in high volume losers. In our smaller sample period the advantage of such cross position is not large. The mean P3(turnover class=1)-P1(turnover class=5) returns are only 6.2 percent. Estimates of trading costs are even larger for the cross-position strategy.[17]

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[16] Lee and Swaminathan assert that turnover and transaction costs are not highly correlated suggesting that turnover provides information about something other than market liquidity. Chordia, Subrahmanyam, and Anshuman (2000), however, find that turnover and market liquidity are highly correlated, and in fact, use turnover as a proxy for liquidity. We find correlation coefficient between Lee and Swaminathan's turnover measure and the LDV and S+C estimates to both be significant at -0.168 and -0.254, respectively.

[17] Lee and Swaminathan recommend a trading strategy that uses eight trades. Four trades in both high and low turnover stocks for the strong performer portfolio and four trades in both the high and low turnover stocks for the weak performer portfolio. Such a strategy roughly doubles trading costs with little effect on returns.

The evidence for positive trading profit net of transaction costs appears to be weak. The magnitude of trading costs, particularly for those firms which play an important role in generating abnormal performance, appears to be sufficiently large such that realizing net trading profits is illusive. Given the magnitude of transaction costs, we see little evidence to suggest that momentum strategies generate systematic positive trading profit across the variety of strategies we have examined.[18] Although we observe that trading costs exceed the magnitude of the relative strength returns for the specific strategies we consider, there is an infinite number of momentum-oriented strategies to evaluate so we can not reject the existence of trading profits for all strategies. Moreover, the lack of comprehensive daily return data prohibits us from directly estimating the specific trading costs associated with the longer sample period used by JT or Moskowitz and Grinblatt (1999). However, given the magnitude of the estimates in Table 2, the three to six percent semi-annual return generated by these strategies does not appear to be extraordinary given the likely trading costs required for implementation.

V. Are Relative Strength Returns an Information Diffusion Effect?

In this section, we examine the source of the underlying "momentum" pattern in stock returns. We focus particularly on the implications of the Hong and Stein model because of its cross-sectional predictions.[19] Hong and Stein advocate that relative

[18] Grundy and Martin (2001) report that momentum strategy profits are no longer statistically significant with round-trip transaction costs of 1.5 percent. Our evidence suggests that trading costs are substantially larger.

[19] Lee and Swaminathan (2000) find that relative strength returns are increasing in share turnover. We devote more space to the Hong and Stein implications because of their stronger theoretical motivation. We abridge our findings regarding the Lee and Swaminathan results in this footnote. We use our previous turnover class specification to compare relative strength returns across turnover and trading cost class. In unreported results, we find that controlling for turnover, P3-P1 returns are generally increasing in trading cost, especially for the higher turnover classes of stocks. For the highest turnover class, the lowest transaction costs stocks experience a 1.4 percent return while the highest transaction costs stocks experience a 7.3 percent return. Similar results are obtained for share turnover classes 3 and 4 with returns increasing in the transaction costs. The rise in P3-P1 returns is more pronounced for turnover class 4 than for turnover class 5 and much more pronounced than for turnover class 3. Turnover class 3 stocks do experience a monotonic rise in P3-P1 returns, but the rise in return are much less extreme than that experienced for turnover classes 4 and 5. The results for turnover classes 1 and 2 demonstrate little monotonicity in P3-P1 returns with negative returns realized, -1.4 percent in transaction costs class 2 and -6.3 percent in the highest trading cost class for share turnover 1. Peak returns are experienced in trading

strength returns are explained by sluggishness in the diffusion process of information rather than by friction in price formation. Because of the information sets used by investors to evaluate asset prices, assets with slow information diffusion experience slow price arrival. To test the information-diffusion theory, HLS choose size and coverage as proxies for information diffusion speed, suggesting that small, thinly covered stocks should experience slow information diffusion. Their results are consistent with their predictions.

Our concern with this inference is that the HLS findings may also be consistent with the friction hypothesis. Firstly, the size of market capitalization of a stock is certainly correlated with its share price. Because percentage trading costs are inversely related to share prices, trading costs for small-cap stocks are typically higher than for trading costs for big-cap stocks. The friction explanation suggests that price updating is slower for high cost stocks, resulting in some serial correlation of returns. HLS acknowledge the inference problems that arise due to the correlation between size and transaction costs. Their choice of the coverage proxy attempts to avoid this problem. They claim that coverage is uncorrelated with transaction costs, but only weakly test this important assumption.[20] We provide a more rigorous test. Our objective is to test the source of the underlying "momentum" phenomenon. We investigate whether return patterns are more consistent with an information diffusion story or with a friction-based explanation.

To distinguish between the two theories, we re-examine the HLS cross-sectional evidence incorporating our transaction-cost estimates. We begin by replicating their size

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cost classes 3 and 4. However, none of the returns exceed the transaction cost estimates enhancing the central premise of our no-arbitrage hypothesis. The lack of monotonicity in P3-P1 returns may be a feature of how share turnover is defined: trading volume divided by firm size. Low turnover stocks may simply proxy for low trading volume relative to high share price with high share price stocks exhibiting less of a trend with transaction costs due to a reduced transaction costs effect. The opposite is true for high turnover stocks where higher trading volume coupled with a lower share price enhances the trend with P3-P1 returns and transaction costs.

[20] In fact, analyst coverage has been used as a proxy for transaction costs (Brennan and Subrahmanyam, 1995). HLS do test their assumption using alternative transaction-cost proxies: turnover and option listing. We expect these measures are rather noisy proxies.

and coverage portfolio results and then comparing the cross-sectional effect of the variables on relative strength profits.

