The illusory nature of momentum profits ☆

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Abstract

Our paper re-examines the profitability of relative strength or momentum trading strategies (buying past strong performers and selling past weak performers). We find that standard relative strength strategies require frequent trading in disproportionately high cost securities such that trading costs prevent profitable strategy execution. In the cross-section, we find that those stocks that generate large momentum returns are precisely those stocks with high trading costs. We conclude that the magnitude of the abnormal returns associated with these trading strategies creates an illusion of profit opportunity when, in fact, none exists.
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1. Introduction

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 12 month horizon. A growing literature finds this evidence at odds with classical models of rational price formation (Jegadeesh, 1990; Cutler et al., 1991; Jegadeesh and Titman, 1993, 2001; Chan et al., 1996; Rouwenhorst, 1998). They suggest that characteristics of investor behavior generate a certain inertia or momentum in abnormal returns that creates persistent arbitrage opportunity. Investor attributes that 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), disposition (Grinblatt and Han, 2001), and selective information conditioning (Hong and Stein, 1999).

Strict market efficiency requires that ''security prices fully reflect all available information'' (Fama, 1991). Evidence of momentum in stock returns surely appears inconsistent with strict market efficiency since current prices do not reflect past prices. In markets with nonzero trading costs, however, the vehicle that delivers efficiency, the arbitrage mechanism, is weakened since if trading costs are binding, arbitrageurs will make negative net profit. Since trading friction in securities markets is surely not zero, ''an economically more sensible version of the efficiency hypothesis says that prices reflect information to the point where the marginal benefits of acting on information (the profits to be made) do not exceed the marginal costs'' (Fama, 1991).[1] Thus in a fully rational market, the lack of zero cost arbitrage 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 impact of trading costs on price behavior is much larger than previously acknowledged. Our evidence suggests that stocks that generate momentum returns are precisely those stocks with high trading costs. We conclude that the abnormal momentum returns observed in security prices create an illusion of trading profit opportunities when, in fact, none exist.

Jegadeesh and Titman (JT) (1993) maintain that relative strength portfolio returns exceed the costs of trading. Their estimate of trading cost is based on the trade-weighted mean commission and market impact of early 1985 NYSE trades computed by Berkowitz et al. (1988). We find this trading cost estimate 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 performer stocks. We show that the securities used in relative strength strategies are disproportionately drawn from among stocks with large trading costs. Second, a single period measure is unable to capture the substantial time-series variation in

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[1] See also Rosett (1959), Tobin (1965), and Goldsmith (1976), Jensen (1978), and Cohen et al. (1986).

trading costs (Lesmond et al., 1999; Chordia et al., 2001; Jones, 2001) over a long sample period. 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. Fourth, we find that the majority of relative strength returns are generated by return continuation among the poor performing stocks. Since profiting from the ongoing poor performance of these stocks requires maintaining short positions, ignoring short-sale costs for these strategies is particularly concerning. Lastly, relative strength strategies are trading-intensive. The standard JT six-month strategy of buying the top-performing 10% and shorting the bottom-performing 10% produces semi-annual returns of about 6%. Since the strategy requires four trades per six-month holding period (opening and closing positions for both the winners and losers), abnormal profit realization requires that per trade costs be less than 1.5%. Since the extreme performer portfolios are comprised primarily of relatively illiquid stocks, we find it difficult to argue that trading costs are so low.

Using conservative assumptions and a battery of trading cost estimates, we find little evidence that trading costs for the standard strategy are below 1.5% per trade. Our results suggest that the costs of relative strength strategy execution are much larger than those previously reported. We conclude that the understatement of the trading costs associated with relative strength strategy execution calls into question the profitability of such strategies.[2] In the cross-section, we find that relative strength strategies that produce larger gross profits are generally associated with larger trading costs and vice versa. Relative strength portfolio returns appear to be bounded by transaction costs such that the profitability of these strategies is overstated in the literature. We find little evidence to reject the no-arbitrage rule and argue that the literature is too dismissive of the economic significance of trading costs.

This paper is organized as follows. Section 2 reviews the return behavior and composition of relative strength portfolios. Section 3 discusses our estimates of trading costs. Section 4 compares the level of gross trading profits with transaction cost estimates. Section 5 investigates cross-sectional evidence in relative strength investing returns. Section 7 provides concluding remarks.

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[2] 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), the book-to-market effect (Ali et al., 2003), 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, 2002), post-earnings price drift (Lesmond, 2000), and analyst recommendation underreaction (Copeland and Mayers, 1982; Barber et al., 2000; Choi, 2000). Other studies that consider the trading costs of relative strength strategies include, Hanna and Ready (2001), Chen et al. (2001), Sadka (2002), and Korajczyk and Sadka (2002).

2. The momentum anomaly

We examine conventional relative strength strategies over a period from January 1980 to December 1998. Our classification procedure follows JT (1993), Hong et al. (HLS) (2000), and JT (2001). 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). Using rolling six month formation period windows, 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. Following JT, the mean monthly return for each of the portfolios is calculated using overlapping past portfolios, such that in any month the returns of the relative strength portfolios are equally weighted with the contemporaneous monthly returns of the corresponding portfolio formed over the past six months. We focus on the six-month formation period and six-month holding period to be consistent with the dominant strategies in the literature. We note that 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. We repeat our tests for a variety of alternative formation and holding periods and find that our conclusions are unchanged.

JT (1993), HLS (2000), and JT (2001) all use different populations and break points in their base-case strategies. JT (1993) consider only NYSE/AMEX stocks and define winners and losers based on 10- and 90-percentile (10–90) performance break points. HLS (2000) include Nasdaq stocks but use 30 to 70 break points. JT (2001) also include Nasdaq stocks but exclude stocks with share price below $5 or stocks within the smallest size decile and define performance at 10–90 break points. We replicate all three approaches over a 1980–1998 sample period. We construct a rolling relative strength portfolio in which stocks enter the P1 portfolio, for example, each month and then remain in the portfolio for six months. Each monthly cohort of P1 stocks is equally weighted and rebalanced monthly. Table 1 presents summary statistics. For the JT (1993) strategy, mean monthly returns for the P1, P2, and P3 portfolios are, respectively, 0.74%, 1.33%, and 1.62%. A trading strategy that maintains a long position in the best performers and a short position in the worst performers (P3-P1) achieves statistically significant "paper profits" of 0.88% per month. For the HLS strategy, the mean performance of the winners and losers is less extreme. The P3-P1 profits decline to a still highly significant 0.45% monthly return. For the JT (2001) strategy, the mean monthly return of the P3-P1 position increases to 1.30%.

We note, as do HLS, that the majority of trading strategy returns is generated by the short position. If we assume that the returns associated with the nontraded, medium-performance P2 stocks represent benchmark performance, the ratio (P2-P1)/(P3-P1) captures the proportion of total P3-P1 performance attributable to the short position in the poor performers. Using the P2 stocks as the benchmark makes

Table 1

Relative strength strategy monthly 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. The CRSP monthly returns file is restricted for each strategy as described in parentheses. Relative strength portfolios are constructed by sorting stocks each month by the return performance over the previous six-month holding period. Firms are classified into three portfolios based on the respective break-point percentiles of past performance. Rolling portfolio returns are constructed based on equal weightings on the six respective equal-weighted relative-strength portfolios formed over each of the past six months. We use the CAPM model with the CRSP value-weighted portfolio return as the market portfolio return. Monthly mean portfolio returns are reported in percentage terms. The t-statistic for the portfolio alpha is in parentheses. * or ** denote 5% and 1% statistical significance, respectively, for the test that the alpha estimate is different from zero. The mean unadjusted 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 using the market price and shares outstanding at the end of the formation period. The median values represent the mean of the monthly portfolio median values.

