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Liquidity and Autocorrelations in Individual Stock Returns

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ABSTRACT

This paper documents a strong relationship between short-run reversals and stock illiquidity, even after controlling for trading volume. The largest reversals and the potential contrarian trading strategy profits occur in high turnover, low liquidity stocks, as the price pressures caused by non-informational demands for immediacy are accommodated. However, the contrarian trading strategy profits are smaller than the likely transactions costs. This lack of profitability and the fact that the overall findings are consistent with rational equilibrium paradigms suggest that the violation of the efficient market hypothesis due to short-term reversals is not so egregious after all.

Asset prices should follow a martingale process over short horizons as systematic short-run changes in fundamental values should be negligible in an efficient market with unpredictable information arrival. However, Lehmann (1990) and Jegadeesh (1990) show that contrarian strategies that exploit the short-run return reversals in individual stocks generate abnormal returns of about 1.7% per week and 2.5% per month, respectively. Subsequently, Ball, Kothari, and Wasley (1995) and Conrad, Gultekin, and Kaul (1997) suggest that much of such reversal profitability is within the bid–ask bounce. Theoretically, the potential role of liquidity in explaining the high abnormal payoffs to short-run contrarian strategies is implied by the rational equilibrium framework of Campbell, Grossman, and Wang (1993) (henceforth, CGW). In the CGW model, non-informational trading causes price movements that, when absorbed by liquidity suppliers, cause prices to revert. Such non-informed trading is accompanied by high trading volume, whereas informed trading is accompanied by little trading volume. Thus, price changes accompanied by high (low) trading volume should (should not) revert. Empirically, Conrad, Hameed, and Niden (1994) (henceforth, CHN) find that reversal profitability increases with trading

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activity in a sample of NASDAQ stocks. Cooper (1999), on the other hand, uses a sample of large NYSE–AMEX stocks and finds that reversal profitability declines with trading activity.[1]

The CGW model also points to a potential role for liquidity, which need not be captured by trading volume-based measures, as the model implicitly assumes that the demand curves for stocks are not perfectly elastic (otherwise, trades would not impact prices and subsequent price reversals would not occur). The model therefore suggests that the slope of the demand curve should be steeper for illiquid stocks. With downward-sloping demand curves, price reversals should follow non-informational liquidity trading. Specifically, non-informational demand for liquidity generates price pressure that is subsequently reversed as liquidity suppliers react to potential profit opportunities attributable to price deviations from fundamentals. Accordingly, we conjecture that the price pressure caused by demand for immediacy from liquidity traders leads to, or at least enhances, price reversals. Controlling for trading volume and liquidity, or rather, the lack of liquidity, should therefore have an impact on stock return autocorrelations. This paper demonstrates strong predictability and high potential profits from a contrarian strategy that incorporates an illiquidity measure.

While liquidity is an elusive concept, most market participants agree that liquidity generally reflects the ability to buy or sell sufficient quantities quickly, at low trading cost, and without impacting the market price too much. Following Amihud (2002), we measure weekly as well as monthly illiquidity as the average of the daily price impacts of the order flow, that is, the daily absolute price change per dollar of daily trading volume.[2] It should be noted that illiquidity and trading volume are markedly different both conceptually as well as empirically—they measure different behaviors and are only mildly correlated. Thus, illiquidity can potentially contribute to our understanding of reversal profitability and indeed, we demonstrate that it does.

Studying a sample of NYSE–AMEX stocks over the period 1962 to 2002, we find that while there are reversals in weekly and monthly stock returns, they are mainly confined to the loser stocks, that is stocks that have negative returns in the past week or month. At the weekly frequency, high turnover stocks exhibit higher negative serial correlation than low turnover stocks. The empirical evidence therefore supports the trading activity implications of CGW and findings of CHN.[3] The evidence also strongly supports the illiquidity implications of CGW, namely liquidity has a robust effect on stock return autocorrelations,

[1] Cooper's (1999) results support the asymmetric information model of Wang (1994) in which price continuations are accompanied by high trading volumes when informed investors condition their trades on private information.

[2] The Amihud measure was inspired by Kyle's (1985) lambda, the market impact measure.

[3] The fact that our results are apparently at odds with the predictions of Wang (1994) suggests that the degree of information asymmetry in our sample of NYSE–AMEX stocks may not be sufficiently large to have an impact on individual stock return autocorrelations. Indeed, when the degree of asymmetric information is low, the equilibrium framework of Wang reduces to that of CGW.

even after controlling for trading volume. In particular, there is substantially more reversal in less liquid stocks than in highly liquid stocks. Taken together, our results suggest that the high turnover, low liquidity stocks face more price pressure in week $t-1$ (have the largest initial price change) and observe a greater fraction of that return reversed in week t (have the highest negative serial correlation in cross-sectional regressions) than the low turnover, high liquidity stocks. The result of both these effects—a larger price response in week $t-1$ combined with a larger fraction reversed in week t—is a nonlinear increase in week t returns as one moves from low turnover, high liquidity stocks to high turnover, low liquidity stocks.

Interestingly, we find that the impact of liquidity on autocorrelations is similar at the weekly and monthly frequencies. In contrast, at the monthly frequency the impact of turnover on autocorrelations reverses relative to that based on the weekly frequency; low turnover stocks exhibit more reversals than high turnover stocks. This could arise because demand shocks are attenuated at the monthly frequency as compared to the weekly frequency, which would suggest that turnover may be a poor proxy for non-informational trades at the monthly frequency. Overall, our findings show that non-informational demand for liquidity generates price pressure that is subsequently reversed as liquidity suppliers react to potential profit opportunities that are attributable to price deviations from fundamentals. Our findings are consistent with the notion that the predictability in short-horizon returns occurs because of stresses in the market for liquidity.

The large contrarian strategy profits documented by Lehmann (1990) and Jegadeesh (1990) reflect a violation of weak-form market efficiency as defined by Fama (1970). However, we demonstrate that a high frequency trading strategy that attempts to profit from the negative serial correlations generates high transactions costs and substantial price impact. Specifically, we use the transaction cost estimates of Keim and Madhavan (1997) within a dynamic framework to estimate net returns based on a strategy that buys the losers and sells the winners. We also consider the market impact cost analysis of Korajczyk and Sadka (2004). The evidence conclusively shows that potential profits to outside investors (as opposed to market makers) are overwhelmed by transactions costs under each and every choice of liquidity and turnover. Consequently, while the presence of statistically significant negative autocorrelations in individual security returns is undeniable, it is not possible to profit from the short-run predictability. This lack of profitability is consistent with the Jensen's (1978) definition of market efficiency and Rubinstein's (2001) definition of minimally rational markets.[4]

To summarize, this paper provides two main contributions. First, we test the implicit CGW assumption of downward-sloping demand curves as well as the hypothesis that more illiquid stocks have steeper demand curves by explicitly

[4] The concept of market efficiency with respect to an information set has been defined by Jensen (1978) as the inability to profit from that information. Rubinstein (2001) defines this as minimally rational markets.

accounting for illiquidity in forming price reversal strategies. We show that, over and above the impact of turnover, illiquidity has a consistent impact on short-run reversals both at the weekly and monthly frequencies. Second, we show that potential contrarian strategy profits, albeit robust to the bid–ask bounce effect, do not reflect violations of market efficiency because such profits are overwhelmed by transactions costs. The lack of profitability from short-run contrarian strategies and the fact that the overall findings are consistent with the rational equilibrium paradigm of CGW suggest that the violations of the efficient market hypothesis due to short-term reversals are not so egregious after all.