A. Cross-sectional Correlation

As an initial test, we examine the correlation between our trading cost estimates and the HLS information diffusion speed proxies. The HLS findings may be consistent with the friction hypothesis if firm trading costs are negatively correlated with the selected information-diffusion proxies. In Table 3 we provide cross-sectional correlation coefficients between size, coverage, and trading cost. Following HLS, we exclude size class 1. All estimates are log transformed to reduce the effect of skewness.

As with HLS, our data on analyst coverage comes from the I/B/E/S Historical Summary File which is available on a monthly basis beginning in 1976. For each security in our sample we set the coverage to the number of analysts who provide fiscal year one forecasts six months before we implement our trading strategy. Thus, for a trading strategy that begins in June, we use the number of analysts making fiscal year one forecasts in December of the prior year.[21] If no analyst coverage is available from I/B/E/S we set the analyst coverage to zero. We use the I/B/E/S provided ticker symbol which is converted to the "true" ticker symbol along with the CUSIP number provided by I/B/E/S to uniquely identify each firm six months prior to the performance evaluation period. We are unable to uniquely identify approximately 0.5 percent (approximately 600 firms-years) of the I/B/E/S firms due to missing ticker symbols on CRSP or CUSIP numbers that do not match those of CRSP. Comparisons of our data to the summary statistics of HLS suggests that our data sets are nearly identical.[22] As in HLS, we find strong positive correlation of 0.67 between coverage and size. The high correlation

[21] HLS note that the coverage results are robust regardless of exactly when the analyst coverage is measured. They experimented with zero (as is our case), 12, and 18 months prior to the ranking period and obtain very similar results.

[22] To be certain that our results are not driven by differences in data, we replicate the summary statistics of HLS's Table III. We find that the two data set are very similar. Our data set contains slightly more firms.

between size and coverage motivates HLS's residual coverage measure which is the error term obtained from regressing the number of analysts on firm market capitalization and a Nasdaq listing dummy within each size class and period. We generate the same variable (Residual coverage).

We find that all three information diffusion proxies, size, coverage, and residual coverage, are significantly negatively correlated with our four trading cost estimates with correlation coefficients ranging from -0.68 to -0.11. The sign and magnitude of the correlation coefficients between the trading cost estimates and the information-diffusion proxies are such that the HLS variables may just be picking up trading cost effects. If residual coverage is correlated with trading costs, it is unclear whether coverage proxies for information diffusion speed or trading costs. We also report correlation coefficients with a residual α_2-α_1 estimate which removes the size effect. This estimate is obtained by regressing α_2-α_1 on firm size and a Nasdaq dummy within each size class and for each period in the same manner as for coverage. Still we find significant correlation between the coverage estimates and that of residual α_2-α_1. The correlation coefficient between residual coverage and residual α_2-α_1 is significant at -0.18.

The strong negative correlation between trading costs and the information diffusion speed proxies call into question the legitimacy of the Hong at al. inferences. From their findings, it is difficult to distinguish whether returns decline in information diffusion speed or they increase in transaction costs.

B. Size Effects

HLS propose that (P3-P1) momentum profits are inversely related to market capitalization. They attribute this pattern to the information diffusion model proposed by Hong and Stein (1999). HLS predict that firms with slower rates of information

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For example, HLS list 5935 firms in 1988 whereas our data set includes 6047. HLS report that 50 percent of their firms are covered by I/B/E/S in 1988. Our figure is slightly less with 46 percent.

diffusion, such as small capitalization stocks,[23] will exhibit greater momentum. They find that beyond the smallest stocks, momentum profits become strongly positive and then diminish to zero as one increases the size of the firms used in the strategy. They argue that the unexpected negative momentum observed for the smallest class of stocks is due to the thin market capacity or price discreteness characteristic of the tiniest stocks and can be ignored.

Panel B of Table 2 provides the size-based sorting procedure of HLS. As in HLS, the relative strength returns exhibit a decreasing pattern. Across size classes, semi-annual returns are 1.4 percent for the smallest size class. Relative strength returns among the medium size classes are strongly positive with mean returns of 5.3 percent, 4.2 percent, and 2.9 percent for classes 2, 3, and 4, respectively. Relative strength returns are much smaller among the largest firms with a sample period point estimate of -0.2 percent.

C. Share Price Effects

Since market capitalization is a function of market price, it may be that the pattern for relative strength returns observed across size classes is more precisely a price effect rather than a size effect. To test this implication, we sub-divide the size sub-samples into 5 price classes. Within each size class, we classify firms based on price level six months prior to portfolio formation. The five categories are in increasing order: under $5, between $5 and $10, between $10 and $20, between $20 and $30, and over $30.[24] Each of the 25 size/price groups is further divided into the three performance portfolios as before. Momentum profits (P3-P1) are calculated for each of the 25 classes across the 19 year sample period using the semi-annual holding period. Results are provided in Table 4. Since there are few firms with large market capitalization and low stock price and vice versa, the estimates for these portfolios may be poor. Portfolio returns and associated

[23] If investors face fixed costs of information acquisition, Hong and Stein (1999) and HLS suggest that information will diffuse faster for those larger firms among which their effort affords them to take greater positions.

statistics are invalidated for portfolios with less than ten stocks and statistics for groups with less than 10 valid period observations are not reported.

Controlling for price class, there appears to be little consistency in the return pattern across size classes. Only price class 2 shows the decreasing pattern prescribed by HLS with P3-P1 returns peaking with a small size class. Peak returns for price class 3, 4, and 5 occur with the size class 3 and 4, much larger than predicted by the information-diffusion model. The integrity of the size level patterns appears weak.