	Jegadeesh and Titman (1993) strategy 10–90 performance break points (NYSE/AMEX stocks)				Hong et al. (2000) strategy 30–70 performance break points (NYSE/AMEX/NASDAQ stocks)				Jegadeesh and Titman (2001) strategy 10–90 performance break points (NYSE/AMEX/NASDAQ; P > $5 stocks; Size above 1st NYSE decile)			
	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1	P1	P2	P3	P3-P1
Monthly portfolio returns												
Mean	0.739%	1.331%	1.623%	0.884%	1.038%	1.289%	1.515%	0.447%	0.408%	1.322%	1.712%	1.304%
Portfolio characteristics												
Portfolio alpha	−0.815	−0.040	0.086		−0.386	−0.018	0.081		−1.190	−0.077	0.045	
	(−2.09**)	(−0.33)	(0.46)		(−1.35)	(−0.13)	(0.46)		(−5.22**)	(−0.74)	(0.20)	
Portfolio beta	1.216	0.991	1.195		1.057	0.912	1.07		1.271	1.026	1.356	
Share price Mean	8.95	30.48	35.31		8.86	21.18	23.47		16.20	32.74	33.12	
Median	6.32	20.60	19.36		5.35	15.00	15.28		13.71	23.81	23.51	
Market cap Mean	308.0	1,652.5	1,197.7		241.1	820.9	764.1		556.8	1,446.3	913.4	
($ millions) Median	55.4	304.4	210.3		27.4	86.9	82.19		175.1	305.8	220.4	
Proportion of stocks traded on the NYSE	0.532	0.729	0.594		0.183	0.329	0.256		0.428	0.530	0.327	

sense since the opportunity cost of trading in the relative strength stocks is the returns associated with the nontraded P2 stocks. Computing this ratio we find that the P2-P1 position provides 67% of the total P3-P1 return for the JT (1993) strategy, 53% of the total P3-P1 return for the HLS strategy, and 70% of the total P3-P1 return for the JT (2001) strategy. If we use the CRSP value-weighted or equal-weighted portfolios as the benchmark rather than portfolio P2, the abnormal profit still appears to come primarily from the short position.

We also consider the abnormal return based on the CAPM associated with the three portfolios. Subtracting the Treasury Bill rate, we regress the excess rolling relative strength portfolio returns on the excess value-weighted CRSP market portfolio returns. The intercept estimates (portfolio alphas) are reported in Table 1. For the JT (1993) strategy, the intercept terms are -0.82%, -0.04%, and 0.09% for portfolios P1, P2, and P3, respectively. The respective *t*-statistics are -2.1, -0.3, and 0.5. The results are similar for the other strategies. The tests reconfirm that the abnormal performance appears to be concentrated among the poor performers.

We observe some discrepancy between our alpha estimates and those reported by JT (2001). The discrepancy is explained by differences in sample period (JT use a 1965 to 1998 sample period). If we extend our sample period back to 1965, the estimates are nearly identical to those of JT (2001). In unreported tests, we regress the relative strength portfolio returns on the Fama-French factors. We observe with the Fama-French model, as do Fama and French (1996), significant negative abnormal performance among the P1 stocks as well as significant positive abnormal performance among the P3. Although these tests do support abnormal returns for the strong performers (P3), the alpha estimates of the P1 portfolio are much larger in magnitude than those of the P3 portfolio.

2.1. Relative strength portfolio characteristics

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. The exception includes Conrad and Kaul (1998), Berk et al. (1999), Johnson (2002), and Chordia and Shivakumar (2002). Jegadeesh and Titman (2002) reject the Conrad and Kaul explanation that momentum strategy profitability is due merely to cross-sectional variation in individual mean returns on the basis of small sample biases. Grundy and Martin (2001) observe that standard risk measures do not explain relative strength portfolio performance. Ang et al. (2002) argue that relative strength portfolio returns are consistent with compensation for downside risk.

JT (1993) and HLS (2000) 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 the costs of trading relatively large 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 in these studies are highly understated.

Table 1 provides some statistics on the composition of the relative strength portfolios. The statistics represent the average mean or median observation for all stocks within each portfolio for each period. We find that the extreme performing stocks that comprise the securities traded in relative strength portfolios are unique. For the JT (1993) strategy, the portfolio beta estimated over the sample period is largest for portfolios P1 and P3 with P1, P2, P3 estimates of 1.22, 0.99, and 1.20, 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 unadjusted share price for stocks in JT (1993) portfolios P1, P2, and P3 over the sample period is $8.95, $30.48, and $35.31, respectively. The median share price for portfolio P1 is only $6.32, whereas the median for portfolios P2 and P3 is substantially higher at $20.60 and $19.36, respectively. 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 nominal market capitalization for stocks in portfolios P1, P2, and P3 over the sample period is respectively, $0.3 billion, $1.7 billion, and $1.2 billion. The pattern is similar for the median values, but the values are much lower. The median size of stocks in the P1 portfolio is only $55 million. We also find that the P1 and P3 stocks are less likely to be traded on the NYSE. Of the NYSE/AMEX sample considered in the JT (1993) strategy, the proportion of portfolio P1, P2, and P3 stocks that are traded on the NYSE is 53%, 73%, and 59%, respectively. The composition pattern for the HLS (2000) and JT (2001) portfolios that also include Nasdaq stocks is similar weighted against NYSE stocks. In summary, the relative strength portfolios, and particularly portfolio P1 that generates the majority of the total strategy abnormal return, are comprised of stocks that can be characterized as small, low price, high beta, off-NYSE stocks.

The Table 1 characterization of the relative strength portfolios suggests that the securities that generate the abnormal returns are relatively less liquid. We investigate the relative liquidity of the portfolios by examining the mean distribution of CRSP daily returns during the holding period for the stocks which comprise the three JT (1993) portfolios. Fig. 1 summarizes the results. First, we note that daily returns of exactly 0% are quite common among NYSE/AMEX stocks. Over the sample period, zero return days occur on more than 20% of the trading days for the average stock. 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% of the days for small capitalization firms. Fig. 1 shows that the number of zero return days is particularly large for the P1 portfolio, with 30% of the daily return values at exactly zero.

Second, we find that the variation of nonzero 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% to 1% range at a rate of only 9% for portfolio P1, 29% for portfolio P2, and 23% for portfolio P3. In general the frequency of small,
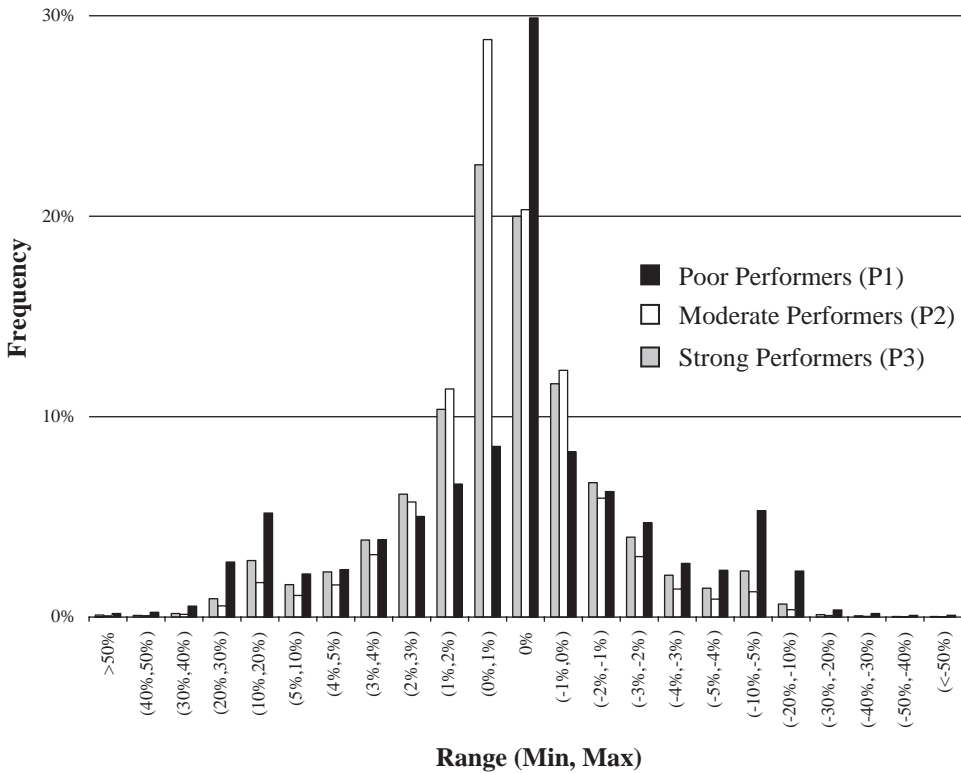
Fig. 1. Histogram of mean frequency of daily returns during the holding period by Jegadeesh and Titman (1993) relative strength portfolio. The sample is composed of all NYSE/AMEX stocks listed on CRSP from January 1980 to December 1998. Using the CRSP monthly returns file (ordinary common shares, excluding 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 break points at the 10th and 90th percentiles of past performance. Within the three portfolios, firms are initially equally weighted and held for the respective period. Firm returns are sorted within daily returns categories where the daily return is within the (Min, Max) range.

but nonzero 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% to 20% range at a rate of 5.2% for portfolio P1, 1.7% for portfolio P2, and 2.8% for portfolio P3. The pattern is similar for other large magnitude ranges. For the −10% to −20% range the pattern is similar with P1, P2, and P3 daily return frequencies of 5.3%, 1.3%, and 2.3%, respectively. The pattern of high frequency zero returns, low frequency small magnitude returns and high frequency large magnitude returns is characteristic of market friction. It may be that with large trading costs, prices are sticky over time since trading friction prevents price updating.