The remainder of the paper proceeds as follows. Section I presents the data. Section II presents the results. A detailed discussion of transactions costs is presented in Section III and Section IV concludes.

I. Data

We obtain the return and trading volume data from CRSP for the universe of NYSE–AMEX stocks over the sample period 1962 through 2002. The average number of stocks in the sample is 2,070. As noted earlier, our proxy for illiquidity is the Amihud (2002) measure, which is computed as the absolute price change per dollar of daily trading volume,[5]

$$ILLIQ_{it} = \frac{1}{D_{it}} \sum_{t=1}^{D_{it}} \frac{|R_{itd}|}{DVOL_{itd}} * 10^6, \tag{1}$$

where R_{itd} is the daily return, $DVOL_{itd}$ is the dollar trading volume of stock i on day d in week (or month) t, and D_{it} is the number of days in week (or month) t for which data is available for stock i. We compute the Amihud illiquidity measure for both the weekly as well as the monthly frequency. In the weekly analysis, we require that a stock trade every day of the week before it is included in the sample for that week.[6] In the monthly analysis, we require at least 10 days with trades each month. In order to avoid extremely illiquid stocks, we eliminate penny stocks, that is, stocks with prices less than one dollar, from the sample.[7]

The mean (median) cross-sectional return is 0.24% (−0.09%) per week and the mean (median) weekly turnover (defined as dollar trading volume divided by market capitalization) is 0.24% (0.15%). The mean (median) cross-sectional illiquidity measure is 1.45 (0.16), in other words, the mean absolute daily return for one million dollars of trading volume is 1.45%. The correlation between returns and turnover is positive at 0.13. The correlation between returns and

[5] Hasbrouck (2003) compares effective and price impact measures estimated from daily data to those from high frequency data and finds that the Amihud (2002) measure is the most highly correlated with trade-based measures.

[6] We verify that our results are robust to requiring only 2 days of trading in each week.

[7] In the context of long-term contrarian investment strategies, Ball, Kothari, and Shanken (1995) show that microstructure issues can create severe biases amongst low-priced stocks.

illiquidity is essentially zero. Since turnover has often been used as a measure of liquidity,[8] one may expect the illiquidity measure to be related to turnover. However, the cross-sectional correlation between turnover and liquidity is only −0.08. The information in the Amihud illiquidity measure is not subsumed by that in turnover, which thereby allows us to separately study the impact of both turnover as well as illiquidity on the serial correlation pattern of stock returns at the weekly and monthly frequencies.

II. Results

Lehmann (1990) and Jegadeesh (1990) document negative serial correlation in the cross-section of weekly and monthly stock returns, respectively. In particular, they show that contrarian strategies that exploit the return reversals in individual stocks generate abnormal returns of about 1.7% per week (Lehmann) and 2.5% per month (Jegadeesh). This economically significant predictability seems to be at odds with the notion of weak-form market efficiency; prices should follow a martingale process over short time intervals since systematic short-run changes in fundamental values should be negligible in efficient markets with a random information arrival process. In this paper, we conjecture that a lack of liquidity around large price changes causes deviations from the so-called martingale process and price reversals arise as the price pressure response of uninformed investors to a demand for liquidity abates.

Our conjecture builds on CGW, who argue that price reversals occur as risk-averse market makers absorb order flow from uninformed or liquidity traders. In their model, a decline (increase) in stock prices could occur due to public information or due to liquidity-driven selling (buying) pressure. When the price change is information-driven, price reversals are unlikely. However, suppliers of liquidity who accommodate the non-informational sell orders demand higher expected returns and must be compensated for bearing portfolio risk when buying shares that they would otherwise not trade. In fact, liquidity suppliers are attracted by prices that move away from fundamentals in response to liquidity-driven buying or selling pressure. We do not expect price changes after the public information has been incorporated into prices. In contrast, price reversals are to be expected following liquidity-driven trading. Of course, if demand curves were perfectly elastic, price reversals would not obtain. Given downward-sloping demand curves, however, price reversals should follow liquidity or non-informational trading.[9] The CGW model suggests that more illiquid stocks have steeper demand curves, and liquidity, or the lack of it, should have an impact on price reversals. Consequently, in our empirical analysis, we form portfolios sorted on returns, trading volume, and illiquidity.

[8] See, for example, Brennan, Chordia, and Subrahmanyam (1998) and Chordia, Subrahmanyam, and Anshuman (2001).

[9] Avramov, Chordia, and Goyal (2005) show that trading (selling) activity causes negative serial correlation in daily stock returns.

A. Illiquidity and Reversal Profitability

Each week, we sort stocks based on the Wednesday-to-Tuesday close returns in week $t-1$. Following Lehmann (1990) and Jegadeesh (1990), we skip a day at the end of each week in order to avoid the negative serial correlation induced by the bid–ask bounce. Additionally, Ball, Kothari, and Wasley (1995) and Conrad, Gultekin, and Kaul (1997) argue that it is very important to control for the bid–ask bounce when computing the profitability of short-run trading strategies.[10] We further sort negative and positive return portfolios into extreme and non-extreme portfolios. That is, we form four portfolios: the first is the extreme negative return portfolio with an average equally weighted return of −5.69% per week; the second is the medium negative return portfolio; the third is the medium positive return portfolio; and the fourth is the extreme positive return portfolio with an average return of 6.11% per week. We form a total of 64 portfolios by sorting independently on illiquidity and turnover within each return portfolio. The turnover and illiquidity portfolio that is numbered one (four) has the lowest (highest) turnover and illiquidity, respectively.[11]

In untabulated results (available upon request) we find that, for the loser stocks, for any illiquidity (turnover) portfolio, the equally weighted average return for week $t-1$ decreases with turnover (illiquidity). For any portfolio, the return differential between turnover portfolios four and one is negative and this difference becomes monotonically more negative as illiquidity increases. Similarly, for any turnover portfolio, the return differential between illiquidity portfolios four and one is negative and this difference becomes monotonically more negative as turnover increases. An analogous pattern obtains for the extreme winner stocks as well. These return patterns are depicted in Panel A of Figure 1. In sum, during the formation period, the impact of price pressure increases with illiquidity and turnover. The large price changes occur in the high turnover portfolios and in portfolios with high illiquidity.