It is also worthwhile to examine the total variation across price class keeping size class constant. The evidence in Table 4 suggests that the variation in momentum profits is relatively small across size classes once adjustments are made for price. Within price class 2, P3-P1 profits are all between 6 and 10 percent across the size classes. For price class 5, P3-P1 profits range from -1 to 3 percent. The total variation and monotonic pattern of P3-P1 appears to be much stronger across price class than size class. For example, across size class 3, the ascending price class momentum portfolio return estimates are respectively, 22.7 percent, 7.8 percent, 6.1 percent, 3.4 percent and 2.6 percent. Across price class 3, the ascending size class return estimates are respectively, 4.0 percent, 4.9 percent, 6.1 percent, 5.5 percent and 0.6 percent. The P3-P1 estimates for the low price classes are nearly always consistently larger than that of the high price classes, with much greater cross-sectional variation in returns. Relative strength investing returns appear to be much more a price effect than a size effect. Since share-price level is strongly inversely correlated with trading costs, such as bid-ask spread (Demsetz, 1968; Stoll and Whaley, 1983), the relative strength returns appear to be more likely related to trading costs than information diffusion.

D. Coverage Effects

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[24] Bhardwaj and Brooks (1992) use a slightly different price classification scheme. We prefer our breakpoints due to the increase in cross-sectional variation. We repeat our tests with the Bhardwaj and Brooks breakpoints and find little substantive change in the implications.

To further test the explanatory power of analyst coverage, we estimate relative strength profits across analyst coverage classes. HLS find that controlling for size effects, relative strength profits are decreasing in coverage. We repeat their experiment. We sort all firms within size classes 2 through 5 by residual coverage and form coverage classes based on breakpoints at the 30th and 70th percentiles. Across the 3 by 4 matrix we construct relative strength portfolios as before and report the associated P3-P1 profits in Panel A of Table 5. As HLS, we find that relative strength profits generally decline in residual coverage, with some exceptions for the largest size classes. Our data set replicates the findings of HLS Since residual coverage is negatively correlated with estimates of trading costs, the results are also consistent with the friction hypothesis. In order for the information diffusion proxies to be convincing they must provide explanatory power beyond that provided by trading costs.

As the information-diffusion model predicts that relative strength returns are decreasing in information-diffusion speed, the friction hypothesis predicts that relative strength returns are increasing in trading costs. To control for trading costs we re-sort the stocks in Panel A by their α_2-α_1 estimate each period and form five equal trading cost classes. Mean $(\alpha_2-\alpha_1)_1+(\alpha_2-\alpha_1)_3$ estimates vary from 2.7 percent for class 1 to 19.0 percent for class 5 and are reported in Panel B of Table 5. We form trading-cost-based relative strength portfolios and compute the P3-P1 returns. We find the estimates to be generally increasing in trading-cost estimate. P3-P1 profits are respectively 3.8, 2.7, 4.6, 5.4, and 6.7 percent, respectively for classes 1 through 5. The positive relationship between trading costs and returns is consistent with the friction hypothesis. Also, consistent with the implications of the friction hypothesis, all of the P3-P1 estimates are less than the mean trading cost estimates.

To compare the explanatory power of residual coverage with that of our α_2-α_1 estimates, we form residual coverage portfolios which control for trading cost. Within each size and α_2-α_1 class, we compute breakpoints at the 30th and 70th percentile and form residual coverage classes. We compute the P3-P1 estimates for each class. The revised results are reported in Panel B. After controlling for trading costs, residual coverage appears to provide little explanatory power. We find that relative strength returns for firms among only the largest trading costs (class 5) are decreasing in residual coverage. Otherwise, there is little return relationship across coverage class. We find little evidence to reject the friction hypothesis in favor of the Hong and Stein explanation. Scanning across the residual coverage classes the returns tend to increase in trading cost. Except for the large profits generated in the residual class 1, trading cost class 1 cell, the P3-P1 returns within each coverage class rise with trading costs.

E. Information Diffusion Asymmetry and Trading Cost Asymmetry

HLS predict and find asymmetry in the returns from relative strength positions. However, such asymmetry in returns is also consistent with the implications of transaction costs. Diamond and Verracchia (1987) and Alexander (2000) discuss how short positions are particularly costly. For example, borrowing costs and margin requirement costs are greater for short versus long positions. Short sellers face risks of premature short-squeeze repayment. Some stocks may be shortable only at high cost. All of these factors make classic relative strength strategies (short weak performers and long strong performers) particularly costly on the short side. D'Avolio (2001) finds that stocks that have experienced past weak performance are more likely to maintain larger short sale costs. A testable implication of this institutional feature is to expect that the relative strength returns be greater for weak performers (the short position) than for strong performers (the long position).

We calculate the ratio of P2-P1 mean returns divided by P3-P1 mean returns. This ratio measures the proportion of total returns which is due to the short position. Consistent with HLS, the ratio for our sample is greater than 0.50 at 0.66. HLS attribute the asymmetric nature of relative strength returns to asymmetries in news publication. We argue that the increased returns found in weak performers may alternatively be due to the increased costs associated with short positions. These increased costs allow greater mispricing to persist for securities which are overpriced rather than underpriced.

To test this implication, we compute the mean period LDV estimates α_1 and α_2. Since α_1 is the trading cost estimate for price declines and α_2 is the trading cost estimate for price increases, we can compare the relative magnitude of the two estimates to determine whether return behavior implies an asymmetry in trading costs. We do this by computing the proportion of total roundtrip costs $(a_2 - a_1)$ that are represented by the sell-side costs $(-a_1)$. The proportion is calculated as $-a_1/(a_2 - a_1)$. The estimate for the full sample is 0.54. Although not much larger than 0.50, our trading costs estimates exhibit some asymmetry.[25] The price decline reservation point estimate is systematically below the price increase point. These findings give further evidence against rejecting the friction hypothesis since market friction is likely to be greater for price declines than price increases.