3. Trading cost estimation

Assessing the profitability of relative strength trading strategies requires an assessment of the trading costs facing the arbitrageur. Total trading costs include not only the bid-ask spread (estimated using the quoted spread, the direct effective spread measure, or Roll's effective spread measure) but also applicable commissions, price impact costs, taxes, short-sale costs, and other immediacy costs. Keim and Madhaven (1995) find that institutions that are passive traders (using limit orders or crossing trades) incur opportunity costs because trades are not always executed and those that are active traders (using market orders) incur sizeable immediacy costs. Arbitrageurs also face holding costs such as tracking error and short sale constraints. Since relative strength trading requires holding particular risky positions for extended periods of time, strategy execution generates exposure to holding period tracking error. Foregone investment returns associated with short sale proceeds restrictions represent an additional relevant holding cost to relative strength investing. Since capturing all of the components of the comprehensive trading cost facing arbitrageurs is empirically challenging, our estimates of trading costs are conservative, in that they include only the most empirically demonstrable and available components of trading costs.

The literature provides a menu of trading cost estimation procedures for consideration. The first class of estimators measures 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" costs by directly examining quoted market bid-ask spread data and prevailing commission schedules. Since trades frequently occur off the quoted prices and with variations in commissions, quoted measures are likely to be inaccurate (Lee, 1993; Peterson and Fialkowski, 1994; Seppi, 1997). As an alternative, a number of techniques produce estimates of the "effective" or "realized" trading cost estimates by matching the quotes to the transaction record. These direct effective-spread estimates are also imperfect measures of the true marginal spread due to institutions "legging into" large positions by breaking up trades (Keim and Madhavan, 1995) and because of information leakage prior to execution that causes quotes to move in anticipation of a trade (Plexus Group, 1996).

The second class of estimators indirectly infers trading costs based on price behavior. These approaches are advantageous to us because they rely on price data rather than transaction data that are available for only a limited part of our sample period. Roll (1984) proposes an estimator of the implied effective spread based on measuring the negative autocorrelation produced by bounces between the bid and ask prices. Particular to relative strength strategies, this approach assumes that successive trade types are independent, spreads are constant, and order flow and value are independent. Harris (1990) shows that the Roll estimator is a severely downward-biased estimator of the quoted spread. Huang and Stoll (1996) defend the approach. One limitation with this approach, as well as the other direct spread estimates, is that they all understate the true costs of trading for the arbitrageur by omitting such relevant trading costs as price impact, immediacy costs, commissions,

or short-sale constraints. Omitted trading cost components, such as price impact, immediacy costs, 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 spreads are actually wider for trades of any significance on small 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). This measure provides a more comprehensive estimate of the cost of trading by implicitly including not only the spread component but also the implied commissions, immediacy costs, short sale costs, and at least some of the price impact costs. The maintained hypothesis of this approach is that arbitrageurs trade only if the value of the accumulated information exceeds the marginal cost of trading. 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. As a result, securities with near-zero trading cost experience few zero returns while securities with high costs experience more zero returns. This observation is consistent with that of Easley et al. (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 11-year period. One characteristic of such infrequently traded stocks is their large bid-ask spreads." This pattern also follows our discussion of Fig. 1. The limitations of the LDV model include the assumptions that the underlying true return (in a frictionless market) distribution is normally distributed, while the observed or measured return distribution is nonnormal, and that prices only respond to information when the value of the information is greater than the costs of trading.

Our trading cost estimates tend to be conservative. For the spread estimates, we specifically exclude other relevant costs such as commissions, short-sale constraints, and opportunity costs. This restriction impacts the Roll estimator as well. For the LDV measure, Lesmond et al. (1999) shows that using only the observed number of zero returns understates the true number of zero returns (i.e. those zero returns that would result from information-less trades) producing conservative LDV transaction cost estimates.

Due to the varying strengths and weaknesses of the various trading cost measures, we employ all four trading cost measures to test our transaction cost hypothesis. We produce relative strength portfolio-trading cost estimates using all four approaches. For each of the estimators we use a sample period that precedes the portfolio formulation period to estimate the trading costs. This is done to avoid contamination, either distributional or causal, between the portfolio formation and/or the performance returns and those returns used by the trading cost estimates. Thus, for a portfolio performance period that began in January 1980, we estimate the trading costs for each firm individually from July 1, 1978 to June 24, 1979. We end the trading cost estimation procedure one week prior to the portfolio formation period to avoid again any test contamination concerns.

This procedure is replicated for each firm, time period, and trading cost estimate in our sample. We find that using the earlier estimation period, as opposed to the including the portfolio formation period, produces smaller P1 trading cost estimates and larger P3 trading cost estimates. One explanation for this is that, by requiring return data 18 months, rather than 12 months prior to the performance period, we systematically exclude younger firms that experience larger trading costs for the P1 portfolio of firms. If this is so, our reported trading costs are conservative for the most critical component of the momentum strategy, namely P1 returns. We outline each trading cost measure in turn.

3.1. Quoted spread estimate

We obtain quoted spread 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. For each stock we obtain closing quotes for a randomly selected day during the third or fourth week of each calendar month for a total of 12 estimates per year. This procedure is used to mitigate any turn-of-the-month effects in quote behavior and to provide a relatively evenly spaced quote estimate throughout the year. It should be noted that NASDAQ securities are reported on a net basis with commissions embedded into the reported trade prices. For these trades the quoted spread overstates the spread costs, though not total trading costs. The monthly quoted spread measure is tabulated on a proportional basis defined as

$$\text{Quoted spread}(i,t) = \frac{1}{12} \sum_{\tau=-18}^{-6} \frac{(Ask(i,t+\tau) - Bid(i,t+\tau))}{\frac{1}{2}(Ask(i,t+\tau) + Bid(i,t+\tau))}. \tag{1}$$

3.2. Direct effective spread estimate

We compute the direct effective spread by comparing the quoted spreads to the contemporaneous execution prices. We follow the standard approach defined as twice the absolute value price deviation from the bid-ask midpoint. 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. In essence, the direct effective spread is the expected purchase price minus the expected sales price. The TAQ data quotes from Section 3.1 are matched to the contemporaneous closing prices from CRSP. Monthly firm estimates are produced using 12-monthly estimates obtained prior to the performance measurement period, similar to the

method used for the quoted spreads. We omit the few monthly firm estimates greater than 100%. The direct effective spread is tabulated as

$$\text{Direct efffective spread } (i, t)$$
$$= \frac{1}{12} \sum_{\tau=-18}^{-6} \left| \frac{Price(i, t+\tau) - \frac{1}{2}(Ask(i, t+\tau) + Bid(i, t+\tau))}{Price(i, t+\tau)} \right|. \tag{2}$$

This definition follows Chordia et al. (2000). We altered the definition to use the bid-ask midpoint rather than the price in the denominator (as with the definition of the quoted spread) and found that it makes little difference.