CGW suggest that non-informational or liquidity trades cause high turnover. Thus, the demand for liquidity from the non-informational trades combined with illiquidity cause large price changes. We conjecture that the large price changes in week $t-1$ noted in the previous paragraph should be reversed in week t as liquidity suppliers step in to profit from prices that temporarily

[10] We follow the skip-day methodology throughout the rest of the paper. In unreported results, we verify the impact on the profitability of reversal strategies when we do not skip a day between the formation and holding periods. The potential profits (including the impact of the bid–ask bounce) are indeed higher. However, when we study the impact of transactions costs (see the next section for details), we still find that the reversal profits do not survive reasonable cost estimates. All results based on full 5-day conditioning on past returns are available upon request.

[11] Conrad et al. (1994) sort on changes in the number of transactions. Cooper (1999) sorts on changes in turnover. We elect to sort on turnover because the CGW model relates the serial correlation patterns in returns to the level and not changes in turnover (see equation (16) in CGW). Also, the empirical analysis in CGW uses the detrended level of turnover and not changes in turnover. Conrad et al. note that their results are unchanged when sorting on changes in trading volume instead of changes in the number of transactions. With two-way sorts on returns and changes in turnover, we find that amongst the loser stocks, the low change in turnover securities revert more (a return of 0.64% in week t) than the high change in turnover securities (a return of 0.25%).

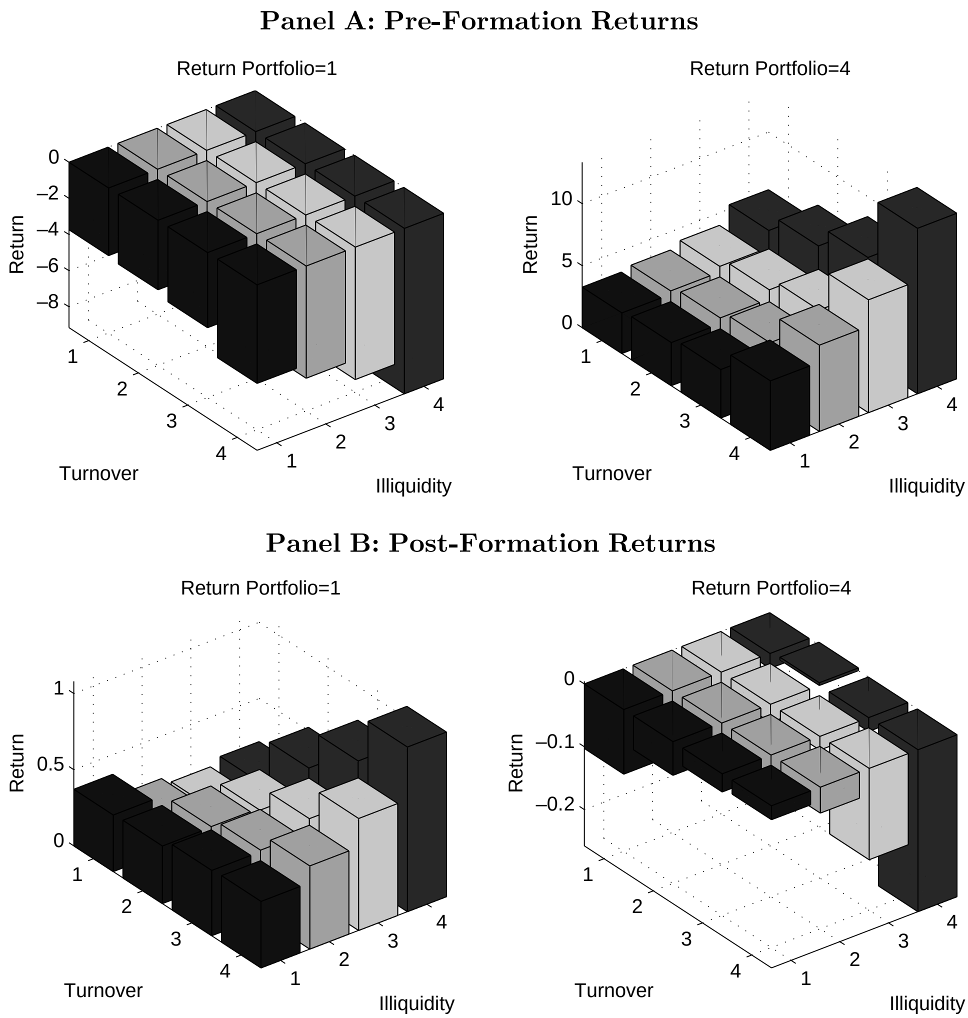

Figure 1. Three-way sorted portfolios: pre- and post-formation returns. This figure shows portfolio returns in the pre- and post-formation week. Equal-weighted portfolios are formed every week. The sorts are based on returns, turnover, and illiquidity. Turnover is measured as the ratio of number of shares traded to number of shares outstanding. Illiquidity is measured by the Amihud measure (ratio of absolute returns to dollar volume). Return breakpoints are determined by the median return for both positive and negative lagged returns. Breakpoints for turnover and illiquidity are based on quartile breakpoints. Return portfolio 1 is the extreme loser portfolio and return portfolio 4 is extreme winner portfolio. Turnover (illiquidity) portfolio 1 has the lowest turnover (illiquidity), and portfolio 4 has the highest turnover (illiquidity). Portfolio returns are in percent per week and are based on skip-day methodology in which the return on the last day of the week is not used in computations. The sample period is 1962 to 2002 and the portfolios include all NYSE and AMEX stocks that have data for all days of the week.

deviate from fundamentals. In particular, we should see such reversals amongst the high turnover and high illiquidity stocks in week t.