VI. Concluding Remarks

The documentation of abnormal return anomalies has generated considerable support for the abandon of traditional rational-expectations-based asset pricing models in favor of behavioral-based explanations. This reaction may be premature. We find that the returns associated with relative strength investing strategies (buying past winners and selling past losers) can be explained by transaction costs or friction effects. We find little evidence that momentum strategies provide positive abnormal return opportunities net of trading costs. The magnitude of the trading costs associated with these momentum strategies is much larger than previously appreciated, since the composition of standard relative strength portfolios is heavily weighted toward trading of particularly high transaction cost stocks. Moreover, large cross-sectional variation in relative strength

[25] Since this test references a 0 intercept, the estimates of the asymmetry/short sale costs may suffer from model misspecification bias as discussed in Footnote 11.

returns is increasing in trading-cost proxies, suggesting that trading costs are binding to arbitrage.

HLS find that relative strength returns are stronger for small and poorly covered stocks and attribute this finding to slower information diffusion among small stocks (Hong and Stein, 1999). We argue that the variables used to proxy for information diffusion speed are also highly correlated with trading costs. In fact, the information diffusion speed variables appear to provide little explanatory power after controlling for trading costs. The size effect HLS document for relative strength returns is more precisely a price-level effect. Transaction cost controls also largely eliminate the analyst coverage effect. We accept that the Hong and Stein or other behavioral hypotheses may provide some additional impact on the mechanism that generates the underlying behavior of prices but our evidence suggests that momentum patterns are largely an artifact of the slow price updating of high transaction cost stocks. The existence of performance persistence patterns in returns does not appear to conflict with information efficiency or suggest the existence of arbitrage opportunity.

Although our evidence casts doubt on the gains from any momentum strategy, we do not attempt to reject all momentum strategies. Explicitly investigating the host of existing recommended momentum strategies (e.g., Rouwenhurst's (1989, 1999) non-U.S. momentum strategies, Daniel and Titman's (2000) book-to-market portfolio strategies, and Gebhardt's (1999) bond market strategies) is left to future research. Our work also calls into question the growing use of momentum factors in asset pricing models (Carhart, 1997; Jegadeesh, 2000; Choi, 2000). Our findings suggest that such factors are more appropriately characterized and would be better modeled as trading cost or liquidity factors consistent with Amihud and Mendelson (1986), Amihud (2000), Hasbrouck and Seppi (1998), and Chordia et al. (2000).

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Table 1
Relative strength strategy holding period returns and portfolio characteristics

The sample is composed of all ordinary common shares, excluding ADRs, REITs, and closed-end funds, listed on CRSP from January 1980 to December 1998. Using the CRSP monthly returns file, relative strength portfolios are constructed by sorting all listed firms by the return performance over the previous holding period. Firms are classified into three portfolios based on the respective breakpoint percentiles of past performance. Within the three portfolios, firms are initially equally weighted and held for the respective period. The portfolio beta is estimated from the CAPM model with the CRSP value-weighted portfolio return as the market portfolio return. Beta estimates are obtained for each portfolio over the 228 months of the sample period. The mean share price is estimated using the stock price at the end of the formation period and weighting each holding period equally. The mean market cap is estimated identically to the mean share price using the market price and shares outstanding at the end of the formation period. Standard errors are reported in parentheses.

	Jegadeesh and Titman strategy 10-90 performance breakpoints (NYSE/AMEX stocks)				Hong, Lim, and Stein strategy 30-70 performance breakpoints (NYSE/AMEX/NASDAQ stocks)			
	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1
Semi-annual portfolio returns								
Mean	0.0433	0.0868	0.0980	0.0546	0.0552	0.0850	0.0917	0.0366
	(0.036)	(0.023)	(0.029)	(0.026)	(0.033)	(0.023)	(0.027)	(0.017)
Minimum	-0.451	-0.228	-0.232	-0.547	-0.331	-0.231	-0.258	-0.261
Maximum	0.732	0.407	0.533	0.291	0.557	0.415	0.538	0.187
Portfolio characteristics								
Portfolio beta	1.19	1.02	1.25		1.04	0.93	1.11	
	(0.08)	(0.03)	(0.05)		(0.06)	(0.03)	(0.04)	
Mean share price	9.19	30.31	34.51		9.56	21.34	23.20	
	(0.67)	(1.60)	(3.48)		(0.73)	(0.88)	(1.21)	
Mean market cap ($ millions)	407.8	1695.5	1009.2		309.4	878.6	695.3	
	(50.4)	(167.7)	(197.3)		(24.4)	(81.8)	(93.9)	
Proportion of stocks traded on the NYSE	0.527	0.730	0.591		0.182	0.333	0.259	

Table 2
Estimates of relative strength strategy trading costs

The sample is composed of all ordinary common shares, excluding ADRs, REITs, and closed-end funds, listed on CRSP from January 1980 to December 1998. Using the CRSP monthly returns file, relative strength portfolios are constructed by sorting all listed firms by the return performance over the previous holding period. Firms are classified into three portfolios based on the respective breakpoint percentiles of past performance. Within the three momentum portfolios, firms are initially equally weighted and held for the respective period. The table reports the returns associated with a short position in portfolio P1 and a long position in P3, return P3-P1. α_2-α_1 is the mean LDV trading cost estimate. The α_2-α_1 reported figures are the mean estimates for all firms in portfolios P1 and P3 weighted equally by period. The S+C estimate is the direct quoted spread plus commission estimate for the abbreviated 1994 to 1998 sample period. The Roll spread is the Roll (1984) spread estimate. The mean effect. spread is the mean effective spread estimate. The proportion of zero return days is the mean ratio of days with returns equal to zero to the total number of trading days for stocks in portfolios P1 and P3. The proportion of positions retained is the mean ratio of stocks in portfolios P1 and P3 that remain in the respective portfolio in the following period. Standard errors are reported in parentheses. In Panel B, the size class sub-samples are formed based on NYSE/AMEX market capitalization breakpoints calculated six months prior to the portfolio holding period but include all NYSE/AMEX/NASDAQ firms. The turnover class sub-samples are formed based on NYSE/AMEX market capitalization breakpoints calculated six months prior to the portfolio holding period. $(\alpha_2$-$\alpha_1)_k$ is the LDV estimate for portfolio k. Panel C includes only stocks trading on NYSE/AMEX and for more than $1 following Lee and Swaminathan (2000).