3.3. Roll effective spread estimate

The Roll (1984) approach uses the bid-ask bounce-induced negative serial correlation in returns to estimate the effective spread. To implement the method, we estimate the autocovariance structure of firm returns, using the daily CRSP return data during the year prior to portfolio formation period. Since Roll's model requires a negative autocovariance structure in the returns, we omit all estimates produced for firms with positive return autocovariance, consistent with Shultz (2000). Shultz (2000) finds that when the Roll effective spread estimator can be accurately estimated, it is highly correlated with the corresponding direct effective spread estimate. We find similar evidence. To test our assertion, we examine the correlation between the Roll effective spread estimates and the independently generated direct effective spread estimates for the two samples including—those with positive autocorrelation and those with negative autocorrelation. The mean correlation coefficient between the two estimates for the positive serial covariance sample is less than 20% while the mean correlation coefficient for the negative serial covariance sample is greater than 61%.

By omitting those stocks that violate Roll's conjecture, we eliminate those stocks whose effective spread is presumed to be negative (Harris, 1990). Harris (1989) explains that positive autocovariance can result from closing prices that cluster at the ask price. This violates Roll's assumption of trade independence. On a purely statistical basis, Harris (1990) shows the auto covariance to be defined as Roll estimate $\simeq$ E(serial covariance) + variance of daily returns, where E is the expectations operator. The expectation of serial covariance is always negative while the variance term is always positive. Positive serial correlation occurs more frequently using daily data because the variance of price changes can be larger than the covariance.

3.4. Quoted commission estimate

The commission schedule is determined using the discount brokerage schedule from CIGNA financial services, which is a standard (broker-assisted) commission schedule. Although the commission rates are substantially larger than those

available at the end of the sample period through online brokerage accounts, the rates reflect average competitive commission rates over the length of our sample period. 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. The magnitude of the commissions in this schedule appears high with respect to the online 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. This schedule is similar to that of Bhardwaj and Brooks (1992). The use of a commission schedule for Nasdaq firms can 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 overstate the quoted costs for trading in those securities.

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 1997. TAQ data is unavailable prior to 1993. Since we are estimating the bid-ask spread for the year prior to the performance period, we lose an additional year and begin in 1994 for the spread comparisons and stop in 1997. For comparison purposes the average trade size in 1997 is 1,063 shares, 2,334 shares, and 1,236 shares, respectively for the NYSE, AMEX, and Nasdaq. Thus the principal amount is determined using the share price multiplied by the average trade size of the listing market.

3.5. The LDV estimate

Our estimation of the LDV trading cost follows Lesmond et al. (1999). The intuition for the approach is that the trading costs of arbitrageurs are revealed in firm returns if arbitrageurs (informed traders) trade only when the returns associated with trading on mispricing exceed the costs of trading. Lesmond et al. (1999) argue that the frequency of experiencing a daily return of exactly 0% is greater for firms with larger trading costs, since larger trading costs discourage arbitrageurs from trading on the same news. Also, since firms with larger trading costs require a larger accumulation of news, the returns associated with nonzero-return days are expected to be larger to overcome the trading cost threshold.

More specifically, the LDV approach is characterized by the following equation:

$$
\begin{aligned}
R(i,t) &= R^*(i,t) - \alpha_1(i) &&\text{if } R^*(i,t) < \alpha_1(i) \\
R(i,t) &= 0 &&\text{if } \alpha_1(i) \leqslant R^*(i,t) \leqslant \alpha_2(i) \quad\quad (3)\\
R(i,t) &= R^*(i,t) - \alpha_2(i) &&\text{if } R^*(i,t) > \alpha_2(i),
\end{aligned}
$$

where $\alpha_1(i) < 0$ is the sell-side trading cost for asset i, $\alpha_2(i) > 0$ is the purchase side cost, $R(i,t)$ is the measured return from CRSP, and $R^*(i,t)$ is the unobserved return in a frictionless market. The informed trader's reservation price for trades, $R^*(i,t)$, is bounded by the applicable trading costs, $\alpha_1(i)$ and $\alpha_2(i)$. As a simple specification of the return-generating process for the informed arbitrageur, Lesmond et al. (1999) use the common "market model" regression with the intercept suppressed, $R^*(i,t) = b(i)R_M(t) + e(i,t)$ where $R_M(t)$ is the measured CRSP daily return on the market index and $e(i,t)$ captures all other information. 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 marketwide information and all other information. The other information could contain accumulated past marketwide and firm-specific information that has not yet been incorporated into the price. A more detailed summary of the LDV approach is provided in the appendix.

For our estimates, we use the CRSP equally weighted market return as the market index because of the equal weight each firm receives in our relative strength portfolios. The LDV estimate of transaction costs, by considering the arbitrageurs' reservation returns, includes not only the explicit costs, such as the bid-ask spread and commissions, but also the implicit costs, such as short-sale constraints, taxes, and price impact, to produce trading cost estimates that should be higher than just the spread costs. Lesmond et al. (1999) show that the LDV estimate is actually at least 30% lower than quoted spread plus commission regardless of firm size. Thus, the LDV estimates appear relatively conservative compared to the most demonstrable immediacy estimate of transaction costs. Interestingly, Keim and Madhavan (1995) find that active institutional traders (i.e., technical traders whose decisions to trade are based on momentum) prefer to use market orders to assure rapid execution and consequently incur immediacy costs.

We expect that any bias in the LDV estimate due to distribution concerns or information impounding concerns to be more in evidence for smaller firms. Smaller firms exhibit more zero returns and, not unexpectedly, exhibit a higher degree of nonnormality in observed returns. To test the impact of any potential bias, we regress the LDV estimates on the quoted spread estimates for each size quintile. We find that the regression tests show a higher R-squared statistic for smaller firms, 46.2%, than for larger firms, 23.8%. The quoted spread coefficients are approximately 0.6 and significant at the 1% level. Lesmond et al. (1999) find that smaller firms have a higher R-square statistic than do large firms but they find all of the quoted spread coefficients are greater than one.

3.6. Reasonability of estimates

Large cross-sectional variation is common in trading cost estimates (Bessembinder, 1999). For large capitalization stocks, round-trip trading cost estimates are generally between 1% and 2% over our sample period. However, for small capitalization stocks, the estimates are much larger at 5% to 9% (see Stoll and Whaley, 1983; Kothare and Laux, 1995; Knez and Ready, 1996; Chan and Lakonishok, 1997; Keim and Madhavan, 1998). Jones and Seguin (1997) find that the mean bid-ask spread for all Nasdaq stocks is 12% and 18% for small Nasdaq stocks.

In Figs. 2 and 3, we compare the monthly mean round-trip trading cost estimates over the sample period for all NYSE/AMEX/NASDAQ stocks in size class 2 and 5. The figure illustrates both the time-series and cross-sectional variation in the trading cost estimates. For size class 2, the LDV estimate remains between 4% and 7% while the Roll spreads are between 1.5% and 4%. For the larger firms, the mean LDV estimate declines to about 1.5%, and Roll spread is generally below 1%.

The correlation across the trading cost estimates is relatively high. For the firm-years in our sample, the correlation coefficients between the LDV estimates and the quoted spread, the Roll spread measure, and the direct effective spread measure are respectively, 0.84, 0.83, and 0.77, respectively. This high correlation is in evidence across each year of spread cost availability from 1993 to 1997. The remaining correlations between the direct effective spread, the Roll estimator, and the proportional spread are in excess of 0.75.
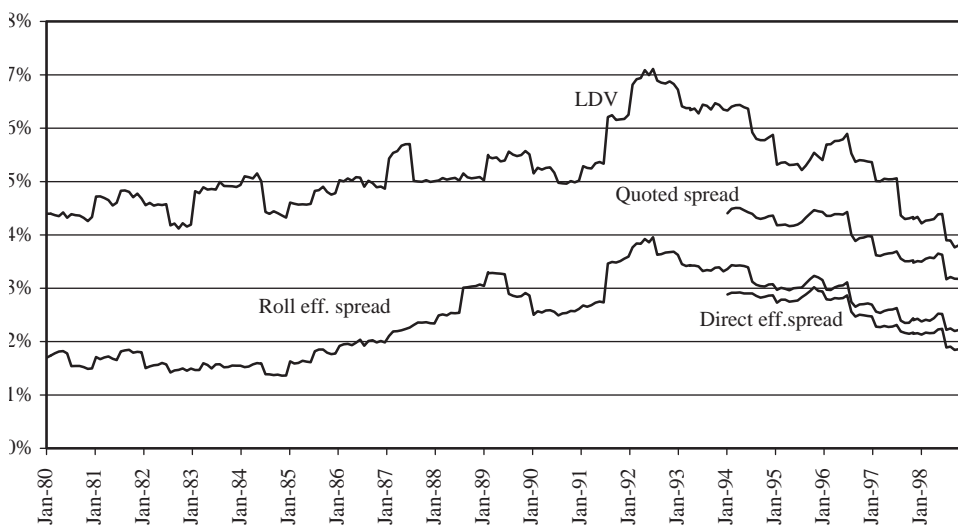