Table I presents the equally weighted average returns and standard deviations for the three-way sorted portfolios in week t. Recall that return portfolio one (four) has the lowest (highest) returns in week $t - 1$. Also, turnover and illiquidity portfolio one (four) has the lowest (highest) turnover and illiquidity, respectively. Focusing on return portfolio one, we note that the returns of each

Table I

Three-Way Sorted Portfolios: Post-formation Returns

This table presents means and standard deviations in the post-formation week. Equal-weighted portfolios are formed for every week. The sorts are based on returns, turnover, and illiquidity. Turnover is measured as the ratio of number of shares traded to the number of shares outstanding. Illiquidity is measured by the Amihud measure (ratio of absolute returns to dollar volume). Return breakpoints are determined by the median return for both positive and negative lagged returns. Breakpoints for turnover and illiquidity are based on quartile breakpoints. Return portfolio 1 is the extreme loser portfolio and return portfolio 4 is the extreme winner portfolio. Turnover (illiquidity) portfolio 1 has the lowest turnover (illiquidity), and portfolio 4 has the highest turnover (illiquidity). Portfolio returns are in percent per week and are based on skip-day methodology in which the return on the last day of the week is not used in computations. Significance levels at 90%, 95%, and 99% are denoted by one, two, and three stars, respectively. The sample period is 1962 to 2002 and the portfolios include all NYSE and AMEX stocks that have data for all days of the week.

	Return Portfolio = 1					Return Portfolio = 2				
	Illiquidity					Illiquidity				
Turnover	1	2	3	4	4–1	1	2	3	4	4–1
1	0.31***	0.28***	0.27***	0.48***	0.26***	0.08**	0.08**	0.09**	0.15***	0.07*
	2.71	2.49	2.33	2.59	2.84	1.91	1.67	1.75	2.14	1.89
2	0.38***	0.41***	0.42***	0.66***	0.27***	0.16***	0.20***	0.21***	0.23***	0.07
	2.56	2.53	2.63	2.95	2.66	1.90	2.12	2.35	2.86	2.29
3	0.42***	0.48***	0.50***	0.89***	0.46***	0.22***	0.25***	0.25***	0.38***	0.15**
	2.59	2.80	2.99	3.46	2.87	2.20	2.45	2.84	3.99	3.46
4	0.42***	0.53***	0.73***	1.16***	0.75***	0.29***	0.27***	0.37***	0.50***	0.24**
	3.09	3.22	3.57	4.37	3.74	2.63	3.02	3.50	5.90	5.50
4–1	0.08	0.25***	0.46***	0.68***	0.82***	0.20***	0.20***	0.29***	0.41***	0.42***
	2.77	2.44	2.52	3.46	4.25	1.96	2.11	2.59	5.46	5.67

	Return Portfolio = 3					Return Portfolio = 4				
	Illiquidity					Illiquidity				
Turnover	1	2	3	4	4–1	1	2	3	4	4–1
1	0.07**	0.09***	0.16***	0.24***	0.17***	−0.01	−0.10**	−0.03	0.14***	0.16***
	1.91	1.57	1.62	2.10	1.81	2.47	1.97	1.87	2.28	2.55
2	0.15***	0.16***	0.20***	0.35***	0.20***	−0.05	−0.06	−0.02	0.10**	0.15***
	1.85	1.91	2.17	2.76	2.16	2.01	2.18	2.29	2.68	2.26
3	0.19***	0.26***	0.33***	0.57***	0.39***	−0.04	−0.05	−0.02	0.02	0.06
	2.12	2.36	2.71	3.43	2.82	2.15	2.37	2.54	3.08	2.48
4	0.21***	0.28***	0.37***	0.70***	0.46***	−0.02	−0.04	−0.13**	−0.17**	−0.14**
	2.50	2.89	3.26	4.79	4.31	2.61	2.79	2.92	3.39	2.87
4–1	0.14***	0.18***	0.21***	0.43***	0.63***	−0.00	0.04	−0.09**	−0.31***	−0.21***
	2.01	2.02	2.46	4.22	4.53	2.38	2.14	2.05	2.73	3.33

of the 16 illiquidity–turnover sorted portfolios are positive, consistent with a reversal in returns. Except for illiquidity portfolio one, the return difference between turnover portfolio four and portfolio one is positive and significant. This return difference increases monotonically across the illiquidity portfolios from an insignificant 0.08% to 0.68% per week, suggesting that reversals increase with turnover and are much more pronounced when illiquidity is higher. Similarly, the return difference between illiquidity portfolios four and one increase across the turnover portfolios from 0.26% to 0.75%.[12] Note that in the highest turnover portfolio, returns increase from 0.42% for the lowest illiquidity portfolio to 1.16% for the highest illiquidity portfolio. This difference of 74 basis points per week is due to illiquidity.

Turning to return portfolio four, we demonstrate that 13 of the 16 returns are negative, albeit significantly so only in three cases. Also, the reversal increases with illiquidity only for the highest turnover portfolio and with turnover only for the two high illiquidity portfolios. There is no reversal in return portfolio three. Return portfolio two does exhibit reversals and the reversals increase with turnover (illiquidity) across the illiquidity (turnover) portfolios. Panel B of Figure 1 illustrates the reversals in the extreme return portfolios.

To summarize, in the extreme return portfolios (especially the loser portfolios), reversals increase with turnover and illiquidity. In addition, the high volatility of the extreme return and the high turnover–illiquidity portfolios suggest that it is the non-informational trades that generate the price movements in these portfolios. The findings suggest the presence of liquidity stresses in the high turnover and high illiquidity portfolios and that reversals occur as these liquidity stresses, which are caused by non-informational trades, are accommodated by suppliers of liquidity.

A.1. Robustness Checks

Number of stocks in each portfolio: Since we are following a strategy of independently sorting stocks into return–turnover–illiquidity portfolios, it is possible that some of these portfolios may end up with a few or no stocks. Recall that we require a stock trade every day of the week before it is included in the sample for that week. Not all stocks trade every day. This lack of trading along with independent sorting can result in some portfolios with no stocks during some weeks. We find that the most problematic portfolio in Table I is the loser portfolio with the lowest turnover and the lowest illiquidity. For this portfolio, out of the possible 2,111 weeks, 562 weeks contain no stocks. The other problematic portfolio is the winner portfolio with the lowest turnover and the lowest illiquidity. For this portfolio, 336 weeks contain no stocks. Given that most of the reversal takes place in the high turnover, high illiquidity portfolios, these missing weeks are not problematic for our reversal results. The high

[12] Note that the return differences across the portfolios are not the same as the differences in the average returns of the two portfolios because some of the portfolios have no stocks during a given week. We provide more details about the number of stocks in each portfolio in Section II.A.1.

turnover, high illiquidity loser portfolio has only 4 weeks with no stocks and the high turnover, high illiquidity winner portfolio has only 2 weeks without stocks. In Section II.B, we also confirm our results using the relative strength strategies that, by design, do not have any missing weeks.[13]

Nonsynchronous trading: Our experimental design ensures that our results are not contaminated by nonsynchronous trading. Recall that our analysis uses only stocks that traded on each and every day of the week to be included in that week. Moreover, the low priced stocks are more likely to have periods with no trading and we eliminate penny stocks from the sample. In addition, we rerun our entire analysis using only stocks with prices larger than $5. Qualitatively, the results remain unchanged.