Panel A. Semi-annual estimates for full sample

	Jegadeesh and Titman strategy 10-90 performance breakpoints (NYSE/AMEX stocks)				Hong, Lim, and Stein strategy 30-70 performance breakpoints (NYSE/AMEX/NASDAQ stocks)			
	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1
Relative strength portfolio returns								
Mean	0.0433	0.0868	0.0980	0.0546	0.0552	0.0850	0.0917	0.0366
(1980-1998)	(0.036)	(0.023)	(0.029)	(0.026)	(0.033)	(0.023)	(0.027)	(0.017)
Proportion of positions retained	0.221	0.837	0.144		0.382	0.463	0.315	
Total trading cost estimates								
Mean α_2-α_1	0.0767	0.0354	0.0594	0.1362	0.1064	0.0628	0.0818	0.1882
(1980-1998)	(0.005)	(0.001)	(0.004)	(0.007)	(0.004)	(0.006)	(0.004)	(0.003)
Mean α_2-α_1	0.0673	0.0317	0.0549	0.1222	0.0854	0.0526	0.0672	0.1526
(1994-1998)	(0.002)	(0.001)	(0.002)	(0.003)	(0.005)	(0.002)	(0.005)	(0.008)
Spread + commissions estimates only								
Mean quotes	0.0928	0.0456	0.0705	0.1632	0.0938	0.0627	0.0753	0.1691
(1994-1998)	(0.002)	(0.004)	(0.002)	(0.002)	(0.004)	(0.001)	(0.004)	(0.003)
Spread estimates only								
Mean Roll spread	0.0353	0.0173	0.0272	0.0625	0.0392	0.0266	0.0312	0.0703
(1980-1998)	(0.002)	(0.001)	(0.002)	(0.003)	(0.002)	(0.001)	(0.002)	(0.003)
Mean effect. spread	0.0310	0.0112	0.0177	0.0488	0.0498	0.0272	0.0335	0.0833
(1994-1998)	(0.001)	(0.001)	(0.002)	(0.004)	(0.005)	(0.001)	(0.004)	(0.006)

Table 2 (Continued)
Estimates of relative strength strategy trading costs

Panel B. Mean semi annual estimates by size class
(30-70 performance breakpoints for all NYSE/AMEX/NASDAQ stocks)

		P3-P1	Proprtn. of positions retained	Number of zero return days	$(\alpha_2-\alpha_1)_1 + (\alpha_2-\alpha_1)_3$	S+C*	Roll spread estimate	Effective spread estimate*
Size class	1 (smallest)	0.0143 (0.019)	0.304	44.3	0.309 (0.011)	0.267 (0.011)	0.097 (0.006)	0.145 (0.008)
	2	0.0532 (0.014)	0.242	29.8	0.131 (0.004)	0.118 (0.005)	0.054 (0.003)	0.056 (0.002)
	3	0.0422 (0.013)	0.239	23.2	0.086 (0.002)	0.080 (0.003)	0.036 (0.001)	0.032 (0.001)
	4	0.0285 (0.013)	0.261	17.8	0.061 (0.002)	0.059 (0.002)	0.027 (0.001)	0.018 (0.001)
	5 (largest)	-0.0017 (0.014)	0.296	13.0	0.048 (0.004)	0.041 (0.001)	0.021 (0.001)	0.010 (0.001)

*Available only for 1994 to 1998.

Panel C. Semi annual estimates by turnover class
(30-70 performance breakpoints for all NYSE/AMEX stocks)

		P3-P1	Proprtn. of positions retained	Number of zero return days	$(\alpha_2-\alpha_1)_1 + (\alpha_2-\alpha_1)_3$	S+C*	Roll spread estimate	Effective spread estimate*
Turnover class	1 (lowest)	-0.0177 (0.019)	0.221	42.4	0.1007 (0.004)	0.138 (0.006)	0.042 (0.001)	0.036 (0.003)
	2	-0.0078 (0.013)	0.152	33.6	0.0881 (0.003)	0.110 (0.002)	0.040 (0.001)	0.028 (0.001)
	3	0.0079 (0.012)	0.137	28.5	0.0752 (0.002)	0.097 (0.002)	0.035 (0.001)	0.026 (0.002)
	4	0.0303 (0.016)	0.147	25.5	0.0750 (0.002)	0.093 (0.002)	0.036 (0.001)	0.023 (0.002)
	5 (highest)	0.0611 (0.015)	0.216	21.4	0.0799 (0.002)	0.092 (0.003	0.038 (0.001)	0.025 (0.001)

*Available only for 1994 to 1998.

Table 3
Sample correlation coefficients

This table includes all firm-period observations for ordinary common shares listed on NYSE, AMEX, and Nasdaq, excluding ADRs, REITs, and closed-end funds from January 1980 to December 1998 above the NYSE/AMEX 20th size percentile. Size is measured by market capitalization. Coverage is the number of analysts reporting earnings estimates with I/B/E/S. S+C is a spread and commission estimate. $\alpha_2-\alpha_1$ is the LDV trading cost estimate. Size, coverage and transaction-cost estimates are logarithm transformed. Residual coverage and residual $\alpha_2-\alpha_1$ is the error term obtained from the respective coverage or $\alpha_2-\alpha_1$ estimate regressed on size and a Nasdaq dummy variable within each size grouping and for each period.