Fig. 2. Mean round-trip trading cost estimates for size quintile 2. Sample includes all NYSE/AMEX/NASDAQ stocks within size quintile 2.
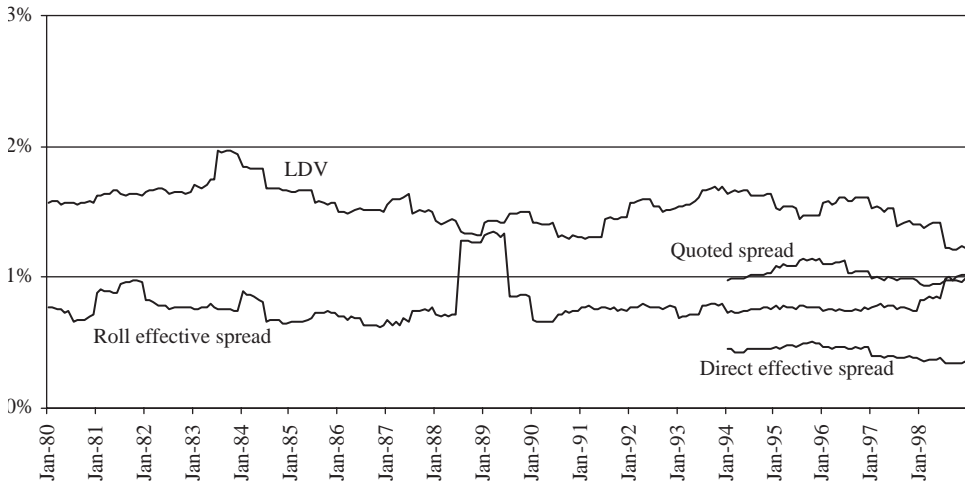
Fig. 3. Mean round-trip trading cost estimates for size quintile 5. Sample includes all NYSE/AMEX/ NASDAQ stocks within size quintile 5.

4. The profitability of standard strategies

We test the magnitude of our trading cost estimates by comparing the gross P3-P1 returns for various momentum strategies to the respective transaction cost estimates. According to the no-arbitrage rule, relative strength returns should not exceed the respective expected transaction costs. In Table 2, we compare the mean raw returns from the various relative strength portfolios to the corresponding trading cost estimates associated with executing these positions. In order to compare raw returns with the trading costs, we must cast the returns on the six-month trading period used to obtain those returns. To do this, we report the simple mean of the six-month buy-and-hold return for each month in our sample period. The standard errors reported accommodate the overlapping nature of both the return and trading cost estimates. We estimate a time-series regression for each series of coefficient estimates on an intercept. The residuals from this regression are modeled as a sixth-order moving average process. The standard error we use is the standard error on the intercept of the time-series regression. For the standard errors of the after trading cost return estimates also reported in Table 3, we repeat the same procedure but adjust the return series by subtracting the monthly portfolio trading cost estimate from the portfolio return each month. We also performed the analysis in Table 3 using nonoverlapping calendar periods (January and July starting dates) and found that it made little difference on the overall inference.

For the JT (1993) strategy, positions P1, P2, and P3 are associated with six-month returns of 2.5%, 8.2%, and 10.4%, respectively, for sample period 1980 to 1998. We report overlap-adjusted standard errors in parentheses. We test whether the returns for the extreme performers (P1 and P3) are statistically different from those of

Table 2
Estimates of trading costs for relative strength portfolios
The table reports the six-month buy-and-hold returns (%) and various trading cost estimates (%) associated with portfolio P1 (weak performers) portfolio P2 and portfolio P3 (strong performers) for various standard relative strength strategies over the sample period from January 1980 to December 1998. Within the three portfolios, firms are initially equally weighted and held for six months. Some of the trading cost estimates are only available for a limited portion of the sample period as noted. Standard errors that correct for the overlapping observations are in parentheses. The symbols,* and**, denote 5% and 1% statistical significance, respectively, for the test that the return or cost associated with the respective extreme performer portfolios (P1 or P3) is significantly different from that of portfolio P2.

	Jegadeesh and Titman (1993) strategy			Hong et al. (2000) strategy			Jegadeesh and Titman (2001) strategy		
	P1	P2	P3	P1	P2	P3	P1	P2	P3
Semi-annual portfolio returns									
Mean (1980–1998)	2.524**	8.176	10.350*	4.920**	8.154	9.660**	2.238**	8.225	11.136**
	(2.34)	(1.63)	(2.15)	(2.24)	(1.72)	(1.96)	(1.78)	(1.49)	(2.15)
Spread estimates									
Mean quoted spread	4.463**	2.548	4.115**	5.480**	4.021	4.855**	2.345	2.317	3.380**
(1994–1998)	(0.13)	(0.07)	(0.12)	(0.16)	(0.13)	(0.17)	(0.14)	(0.08)	(0.27)
Mean direct effect. spread	1.714**	1.323	1.564**	3.464**	2.336	2.959**	1.445*	1.327	2.187**
(1994–1998)	(0.08)	(0.02)	(0.13)	(0.13)	(0.07)	(0.17)	(0.11)	(0.07)	(0.24)
Mean roll effect. spread	2.360**	1.407	2.058**	3.258**	2.409	2.886**	1.625**	1.502	2.153**
(1980–1998)	(0.19)	(0.07)	(0.16)	(0.62)	(0.47)	(0.61)	(0.15)	(0.20)	(0.36)
Commission estimates									
Mean quoted commission	1.903**	1.323	1.781**	2.500**	1.719	2.126**	1.250**	1.183	1.635**
(1994–1998)	(0.06)	(0.03)	(0.09)	(0.02)	(0.02)	(0.09)	(0.04)	(0.03)	(0.13)
Total trading cost estimate									
Mean LDV estimate	5.050**	2.980	4.317**	6.099**	4.163	5.049**	3.419**	2.893	4.364**
(1980–1998)	(0.28)	(0.08)	(0.28)	(0.47)	(0.33)	(0.55)	(0.13)	(0.11)	(0.30)

portfolio P2. We reject return equality of portfolios P1 and P2 at the 1% level and reject equality of portfolios P2 and P3 at the 5% level. The results again suggest some degree of asymmetry in performance between portfolios P1 and P3.

We also report the mean trading cost estimates for the stocks associated with the respective portfolios. Because returns from standard relative strength strategies are computed using an equal weighting, the trading costs are also equal-weighted. Our trading cost estimates represent the mean roundtrip cost for trading the stocks within the respective portfolios for which obtain estimates. Since our experiment allows trading in those stocks for which we do not have cost estimates (firm returns used to calculate portfolio returns do not necessarily have corresponding trading cost estimates), our trading cost estimates are likely to be downwardly biased since the

Table 3

Estimates of relative strength strategy trading strategy profits

The table reports the mean six-month buy-and-hold returns (%) associated with a short position in portfolio P1 (weak performers) and a long position in P3 (strong performers) and return P3-P1 from January 1980 to December 1998. The positions retained proportion is the mean ratio of stocks that remain in the respective portfolio in the following period. * or ** denote 5% and 1% statistical significance, respectively, for the test that the return is greater than zero. *T*-statistics that adjust for the overlapping observations are in parentheses.