In sum, nonsynchronous trading is not the source of return reversals in individual stocks at the weekly frequency. This conclusion is consistent with Foerster and Keim (2000) who report that the likelihood of a NYSE–AMEX stock going without trading for 2 consecutive days is 2.24%. Of course, it is possible that nontrading within the day could lead to erroneously high negative serial correlation, but we do not expect these high frequency intra-day nontrading issues to be severe enough to impact serial correlations at the weekly or monthly frequency.

Seasonality: We check for the presence of seasonalities in the serial correlation patterns of returns. Upon replicating Table I with all weeks in January eliminated, we find that the results are practically unchanged. For instance, in the highest illiquidity winner portfolio the difference in returns between the high turnover and the low turnover stocks is −0.33% compared to −0.31% in Table I. In the highest illiquidity loser portfolio, the difference in returns between the high turnover and the low turnover stocks is 0.60% compared to 0.68% in Table I.

Alternative measures of illiquidity: We check that our results are robust to different measures of illiquidity. Following Chordia, Roll, and Subrahmanyam (2001) we use average daily spreads computed from transactions data (ISSM and TAQ) as a measure of illiquidity over the sample period 1988 through 2002.[14] As in Chordia et al., only NYSE stocks are included in the sample and only the bid and ask quotes on the NYSE are used to calculate the spreads. In addition, the sample selection, quote and trade matching, and filtering rules are the same as in Chordia et al. The weekly illiquidity measures are the averages of the daily measures during the week. The different measures of illiquidity that we use are: (i) proportional quoted spreads, (ii) proportional effective spreads,

[13] We also implement further analysis by sorting sequentially (instead of independently). By design, this ensures that all portfolios are fully and equally populated. The results (available upon request) show that the potential reversal profits are very similar to those reported. After controlling for turnover, the returns increase with illiquidity. Consider, for example, turnover portfolio one (four). The returns to the loser minus winner strategy increase from 0.36% (0.48%) to 0.53% (1.18%), as illiquidity increases from lowest to highest.

[14] This data sample is not the same as in the rest of the paper; however, it provides alternative measures of illiquidity.

(iii) proportional effective spreads divided by depth (average of the ask and the bid quoted trade sizes), and (iv) proportional effective spreads divided by depth.

While we continue to use the skip-day methodology, we also follow Conrad et al. (1994) in calculating the daily returns from closing prices at the mid-point of the bid–ask spread.[15]

In sum, we verify the robustness of our results along three dimensions:

1. We use different measures of illiquidity;
2. We use mid-point returns along with the skip-day methodology to eliminate the bid–ask bounce;
3. We run the analysis for the subperiod 1988 to 2002 for which the transactions data are available.

In untabulated results (available upon request), we find that the empirical findings are robust along all three of these dimensions. The results are essentially the same as those based on the Amihud measure when using the different illiquidity measures. Some of the returns are lower (though still statistically and economically significant) but so are the standard deviations. We observe strong reversals in the high turnover, high illiquidity, loser portfolios regardless of how illiquidity is measured or the sample period analyzed.

A.2. Are High Turnover, Low Liquidity Stocks Really Different?

Table I and Figure 1 show that stocks that face the most price pressure in week $t - 1$ reverse the most in week t. However, from only this evidence it is unclear whether we learn anything more than the fact that individual stocks have negative serial correlations at the weekly frequency. Given the negative serial correlation, it may not be surprising that stocks that have higher (lower) returns in week $t - 1$ will have, on average, lower (higher) returns in week t. Are the high turnover, highly illiquid stocks really different? In particular, do these stocks reverse more than the low turnover, more liquid stocks?

To address this question, we estimate cross-sectional regressions similar to those in Jegadeesh (1990). Specifically, we estimate the following regression for various turnover and/or liquidity groups at the weekly frequency

$$R_{it} = \alpha_t + \beta_t R_{it-1} + \epsilon_{it} \; . \tag{2}$$

If the various turnover–liquidity groups are not different, then the slope coefficient β in the above equation will be similar across the groups.

Table II presents the Fama and Macbeth (1973) coefficients from the cross-sectional regressions. The time-series average of β based on all stocks in the sample is -0.050, confirming the fact that in the cross-section stocks with

[15] See Chordia and Subrahmanyam (2004) for details about calculating returns from closing mid-point prices.

Table II

Cross-Sectional Regressions

This table presents the average β in the following weekly cross-sectional Fama and Macbeth (1973) type regressions

$$R_{it} = \alpha_t + \beta_t R_{it-1} + \epsilon_{it}.$$

t-statistics are given in parentheses below the average coefficients. Separate regressions are run for different categories of stocks. Panel A is for all stocks, Panel B groups stocks by turnover, Panel C groups stocks by illiquidity, and Panel D groups stocks by turnover and illiquidity. Turnover is measured as the ratio of the number shares traded to the number of shares outstanding. Illiquidity is measured by the Amihud measure (ratio of absolute returns to dollar volume). Breakpoints for turnover and illiquidity are based on quartile breakpoints. Return portfolio one is the extreme loser portfolio and return portfolio four is extreme winner portfolio. Turnover (illiquidity) portfolio one has the lowest turnover (illiquidity), and portfolio four has the highest turnover (illiquidity). Portfolio returns are in percent per week and are based on skip-day methodology in which the return on the last day of the week is not used in computations. The sample period is 1962 to 2002 and the portfolios include all NYSE and AMEX stocks that have data for all days of the week.

Panel A: All
−0.050
(−30.18)

Panel B: Turnover		Panel C: Illiquidity	
1	−0.038	1	−0.042
	(−14.77)		(−14.57)
2	−0.047	2	−0.044
	(−19.04)		(−18.33)
3	−0.060	3	−0.051
	(−26.20)		(−23.86)
4	−0.051	4	−0.062
	(−27.59)		(−33.12)

Panel D: Turnover and Illiquidity

	Illiquidity			
Turnover	1	2	3	4
1	−0.045	−0.047	−0.038	−0.043
	(−3.89)	(−9.76)	(−10.90)	(−11.81)
2	−0.060	−0.058	−0.054	−0.050
	(−13.83)	(−16.55)	(−16.49)	(−14.72)
3	−0.066	−0.059	−0.059	−0.074
	(−17.58)	(−17.46)	(−18.56)	(−21.83)
4	−0.035	−0.042	−0.056	−0.072
	(−11.03)	(−15.34)	(−20.22)	(−23.49)

higher (lower) returns in week $t-1$ have lower (higher) returns in week t. Panel B (C) presents the coefficients for stocks sorted by turnover (illiquidity). The average β for the lowest turnover (illiquidity) stocks is −0.038 (−0.042), while for the highest turnover (illiquidity) stocks it is −0.051 (−0.062). Thus, high turnover, less liquid stocks are more negatively autocorrelated than low turnover, more liquid stocks. The same pattern obtains in Panel D when simultaneously sorting on turnover and illiquidity. Consider the highest turnover stocks. The average β from equation (2) increases monotonically from -0.035 to -0.072 with illiquidity. This difference is significant at the 1% level. A similar increase with turnover obtains for the most illiquid stocks. For instance, for the highest illiquidity portfolio the β's increase from -0.043 to -0.072 with turnover. Once again this difference is statistically significant at the 1% level.