	Size	Coverage	Residual Coverage	Price	Roll spread	S+C	Effective spread	α_2-α_1	Residual α_2-α_1
Size	1.000*	0.662*	0.000	0.063*	-0.462*	-0.684*	-0.365*	-0.673*	0.000
Coverage		1.000*	0.694*	0.007	-0.436*	-0.568*	-0.340*	-0.598*	-0.118*
Residual Coverage			1.000*	-0.045*	-0.122*	-0.190*	-0.106*	-0.128*	-0.178*
Price				1.000*	-0.014*	-0.025*	-0.013	-0.042*	-0.006
Roll spread					1.000*	0.662*	0.483*	0.698*	0.299*
S+C						1.000*	0.524*	0.816*	0.453*
Effective spread							1.000*	0.516*	0.367*
$\alpha_2-\alpha_1$								1.000*	0.509*
Residual $\alpha_2-\alpha_1$									1.000*

* Denotes significance at the 1-percent level.

Table 4
Relative strength returns by size and price class

The sample is composed of all NYSE, AMEX, and Nasdaq stocks listed on CRSP from January 1980 to December 1998. Return data is obtained from the CRSP monthly returns file (ordinary common shares listed on NYSE, AMEX, and Nasdaq, excluding ADRs, REITs, and closed-end funds). The size class sub-samples are formed based on NYSE/AMEX market capitalization break points calculated six months prior to the portfolio holding period. Sub-sample 1 contains the smallest firms and sub-sample 5 contains the largest firms. Within each size portfolio, firms are classified based on price level six months prior to the portfolio holding period. The five categories are in order: under $5, between $5 and $10, between $10 and $20, between $20 and $30, and over $30. Each of the 25 size/price sub-samples is further divided into the three performance portfolios. Firms with six-month return performance below the 30th percentile are classified into the P1 portfolio. Firms with performance above the 70th percentile are classified into the P3 portfolio. Within the three momentum portfolios, firms are initially equally weighted and held for a six-month period. The table reports the returns associated with a short position in portfolio P1 and a long position in P3, return P3-P1. Estimates for classes with less than ten valid period observations are not reported. The associated t-statistics are reported in parentheses. The associated number of holding periods in each performance portfolio is reported in brackets.

		Price class				
		1 (lowest)	2	3	4	5 (highest)
Size class	1 (smallest)	0.0067 (0.35) [38]	0.0678 (5.37) [38]	0.0401 (3.03) [38]	0.0242 (1.00) [35]	-0.0127 (-0.23) [13]
	2	0. 1005 (3.27) [38]	0.0991 (6.45) [38]	0.0486 (3.56) [38]	0.0143 (0.98) [38]	0.0060 (0.37) [38]
	3	0.2265 (4.85) [31]	0.0780 (2.89) [38]	0.0605 (4.58) [38]	0.0340 (2.87) [38]	0.0257 (1.27) [38]
	4	n.a.	0.0601 (1.61) [30]	0.0553 (3.29) [38]	0.0311 (2.31) [38]	0.0281 (1.92) [38]
	5 (largest)	n.a.	n.a.	0.0057 (0.14) [35]	-0.0272 (-0.85) [38]	0.0154 (1.20) [38]

Table 5
Semi-annual holding period returns for relative strength strategies by size, coverage, and transaction cost

This table includes all firm-period observations for ordinary common shares listed on NYSE, AMEX, and Nasdaq, excluding ADRs, REITs, and closed-end funds from January 1980 to December 1998 above the NYSE/AMEX 20th size percentile. Firms are classified into class by size, residual coverage, and $\alpha_2-\alpha_1$. The size classification is based on NYSE/AMEX break points. The residual coverage classification is based on full sample break points within each size class at the 30th and 70th percentile. The $\alpha_2-\alpha_1$ classification is based on full sample break points at the 20th, 40th, 60th, and 80th percentile. All classification variables are estimated six-months prior to the holding period. Each of the sub-samples is further divided into the three performance portfolios. Firms with past six-month return performance below the 30th percentile are classified into the P1 portfolio. Firms with performance above the 70th percentile are classified into the P3 portfolio. Within the three momentum portfolios, firms are initially equally weighted and held for a six-month period. In this table we report the returns associated with a short position in portfolio P1 and a long position in P3, return P3-P1. The associated t-statistics are reported in parentheses.

Panel A: P3-P1 returns sorted by size and analyst coverage

		Size Class			
		2 (smallest)	3	4	5 (largest)
Residual Coverage Class	1 (lowest)	0.0517	0.0551	0.0476	-0.0052
		(3.17)	(3.04)	(2.77)	(-0.22)
	2	0.0452	0.0297	0.0058	-0.0092
		(2.82)	(2.17)	(0.40)	(-0.64)
	3 (highest)	0.0304	0.0177	0.0174	0.0016
		(2.00)	(1.50)	(1.28)	(0.10)

Panel B: P3-P1 returns sorted by implied transaction cost and analyst coverage

		Trading Cost ($\alpha_2-\alpha_1$) Class				
		1 (lowest)	2	3	4	5 (highest)
$(\alpha_2\text{-}\alpha_1)_1+(\alpha_2\text{-}\alpha_1)_3$		0.0274	0.0462	0.0674	0.0958	0.1902
Full sample (P3-P1)		0.0380	0.0268	0.0464	0.0544	0.0665
		(2.31)	(2.10)	(3.74)	(4.60)	(4.02)
Residual Coverage Class	1 (lowest)	0.0591	0.0298	0.0327	0.0419	0.0702
		(2.72)	(1.75)	(1.92)	(2.68)	(3.11)
	2	0.0046	0.0091	0.0414	0.0351	0.0533
		(0.33)	(0.68)	(2.75)	(2.35)	(2.64)
	3 (highest)	0.0051	0.0228	0.0379	0.0393	0.0336
		(0.35)	(1.59)	(2.61)	(2.57)	(1.44)