	Jegadeesh and Titman (1993) strategy	Hong et al. (2000) strategy	Jegadeesh and Titman (2001) strategy
Mean semi-annual P3-P1 portfolio return before trading costs	7.826% (6.22**)	4.740% (4.80**)	8.898% (6.67**)
Portfolio positions retained (% of P1)	22.65	37.77	15.23
Portfolio positions retained (% of P3)	14.98	33.18	17.77
Semi-annual returns after trading costs based on 100% turnover			
Mean returns based on LDV estimate	−1.541 (−1.09)	−6.408 (−5.01)	1.115 (0.74)
Mean returns based on Direct effective spread + Commision estimate	0.864 (0.61)	−6.309 (−4.93)	2.381 (1.58)
Semi-annual returns after trading costs based on actual turnover			
Mean returns based on LDV estimate	0.128 (0.07)	−2.473 (−1.90)	2.199 (1.59)
Mean returns based on Direct effective spread + Commision estimate	2.239 (1.22)	−2.321 (−1.78)	3.560 (2.57**)

stocks with missing cost estimates are likely to be relatively less liquid. Since portfolio P2 comprises the majority of the CRSP sample (80%), we begin by reviewing the magnitude of the estimates for this portfolio. The mean spread estimate is 2.5% for the quoted spread, 1.3% for direct effective spread, and 1.4% for the Roll effective spread. We note that, because the data for calculating the quoted spread, direct effective spread, and commission estimates is limited to the latter part of the sample period, the estimates only reflect costs from 1994 to 1998. Since the mean share price for stocks in P2 is $30, the reported proportional effective spread reflects a dollar spread of $0.40 and the reported proportional quoted spread reflects a dollar spread of $0.76. The mean round-trip commission is 1.3%. The mean round-trip LDV total trading cost estimate is 3.0%. Since the literature generally considers trading costs on a value-weighted basis, we expect that the mean trading costs we estimate may appear large to some readers. Given the comprehensive nature of the CRSP data set, the majority of the stocks within portfolio P2 are actually quite small. With such a large portion of small

stocks, we find these estimates to be fully consistent with the magnitudes in literature cited above.

When executing a relative strength strategy, the investor does not trade stocks within portfolio P2, but rather only portfolio P1 and P3 stocks. We find the trading cost estimates associated with these stocks are substantially and uniformly larger than those of portfolio P2. The trading cost estimates for P1 range from 30% to 75% larger than those of P2. The trading cost estimates for P3 range from 18% to 61% larger than those of P2. All of these differences in trading costs are significant at the 1% level. The patterns and inferences for the HLS (2000) and JT (2001) strategy are similar. In only one case (the P1 quoted spread for the JT (2001) strategy) we find the trading costs are not significantly greater for the relative strength portfolios than for portfolio P2. The consistency with which the P1 and P3 costs exceed the P2 costs is striking, since even the benchmark portfolio P2 is comprised of relatively illiquid stocks. Based on the evidence in Tables 1 and 2, we strongly reject the equality of trading costs across relative strength portfolios. We conclude that the stocks traded in relative strength strategies are sampled from stocks with disproportionately large trading costs.

In Table 3 we use the trading cost estimates to examine the after trading cost profitability of relative strength investing. For the JT (1993) strategy results reported in Table 2, the long position (P3) produces returns of 10.4% while the short position only costs 2.5% generating a net six-month before trading cost return of 7.8%. This figure is not only highly significant economically, but also highly significant statistically, with an overlap adjusted t-statistic of 6.2.

To realize the P3-P1 returns, the relative strength investor must short and close the P1 stocks and also buy and sell the P3 stocks. The execution requires paying the full spread on both the long and short positions, incurring the commission fees and price-impact costs on four trades, foregoing the opportunity cost imposed by margin requirements and rebate rates on short positions, as well as facing exposure to holding costs. These costs can be substantial, particularly when the strategy is tilted toward relatively illiquid securities.

Since the LDV measure purports to capture much of the trading costs facing investors, we begin by comparing the P3-P1 profits to the total LDV costs. Since the relative strength investor opens and closes positions in both the P1 and P3 stocks, the P3-P1 LDV estimate is simply the sum of the respective LDV estimates. For the JT (1993) strategy from Table 2, opening and closing the P1 position is associated with LDV costs of 5.1%, while buying and selling the P3 position is associated with LDV costs of 4.3%. The combined trading cost facing the investor is the sum 9.4%. Subtracting the estimated LDV trading costs of 9.4% from the raw P3-P1 returns of 7.8% produces an after-cost profit estimate of −1.5%. Based on this estimate, the costs of frequent trading in such costly securities exceed the strategy's paper profits.

To provide an alternative estimate of after trading cost profits we use the direct effective spread and the commission as an alternative total trading cost estimate. Using this measure for the JT (1993) strategy generates total trading costs of 7.0%. Since the direct effective spread costs are only available from 1994 to 1998,

we assume that the spreads associated with the later part of the sample period are reasonable estimates for the entire sample period. This assumes that the overall mean effective spread plus commission in period 1980 to 1992 roughly matches that of period 1993 to 1998. Based on the other trading cost levels exhibited in Figs. 2 and 3, this assumption does not appear to be unreasonable. Considering the estimates of trading costs, the net six-month return drops from 7.8% to near zero at 0.9%. To avoid over-penalizing the standard error on the spread + commission estimate due to the shortness of the sample period, we compute the *t*-statistic using the smaller LDV-based estimate standard error. The 0.9% is still insignificantly different from zero at the 5% level. For the HLS (2000) strategy, the lower P3-P1 returns are associated with even larger trading costs (since this sample also includes all Nasdaq stocks), such that the post trading costs returns are particularly negative with losses of 6.4% and 6.3% for the LDV and spread + commission estimates. For the JT (2001) strategy, the P3-P1 returns exceed the trading cost estimates in both cases. The after-LDV cost profits are 1.1% and the after spread + commission estimates are 2.4%, neither of which are statistically greater than zero at the 5% level even using the lower LDV standard error.

Since some of the securities remain in portfolios P1 or P3 from one holding period to another, the ongoing relative strength investor does not always need to close the entire position. If a stock was in portfolio P1 last period and remains in P1 for the subsequent period, the investor does not need to incur the costs of closing out the short and then re-shorting that stock. In Table 3 we report the mean proportion of P1 and P3 stocks that are retained in the same portfolio in the subsequent holding period. For the JT (1993) strategy, the proportions for P1 and P3 are 22.7% and 15.0%, respectively. We note, as do JT (1998) and HLS (2000), that these proportions are above the 10% expected from random transition probabilities. In executing the strategy the relative strength investor can save 23% of the cost of the short position and 15% of the cost of the long position by holding the position in those stocks into the next period. To better reflect the actual required turnover, our trading cost estimates can be adjusted down for the fraction of positions retained. We note that eliminating the requirement to open and close the position in stocks that do not switch portfolios results in a slight downward bias in our trading cost estimates since it assumes that the investor infinitely maintains the strategy.

We report the adjusted after trading cost return estimates in Table 3. The adjusted total cost of realizing the JT (1993) P3-P1 gross profits of 7.8% drops from 9.4% to 7.7% for the LDV measure. The estimated profit is near zero at 0.1%. For the spread + commission approach, trading costs drop from 7.0% to 5.6% producing a net profit of 2.2%. This figure is not significant at the conventional levels using the smaller LDV standard errors from the longer sample period. For the HLS (2000) strategy, the reduction in trading costs improves the LDV return estimate to −2.5% and the spread + commission return estimate to −2.3%. For the JT (2001) strategy, the adjustment improves the LDV return estimate to an insignificant six-month return of 2.2% and a significant spread + commission return estimate

of 3.6%. The magnitude of the cost of relative strength investing dramatically reduces the profitability of such strategies. Applying an LDV estimate of trading cost drives the profitability of relative strength investing to near zero in all cases.

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 2.3%, 2.8%, and 1.9%, respectively, for the JT (1993), HLS (2000), and JT (2001) strategies. The magnitude of this trading cost estimate is much larger than previous estimates of relative strength strategy trading costs. For example, JT (1993) base their one-way trading cost estimate of 0.5% 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, price impact, taxes, and short-sale costs. Including just the spread component more than doubles the magnitude of their trading cost estimate. By comparing trading profits to commissions and price impact costs only, JT (1993) 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 Fig. 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 trading cost estimates across portfolios. For the JT (1993) strategy, portfolios 1 and 3 exhibit mean LDV estimates of 5.1 and 4.3%, respectively. Portfolio 2's mean estimate of 3.0% is more representative of stock trading costs since it includes 80% of all stocks, yet the costs are significantly lower than that of relative strength portfolio stocks. The pattern is similar for the other trading cost measures and strategies. 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.