We conclude that high turnover, low liquidity stocks are indeed different from low turnover, high liquidity stocks in their reversal patterns, as they face the most price pressure in week $t-1$ *and* observe a greater fraction of that return reversed in week t. The result of both these effects—a larger price response in week $t-1$ combined with a larger fraction reversed in week t—is a nonlinear increase in returns in week t as one moves from low turnover, high liquidity stocks to high turnover, low liquidity stocks. The reversals documented in Table I demonstrate this nonlinear pattern.

B. Relative Strength Strategies

If the negative serial correlation patterns in individual stocks are more pronounced for stocks with higher turnover and higher illiquidity, then we should observe higher reversals with strategies that overweight the high turnover and high illiquidity stocks, which is what the relative strength strategies do. In this section, we implement a variant of the relative strength strategy of Lehmann (1990), Lo and MacKinlay (1990), and Conrad et al. (1994). The relative strength strategy puts greater weight on stocks with extreme returns, turnover, and illiquidity. Conrad et al. note that the relative strength strategy yields a statistically and economically significant measure of profits linked to reversals.

We focus on the three-way sorts based on returns, turnover, and illiquidity.[16] For each of the eight portfolios, the weight on stock i in week t is given by

$$w_{pit} = \frac{R_{it-1}T_{it-1}L_{it-1}}{\sum_{i=1}^{N_p} R_{it-1}T_{it-1}L_{it-1}}, \qquad p = WHH, WHL, WLH, WLL, LHH, LHL, LLH, LLL, \tag{3}$$

where $T_{it-1}(L_{it-1})$ represents the turnover (illiquidity) of stock i in week $t-1$ less the corresponding cross-sectional median of turnover (illiquidity) in week $t-1$, and N_p represents the number of stocks in each of the eight portfolios formed by the three-way sort between winners (W) and losers (L), and high (H) and low (L) turnover and illiquidity. Thus, we have three-way sorts and different weighting criteria based on return, turnover, and illiquidity. The sorts give us an idea of which portfolios have the highest contrarian strategy payoffs and the

[16] Results on various one- and two-way sorts are available upon request.

weighting criteria enable us to examine the marginal effect of illiquidity vis-a-vis turnover. Table III (weekly frequency) and Table IV (monthly frequency) present the results for three-way sorts and different weighting criteria, that is, by weighting on returns, returns and turnover, returns and illiquidity, and returns, illiquidity, and turnover.

Table III

Relative Strength Portfolios: Post-formation Returns

This table presents portfolio returns in the post-formation week. Portfolios are formed every week. The sorts are based on returns, turnover, and illiquidity. Turnover is measured as the ratio of the number of shares traded to the number of shares outstanding. Illiquidity is measured by the Amihud measure (ratio of absolute returns to dollar volume). Return breakpoints are determined by the median return for both positive and negative lagged returns. Breakpoints for turnover and illiquidity are based on quartile breakpoints. Weights on stock i in week t are based on

$$w_{pit} = \frac{R_{it-1}T_{it-1}L_{it-1}}{\sum_{i=1}^{N_p} R_{it-1}T_{it-1}L_{it-1}},$$

$$p = WHH, WHL, WLH, WLL, LHH, LHL, LLH, LLL,$$

where $T_{it-1}(L_{it-1})$ represents the turnover (illiquidity) of stock i in week $t-1$ and N_p is the number of stocks in each of the eight portfolios formed by the three-way sort between winners (W) and losers (L) and high (H) and low (L) turnover and illiquidity. The results are presented for different weighting criteria. Returns are in percent per week and are based on skip-day methodology in which the return on the last day of the week is not used in computations. Significance levels at 99%, 95%, and 90% are denoted by one, two, and three stars, respectively. The sample period is 1962 to 2002 and the portfolios include all NYSE and AMEX stocks that have data for all days of the week.

Sorting Criterion			Weighting Criterion				
Return	Turnover	Illiquidity	Return	Return Turnover	Return Illiquidity	Return Turnover Illiquidity	Equal Weight
W	H	H	−0.43**	−0.58**	−0.62**	−0.85**	0.09*
			2.89	3.75	5.00	6.69	2.59
W	H	L	−0.09*	−0.09	−0.07	−0.07	0.08
			2.47	2.88	2.44	2.86	2.28
W	L	H	0.00	0.03	0.15**	0.15**	0.16**
			2.17	2.09	3.32	3.28	1.93
W	L	L	−0.05	−0.04	−0.04	−0.04	0.07
			1.81	1.71	1.81	1.70	1.66
W	H	H−L	−0.35**	−0.49**	−0.55**	−0.78**	0.02
			1.89	3.15	4.51	6.40	1.18
W	L	H−L	0.05	0.07**	0.19**	0.19**	0.09**
			1.43	1.40	2.94	2.90	0.97
W	H−L	H	−0.43**	−0.61**	−0.77**	−1.00**	−0.06**
			1.88	3.09	4.80	6.66	1.13
W	H−L	L	−0.04	−0.06	−0.03	−0.04	0.01
			1.38	2.03	1.40	2.03	0.98

(continued)

Table III—*Continued*

Sorting Criterion			Weighting Criterion				
Return	Turnover	Illiquidity	Return	Return Turnover	Return Illiquidity	Return Turnover Illiquidity	Equal Weight
L	H	H	0.99**	1.19**	1.69**	1.83**	0.65**
			3.32	4.72	5.26	6.69	2.94
L	H	L	0.43**	0.37**	0.40**	0.33**	0.36**
			2.78	3.30	2.75	3.27	2.53
L	L	H	0.57**	0.52**	0.99**	0.94**	0.33**
			2.44	2.34	3.26	3.23	2.16
L	L	L	0.29**	0.25**	0.28**	0.24**	0.19**
			2.00	1.91	1.99	1.90	1.83
L	H	H−L	0.55**	0.83**	1.28**	1.50**	0.29**
			1.96	3.94	4.66	6.27	1.31
L	L	H−L	0.28**	0.27**	0.71**	0.69**	0.14**
			1.46	1.45	2.68	2.72	1.11
L	H−L	H	0.42**	0.68**	0.70**	0.89**	0.32**
			1.87	3.82	4.72	6.23	1.21
L	H−L	L	0.15**	0.12**	0.12**	0.09*	0.17**
			1.39	2.23	1.38	2.21	1.10
L−W	H	H	1.43**	1.78**	2.31**	2.69**	0.56**
			2.29	4.61	6.08	8.52	1.20
L−W	H	L	0.52**	0.46**	0.47**	0.40**	0.28**
			1.46	2.35	1.44	2.29	0.83
L−W	L	H	0.56**	0.49**	0.84**	0.78**	0.17**
			1.41	1.38	3.21	3.26	0.76
L−W	L	L	0.33**	0.29**	0.32**	0.28**	0.13**
			1.01	0.95	1.08	0.97	0.64