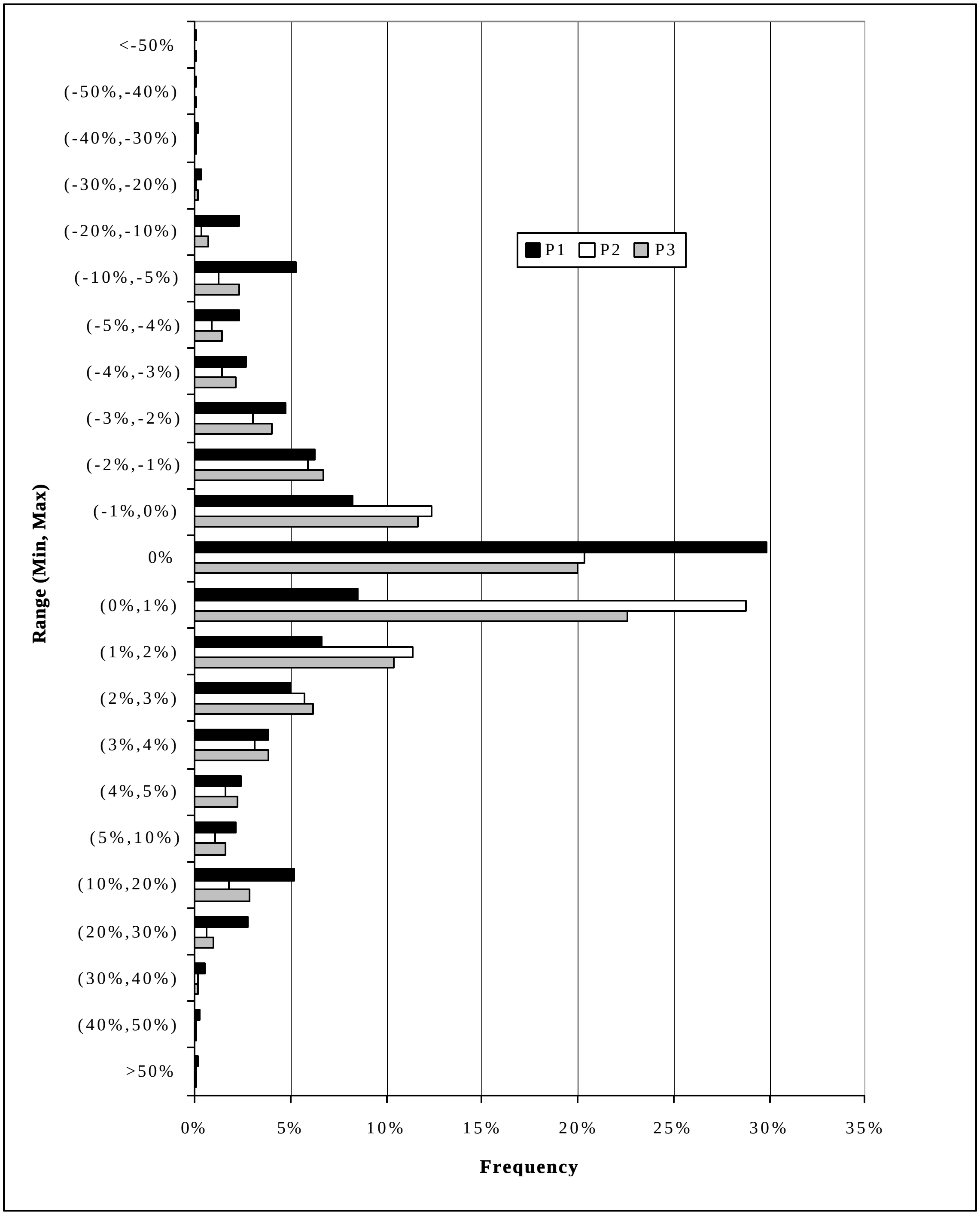

Figure 1. Histogram of daily returns by relative strength portfolio. The sample is composed of all NYSE/AMEX stocks listed on CRSP from January 1980 to December 1998. Using the CRSP monthly returns file (ordinary common shares, excluding ADRs, REITs, and closed-end funds), within each sub-sample relative strength portfolios are constructed by sorting all listed firms by the return performance over the previous holding period. Firms are classified into three portfolios based on breakpoints at the 10^{th} and 90^{th} percentiles of past performance. Within the three portfolios, firms are initially equally weighted and held for the respective period. Firms are sorted within daily returns categories where the daily return is within the (Min, Max) range.