In summary, the evidence for positive trading profit net of transaction costs appears weak. The magnitude of trading costs, particularly for those firms which play an important role in generating abnormal performance, appears sufficiently large such that realizing net trading profits is likely to be 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. Hanna and Ready (2001) and Grundy and Martin (2001) also express some doubt that relative strength investing produces profits after transaction costs. We should note that the frictions facing arbitrageurs are likely to be larger than our estimates of trading costs. Chen et al. (2001), Sadka (2002), and Koraczyk

and Sadka (2002) observe that relative strength strategies require considerable trading in stocks with little depth particularly among the poor performing stocks. Across these papers there is some disagreement as to whether price impact costs prohibit favorable large position execution. Our trading cost measures do not explicitly include price impact costs. Holden and Subrahmanyam (2002) propose that friction in information acquisition plays a role in return continuation. Shleifer and Vishny (1997) argue that holding costs such as hedging costs and tracking error risk provide important barriers to arbitrage. Pontiff and Schill (2002) find empirical support for such holding risk barriers among new equity offerings. We 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 (1993) strategy the standard deviation for the 7.8% P3-P1 return is 11.2%, with single period returns varying from −49% to +32%. 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.

Although we observe that trading costs are of similar magnitude to 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 (1993) or Moskowitz and Grinblatt (1999). However, given the magnitude of the estimates in Table 2, the 3% to 6% semi-annual return generated by these strategies does not appear extraordinary, given the likely trading costs required for implementation.

5. Cross-sectional relationships

We now explore several cross-sectional relationships for relative strength portfolio returns. We provide some evidence about whether strategies which purport larger paper profits are accompanied by larger trading costs.

5.1. Size-based portfolios

HLS (2000) 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 break points. 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 HLS 30–70 break points. Within the size subsamples, we compute the P3-P1 momentum profits. We report our results in Panel A of Table 4. Consistent with HLS, the six-month P3-P1 returns are 3.9%, 8.1%, 5.4%, 3.2%, and 1.0% for size classes 1–5, respectively.

Table 4
Estimates of relative strength strategy trading strategy profits sorted by size, turnover, and trading cost

The table reports the mean six-month buy-and-hold returns (%) and various trading cost estimates (%) associated with a short position in portfolio P1 (weak performers) and a long position in P3 (strong performers) and return P3-P1 using 30–70 percentile performance break points. The positions retained proportion is the mean ratio of stocks that remain in the respective portfolio in the following period. In Panel A, the size class subsamples are formed based on NYSE/AMEX market capitalization break points but include all NYSE/AMEX/NASDAQ firms following Hong et al. (2000). Panel B includes only stocks trading on NYSE/AMEX and for more than $1 following Lee and Swaminathan (2000). Panels C and D includes all NYSE/AMEX/NASDAQ stocks.

			Raw returns					Total trading costs based on actual turnover	
			P1	P2	P3	P3-P1	Positions retained (%)	LDV	Direct eff. spread + Commission[*]
Panel A: mean semi-annual estimates by size class									
Size class	(Lowest)	1	6.12	8.06	10.03	3.91	30.0	12.92	12.13
		2	1.76	7.73	9.88	8.12	23.6	8.38	6.73
		3	4.48	8.48	9.91	5.43	23.5	5.62	4.51
		4	6.50	8.64	9.67	3.16	25.1	3.73	2.96
	(Highest)	5	8.18	8.65	9.18	1.00	27.4	2.32	1.94
Panel B: mean semi-annual estimates by turnover class									
Turnover class	(Lowest)	1	6.59	9.33	10.08	3.49	26.4	5.61	4.25
		2	6.52	9.05	9.77	3.25	25.4	5.14	3.99
		3	5.97	8.67	9.12	3.15	26.4	4.74	3.82
		4	5.71	8.87	9.07	3.36	27.0	4.84	3.62
	(Highest)	5	1.11	6.76	8.51	7.39	27.6	5.33	3.88
Panel C: mean semi-annual estimates by LDV trading cost class									
Trading cost class	(Lowest)	1	7.73	8.73	9.09	1.36	25.6	2.24	2.19
		2	5.43	8.75	9.77	4.34	25.0	3.96	3.60
		3	2.52	8.14	10.4	7.89	25.4	5.90	5.44
		4	1.21	6.97	9.93	8.71	26.4	8.56	8.11
	(Highest)	5	4.37	6.69	9.61	5.24	29.2	15.93	16.07
Panel D: mean semi-annual estimates by residual LDV trading cost class									
Residual trading cost class	(Lowest)	1	4.44	9.05	9.93	5.55	22.9	5.32	5.86
		2	3.76	8.35	9.80	6.05	12.6	6.99	7.13
		3	3.37	7.67	9.83	6.46	11.3	8.29	8.08
		4	3.31	8.25	10.14	6.83	13.1	10.00	9.41
	(Highest)	5	4.29	7.28	9.50	5.21	22.1	14.28	13.96

[*] Available only for 1994–1998.

We report the mean total trading cost estimates by size class. Trading cost estimates include round-trip costs for portfolio P3 plus roundtrip costs for P1 adjusted for the proportion of positions retained. We observe that, for all six trading cost estimates there is a monotonic relationship between size class and trading cost. The LDV estimate adjusted downward for the actual portfolio turnover declines from 12.9% to 2.3% across the five size classes. The adjusted spread + commission

estimate declines from 12.1% for the smallest size class to 1.9% for the largest size class. Although not reported, the patterns are similar for the other trading cost estimates. In all cases, the LDV estimate exceeds the P3-P1 return. For size class 2, 3, and 4, the P3-P1 returns slightly exceed the spread + commission estimate. The largest example is the 8.1% size class 2 return, that exceeds the spread + commission estimate by 1.39% age points. We conclude that strategies that focus on classes of stocks with high expected momentum profits such as size class 2 also face high trading costs.

Panel A suggests that the variation in P3-P1 profits across size class is largely due to variation in the short position returns. The large increase in P3-P1 profits from size class 5 to size class 2 is explained almost exclusively by the monotonic decline in P1 returns from 8.2% to 1.8%. The long P3 position experiences little change across size class. Since much of the gain in holding relative strength positions in small stocks is due to the short position, short-sale costs are likely important considerations to the arbitrageur, particularly with small cap stocks. 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 are 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 (2003) finds that stocks that have experienced past weak performance are more likely to maintain larger short sale costs. The costs of the short position are not fully reflected in our trading cost estimates.

5.2. Turnover-based portfolios

Lee and Swaminathan (2000) identify a relationship between share turnover and momentum returns. They also reject the transaction cost explanation in favor of anomalous behavioral models. 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 et al. (2001), however, find that turnover and market liquidity are highly correlated, and in fact, use turnover as a proxy for liquidity. Sadka (2002) finds a negative correlation between turnover and liquidity in related tests of Lee and Swaminathan momentum strategies.

We follow Lee and Swaminathan's approach by sorting stocks into turnover classifications 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 B. Across turnover classes the P3-P1 returns are between 3.1% and 3.5% for turnover classes

1–4. The low P1 return for turnover class 5 generates a large P3-P1 return for this class of 7.4%. Except for turnover class 5, the trading cost estimates are generally near the trading profits. The large trading costs for turnover class 5 are again due exclusively to the poor performance of the P1 stocks. The profitability of the strategy assumes that the substantially lower returns of the P1 (turnover class = 5) stocks be an equilibrium value. 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. We find in our sample period that the net gain of such a cross position is not large, because the trading costs also rise. The mean P3 (turnover class = 1)-P1(turnover class = 5) returns are 8.9%, whereas the retention-adjusted LDV trading cost estimate is 5.7%. Estimates of trading costs are even larger for other Lee and Swaminathan recommended strategies.

5.3. Trading-cost-based portfolios

One sensible strategy is to minimize trading costs by constructing relative strength positions in securities with the smallest cost of trading. If relative strength returns are independent of trading costs, this approach should be profitable. In Panel C we report return and cost statistics for portfolios sorted by LDV trading cost estimates. Trading cost class definition is based on equal groupings by month for the entire CRSP sample. We use HLS (2000) sample 30–70 performance break points to define P1 and P3. Across trading cost classes the P3-P1 returns increase from 1.4% for the lowest cost class, to 4.3% for class 2, to 7.9% for class 3, to 8.7% for class 4, and finally down to 5.2% for the largest trading cost class. The drop in P3-P1 returns for the highest trading cost class is similar to the drop in returns observed for the smallest size class portfolio. For some unidentified reason, the smallest and/or costliest stocks experience less return continuation. The trading cost estimates appear to be similar in magnitude to the relative strength returns. In certain cases the P3-P1 returns exceed the trading cost estimates, but again the magnitudes are not large. A strategy of trading cost minimization substantially reduces trading returns. The lowest trading cost strategy only generates before-cost returns of 1.4%. Arbitrageurs do not appear able to capture greater after-cost momentum profits by minimizing trading costs.