B.1. Weekly Frequency

In Table III, the different sorting and weighting criteria generate the following main results:

1. Loser stocks exhibit more reversals than winner stocks.
2. High turnover and high illiquidity stocks observe more reversals than low turnover and low illiquidity stocks.
3. Illiquidity has a larger impact on reversals than turnover has.
4. The long–short strategy of going long the loser stocks and short the winner stocks has the highest payoffs for high turnover and high illiquidity stocks.

Loser stocks exhibit more reversals than winner stocks: Across any portfolio (high or low turnover or illiquidity) and for any weighting criteria, loser stocks exhibit higher reversals than winner stocks. Consider the high turnover, high liquidity winners and losers. Depending on the weighting criterion, the winner stocks exhibit returns that range from −0.43% through −0.85% while the loser stocks realize returns that range from 0.99% through 1.83%. For the

Table IV
Relative Strength Portfolios: Post-formation Returns (Monthly Frequency)

This table presents portfolio returns in the post-formation month. Portfolios are formed every month. The sorts are based on returns, turnover, and illiquidity. Turnover is measured as the ratio of the number of shares traded to the number of shares outstanding. Illiquidity is measured by the Amihud measure (ratio of absolute returns to dollar volume). Return breakpoints are determined by the median return for both positive and negative lagged returns. Breakpoints for turnover and illiquidity are based on quartile breakpoints. Weights on stock i in month t are based on

$$w_{pit} = \frac{R_{it-1}T_{it-1}L_{it-1}}{\sum_{i=1}^{N_p} R_{it-1}T_{it-1}L_{it-1}},$$

$$p = WHH, WHL, WLH, WLL, LHH, LHL, LLH, LLL,$$

where $T_{it-1}(L_{it-1})$ represents the turnover (illiquidity) of stock i in month $t-1$ and N_p is the number of stocks in each of the eight portfolios formed by the three-way sort between winners (W) and losers (L) and high (H) and low (L) turnover and illiquidity. The results are presented for different weighting criteria. Returns are in percent per month and are based on skip-day methodology in which the return on the last day of the month is not used in computations. Significance levels at 99%, 95%, and 90% are denoted by one, two, and three stars, respectively. The sample period is 1962 to 2002 and the portfolios include all NYSE and AMEX stocks that have data for at least 10 days of the month.

Sorting Criterion			Weighting Criterion				
Return	Turnover	Illiquidity	Return	Return Turnover	Return Illiquidity	Return Turnover Illiquidity	Equal Weight
W	H	H	−0.00	0.37	−1.07**	−0.66	0.52
			7.01	8.19	9.11	11.07	6.97
W	H	L	0.69**	0.63**	0.72**	0.68**	0.88**
			5.83	6.73	5.63	6.49	5.53
W	L	H	−0.26	−0.23	−1.19**	−1.06**	0.50**
			5.56	5.43	7.56	7.55	5.29
W	L	L	0.45**	0.45**	0.44**	0.42**	0.70**
			4.27	4.15	4.22	4.12	4.09
W	H	H−L	−0.69**	−0.27	−1.79**	−1.34**	−0.36**
			4.14	5.96	7.70	9.81	3.56
W	L	H−L	−0.71**	−0.67**	−1.64**	−1.49**	−0.19
			3.49	3.47	6.40	6.43	3.01
W	H−L	H	0.26	0.59**	0.12	0.40	0.01
			3.69	5.80	7.30	9.63	2.94
W	H−L	L	0.24*	0.19	0.28**	0.25	0.18
			3.04	4.65	2.94	4.53	2.42
L	H	H	1.36**	1.04**	2.63**	2.86**	1.26**
			8.78	9.71	10.86	12.01	8.06
L	H	L	0.81**	0.42	0.80**	0.37	1.01**
			7.15	8.27	6.95	8.04	6.49
L	L	H	1.20**	1.08**	1.21**	1.09**	1.09**
			6.92	6.61	8.57	8.64	6.13
L	L	L	1.20**	1.12**	1.19**	1.13**	1.12**
			5.06	4.89	4.95	4.82	4.58

(continued)

Table IV—*Continued*

Sorting Criterion			Weighting Criterion				
Return	Turnover	Illiquidity	Return	Return Turnover	Return Illiquidity	Return Turnover Illiquidity	Equal Weight
L	H	H−L	0.55**	0.62**	1.83**	2.49**	0.25
			4.40	5.85	8.57	9.83	3.68
L	L	H−L	0.00	−0.04	0.02	−0.04	−0.02
			4.31	4.28	6.89	7.14	3.61
L	H−L	H	0.16	−0.04	1.42**	1.77**	0.16
			3.81	5.72	7.43	9.07	3.08
L	H−L	L	−0.39**	−0.70**	−0.39**	−0.77**	−0.11
			3.38	5.15	3.43	5.21	2.87
L−W	H	H	1.36**	0.68**	3.70**	3.52**	0.74**
			4.86	7.09	9.76	11.84	3.14
L−W	H	L	0.12	−0.22	0.08	−0.31	0.13
			3.79	5.41	3.72	5.20	2.36
L−W	L	H	1.46**	1.30**	2.40**	2.16**	0.59**
			3.34	3.40	5.52	5.92	1.93
L−W	L	L	0.75**	0.67**	0.75**	0.71**	0.42**
			2.52	2.58	2.56	2.65	1.67

low turnover, low illiquidity stocks, the winners display no reversals while the losers record reversal returns that range from 0.24% to 0.29%.