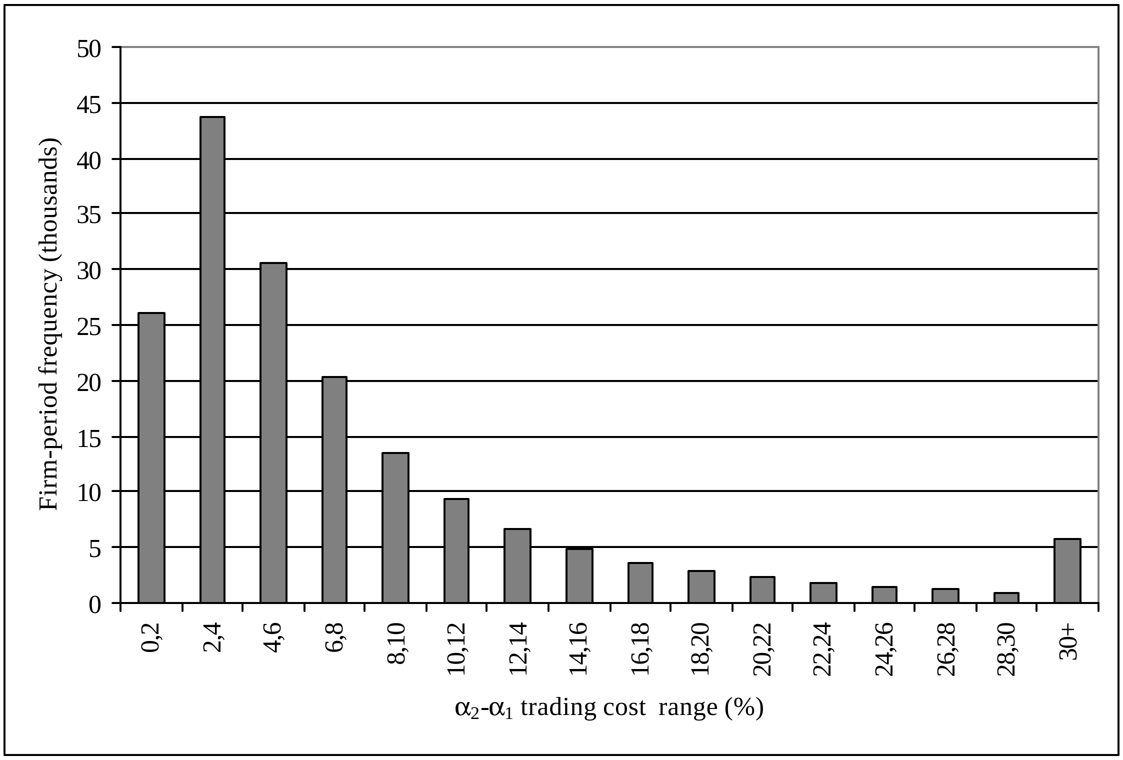

Figure 2. Histogram of firm round-trip trading cost estimates. The sample is composed of all NYSE/AMEX/NASDAQ stocks listed on CRSP from January 1980 to December 1998. α_2-α_1 is the LDV trading cost estimate. The figure reports the number of firm period trading cost estimates within the respective range (min, max).

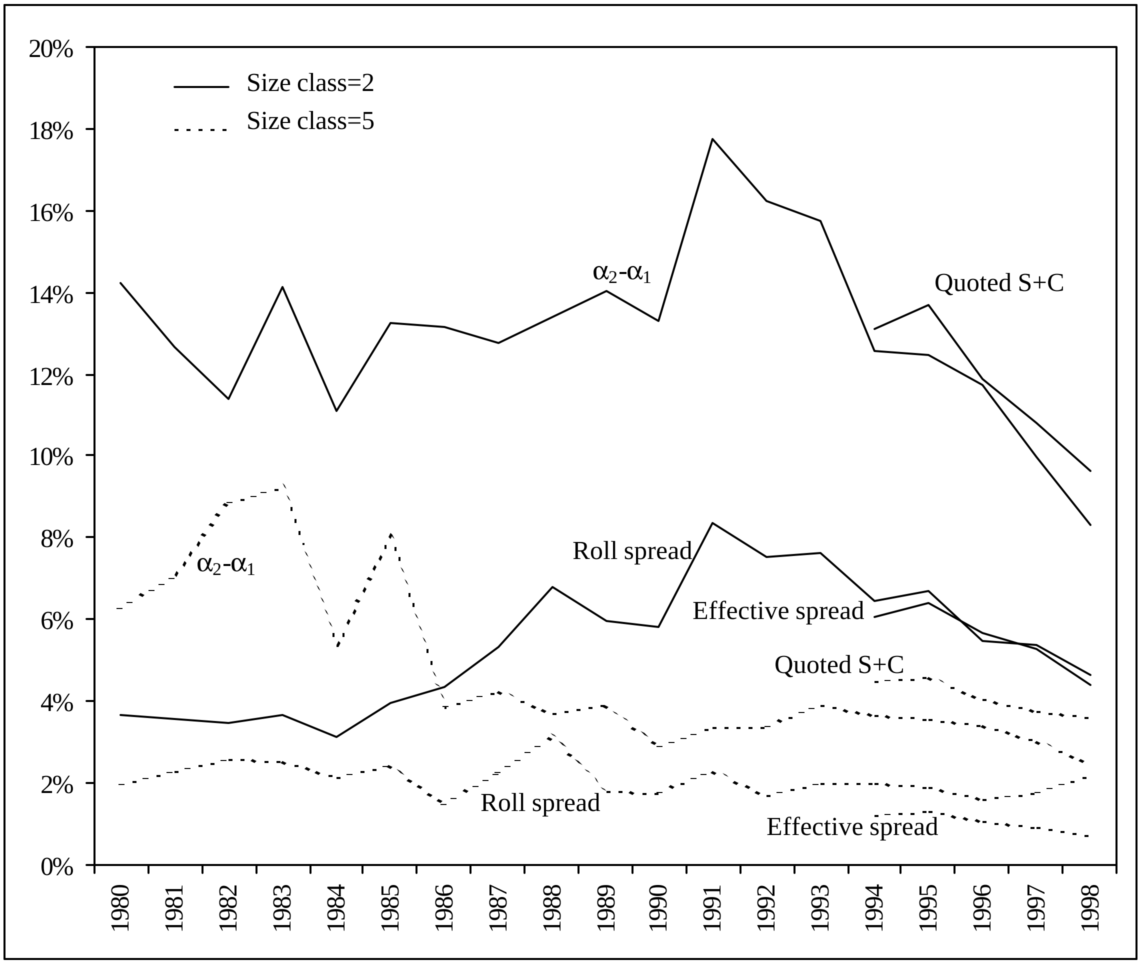

Figure 3. Mean round-trip trading cost estimates by size class and year. Sample includes all NYSE/AMEX/NASDAQ stocks. α_2-α_1 is the LDV trading cost estimate. Quoted S+C is the quoted spread and commission estimate.