Since size and trading cost are highly correlated, we compute a residual trading cost estimate that attempts to control for the influence of size on trading cost. Following HLS (2000), we regress the LDV estimate on firm size and a Nasdaq dummy within each size class and for each month. The residual trading cost class is the error term obtained from the regression. Stocks are sorted into equal-size residual trading cost classes by month based on monthly size-class specific break points. Controlling for size, we observe that P3-P1 returns increase monotonically from 5.6% to 6.8% across residual trading cost classes 1–4. For the highest residual trading cost class, the P3-P1 returns again drop. The relative strength returns do not generally exceed trading costs. Size appears to capture some, but certainly not all of the relationship between LDV costs and trading profits.

5.4. What causes relative strength return patterns?

Hong and Stein (1999) advocate that relative strength returns are explained by sluggishness in the diffusion process of information. 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 (2000) chose 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.

One concern with this inference is that the HLS (2000) findings are also consistent with the friction hypothesis. First, we observe from Panel A of Table 4 that trading costs are correlated with the HLS size portfolios. Since smaller firms also have larger trading costs, it is unclear whether the larger P3-P1 returns for smaller stocks are due to slower information diffusion or merely due to slower price updating induced by larger trading costs. 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. Our findings motivate a more rigorous examination of the underlying source of return patterns.

In fact, analyst coverage has been used as a proxy for transaction costs (Brennan and Subrahmanyam, 1995). HLS test their assumption using alternative transaction-cost proxies including turnover and option listing. We expect these measures are rather noisy proxies. We perform some preliminary analysis of this issue but are unable to produce any conclusive evidence. 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. Following HLS, we exclude size class 1. All estimates are log transformed to reduce the effect of variable skewness. As with HLS, we obtain analyst coverage estimates from the I/B/E/S Historical Summary File and follow their procedure to obtain a residual coverage estimate. We find that size, coverage, and residual coverage, are significantly negatively correlated with our four trading cost estimates with correlation coefficients ranging from -0.74 to -0.04. The sign and magnitude of the correlation coefficients between the trading cost estimates and the information-diffusion proxies are such that the HLS variables could just be picking up trading cost effects.

To 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 2–5 by residual coverage and form coverage classes based on break points at the 30th and 70th percentiles. Across the 3×4 matrix we construct relative strength portfolios as before and compute the associated P3-P1 profits. As HLS, we find that relative strength profits generally decline in

residual coverage, with some exceptions for the largest size classes. The magnitude of the differences across portfolios, however, is substantially less than those reported by HLS. To control for trading costs we re-sort the stocks by their LDV estimate each period and form five equal trading cost classes. The estimates in trading cost monotonically increase across the trading costs classes for all specifications. To compare the explanatory power of residual coverage with that of our LDV estimates, we form residual coverage portfolios which control for trading cost. After controlling for trading costs, residual coverage appears to provide little explanatory power. We find that only trading cost class 5 preserves the decreasing relationship between relative strength returns and residual coverage. Otherwise, analyst coverage appears to have little effect on the returns. Since we are unable to replicate the original HLS, we are unable to determine whether our result is due to differences in portfolio sorting or to trading costs subsuming the explanatory power of analyst coverage. Further work is required to better distinguish these hypotheses.

6. 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 could be premature. We find that the returns associated with relative strength investing strategies (buying past winners and selling past losers) do not exceed 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 returns is increasing in trading-cost proxies, suggesting that trading costs are binding to arbitrage. The existence of performance persistence patterns in returns does not appear to conflict with information efficiency or suggest the existence of arbitrage opportunity. The evidence is consistent with sluggishness in the updating of equity prices. Nagel (2002) argues that relative strength portfolio returns are best characterized by information underreaction.

Although our evidence casts doubt on the gains from any momentum strategy, we do not attempt to reject profitability in all momentum strategies. Explicitly investigating the host of existing recommended momentum strategies including Rouwenhorst's (1998, 1999) non-US momentum strategies, Gebhardt et al. (2001) bond market strategies, or Moskowitz and Grinblatt (1999) and Lewellen's (2002) sector momentum strategies is left to future research.

Appendix. A

Incorporating the market model into Eq. (3), we form an econometric model. Using this model and assuming that returns are normally distributed, estimates of α_1

and α_2 can be obtained by maximizing the following log-likelihood function:

$$
\begin{aligned}
\ln L = {} & \sum_{R_1} \ln \frac{1}{(2\pi\sigma(i)^2)^{1/2}} - \sum_{1} \frac{1}{2\sigma(i)^2} \left(R(i,t) + \alpha_1(i) - b(i)R_M(t) \right)^2 \\
& + \sum_{R_2} \ln \frac{1}{(2\pi\sigma(i)^2)^{1/2}} - \sum_{2} \frac{1}{2\sigma(i)^2} \left(R(i,t) + \alpha_2(i) - b(i)R_M(t) \right)^2 \\
& + \sum_{R_0} \ln(\Phi_2(i) - \Phi_1(i)), \qquad\qquad\qquad\qquad\qquad\qquad \text{(A.1)}
\end{aligned}
$$

where R_1 and R_2 denote the region where the measured return $R(i,t)$ in the nonzero 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 nonzero observed returns. The first term corresponds to the negative market returns and second term corresponds to the positive market returns of Eq. (4). The third term corresponds to the zero-return region that spans both positive and negative market returns and represents the nontrading region of the arbitrageur. The estimate of interest is the difference between $\alpha_2(i)$ and $\alpha_1(i)$, α_2-α_1, which represents the implied round trip transaction costs that we denote as the LDV estimate. Since this difference is an estimate of investors' reservation returns, it is relatively comprehensive in nature.

The LDV model requires several critical assumptions. These revolve around distribution and information flow assumptions. The first distributional assumption is that, in a frictionless market, the underlying true daily security returns are normally distributed, while the measured distribution of daily returns is clearly nonnormal. This estimation procedure, as in many other models, relies on normality assumptions to ease the estimation hurdles of the regression model. Although not specifically modeled, we appeal to asymptotic distributions of returns that rely on a limiting distribution that approximates a normal distribution or a two-parameter distribution. In the second distribution assumption, the return process assumes a continuous sequence of returns that neglects the discreteness of the measured process in price movements at the bid-ask quotes. Petersen and Fialkowski (1994) minimize this concern as they find that at least one-half of all trades occur within the bid-ask spread, thus limiting the discreteness concern of the underlying price process. Thus, we do not believe that these distributional assumptions are uncommon or unduly bias the transaction costs estimates.

The LDV model also implicitly assumes that the marginal trader is the informed trader who possesses more valuable information. However, for liquidity traders, if the need for immediacy is sufficiently high, then we will observe nonzero returns within the transaction costs interval bounded by α_2-α_1. These trades are assumed idiosyncratic and the average valuation effect over time is zero. The LDV model, in using only the measured number of zero returns from CRSP, is conservative in the count of the number of zero returns relative to the number of zero returns that would result if we accounted for all information-less trades (i.e., bid-ask trade bounces or trading around zero volume days). The measured number of zero returns measured from CRSP represents a reasonable estimate for the ''effective'' number of zero

returns. Lesmond et al. (1999) present a more thorough discussion of the effect of informed and uninformed traders and the effect trading of the bid-ask spread on the number of zero returns.

Finally, we model the security returns with no intercept term in the objective function. The intercept is subsumed by the transaction cost estimates including one for the buy-side and one for sell-side costs. Thus any model misspecification bias will now be incorporated into the transaction cost estimates. Assuming a constant misspecification bias for both up and down markets, each intercept term will contain approximately the same bias. Differencing these two intercept terms (to arrive at the round-trip trading costs) mitigates the misspecification bias by differencing any potential bias introduced into the intercept terms to essentially zero.

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