High turnover and high illiquidity stocks have more reversals than low turnover and low illiquidity stocks: This result can be seen most clearly when one considers the zero-investment portfolios that are long the high illiquidity or high turnover stocks and short the low illiquidity or low turnover stocks. With the three-way weighting criterion (Column 7 in Table III), the zero-investment portfolio composed of high (low) turnover loser stocks, that is, long the high illiquidity and short the low illiquidity stocks, has a week-t return of 1.50% in portfolio (L, H, H–L) (0.69% in portfolio L, L, H–L). Also, the zero-investment portfolio composed of high (low) illiquidity loser stocks, that is long the high turnover and short the low turnover stocks, has a week-t return of 0.89% in portfolio (L, H–L, H) (0.09% in portfolio L, H–L, L). The exception to this result occurs for the low turnover winners when a portfolio that is long the high illiquidity stocks and short the low illiquidity stocks exhibits continuations.

Illiquidity has a larger impact on reversals than turnover: This result is clearly seen when one compares the weighting scheme by returns and turnover (column 5 in Table III) to the weighting scheme by returns and illiquidity (Column 6 in Table III). In general, the reversals are higher when weighting by returns and illiquidity as opposed to by returns and turnover. For instance, the high illiquidity, high turnover, loser portfolio (L, H, H) has a weekly return of 1.19% when weighting by returns and turnover. However, when weighting by returns and illiquidity the same portfolio has a weekly return of 1.69%. The 0.5% difference between the two returns reflects the higher impact of liquidity versus turnover. Note also that the zero investment high turnover, high illiquidity, loser minus winner (L–W, H, H) portfolio yields a return of 2.31% (1.78%) when the weighting criterion is returns plus illiquidity (returns plus turnover).

The *incremental* impact of illiquidity can be ascertained by comparing the returns and turnover weighting scheme (Column 5 in Table III) against the returns, turnover, and illiquidity weighting scheme (Column 7 in Table III). In general, the reversals are larger when weighting by returns, turnover, and illiquidity as compared to just returns and turnover. For instance, take the difference between 1.83% and 1.19% for the loser, high turnover, high illiquidity portfolio (L, H, H), which yields 64 basis points per week. One can also look at the strategy (L–W, H, H), for which the illiquidity impact is 91 basis points per week (2.69%–1.78%). That is, regardless of how we slice the data, illiquidity has a significant marginal impact on reversal strategy profits, and the economic impact of illiquidity, over and above that of turnover, can be as high as 91 basis points per week. Overall, our findings provide strong support to the idea that illiquidity contributes additional insights in understanding the nature of short-term reversal profitability.

The strategy of going long the loser stocks and short the winner stocks generates the highest payoffs for the high turnover and high illiquidity stocks: This result follows from the last four rows in the table. Regardless of the weighting scheme, the highest profits from a long–short portfolio obtain in the high turnover, high illiquidity stocks. When the weighting scheme is as in equation (3) the weekly return from this strategy is 2.69%. The standard deviation of returns for this strategy is also the highest, at 8.52%. Note that the weekly return we obtain, at 2.69%, is higher than the 1.7% documented by Lehmann (1990) because of additional conditioning on turnover and illiquidity.

Finally, note that reversal profitability based on the relative strength strategies is typically larger than that based on equally weighting (last column in Table III) the stocks within the various portfolios. This supports our argument that the return reversals are stronger for stocks with extreme returns, trading volume, and illiquidity.

B.2. Monthly Frequency

All our analysis thus far has been confined to weekly returns. Jegadeesh (1990) documents negative serial correlations in the cross-section of monthly stock returns as well. Hence, we study the impact of turnover and illiquidity on reversal profitability at the monthly frequency. The results are presented in Table IV, which is the monthly equivalent of Table III. We show that the impact of liquidity on the serial correlation patterns of individual stock returns continues to be strong at the monthly frequency. In contrast, if anything, reversal profitability declines with turnover at the monthly frequency. Overall, the evidence is consistent with the conjecture that stresses in the market for liquidity lead to large price movements that are subsequently reversed as liquidity suppliers step in to profit from prices that diverge from fundamental values.

The high turnover winners with high illiquidity exhibit reversals only if the weighting criterion includes illiquidity. The high turnover, low illiquidity winners exhibit continuations regardless of the weighting criterion. The same result obtains in the case of low turnover winners. With the weighting criterion based on returns and illiquidity, a zero-investment high (low) turnover, winner portfolio that is long low illiquidity stocks and short high illiquidity stocks, realizes an average monthly return of 1.79% (1.64%). The reversals are far lower with the weighting criterion based on returns and turnover. Moreover, there is no reversal in the zero-investment high (low) liquidity winner portfolio that is long high turnover stocks and short low turnover stocks.

Moving to the loser portfolios, the zero-investment high turnover portfolio that is long the high illiquidity stocks and short the low illiquidity stocks realizes a return of 2.49% when the weighting criterion is as in equation (3). Further, the high turnover stocks exhibit more *continuations* than the low turnover stocks for the low illiquidity losers.

Next, the loser minus winner portfolio exhibits higher profitability for the more illiquid stocks. The profitability is the highest (lowest) when the weighting criterion is based on returns and illiquidity (turnover). For instance, the loser minus winner profitability is 3.70% (0.68%) when the weighting criterion is based on returns and illiquidity (returns and turnover). In fact, the profitability based on weighting by returns and turnover is lower than that based on returns alone, suggesting that conditioning on turnover hurts the profitability of the loser minus winner portfolio.

The marginal impact of illiquidity, controlling for turnover, on reversal profitability can again be assessed by comparing the return and turnover weighting scheme (Column 5 in Table IV) against those of returns, turnover, and illiquidity weighting scheme (Column 7 in Table IV). For instance, the high turnover and high illiquidity loser portfolio (L, H, H) has a liquidity impact of 1.82% [2.86%−1.04%] per month while high illiquidity, high turnover, loser minus winner portfolio (L−W, H, H) has a liquidity impact of 2.84% [3.52% − 0.68%] per month. Once again, regardless of how we slice the data, illiquidity has a significant impact on reversal strategy profits at the monthly frequency.

To summarize, at the monthly frequency the negative serial correlation results are weaker for sorts based on turnover, whereas illiquidity has a strong impact on serial correlation. One may wonder why the effect of turnover is so different between the monthly and the weekly frequencies. We conjecture that demand shocks are attenuated at the monthly frequency as compared to the weekly frequency. We confirm this conjecture by examining order imbalances at the weekly and monthly frequencies. The order imbalances for individual stocks come from the transactions data as in Chordia, Roll, and Subrahmanyam (2002). Order imbalance (OIB) defined in terms of transactions is the number of buy orders less the number of sell orders as a fraction of the total orders, and OIB defined in terms of shares is the number of shares bought less the number of shares sold as a fraction of the total shares traded. The volatility of OIB in individual stocks is higher at the weekly frequency than at the monthly frequency. When OIB is defined in terms of the number of transactions, the weekly (monthly) volatility is 0.22 (0.13) and when it is defined in terms of shares, the weekly (monthly) volatility is 0.24 (0.13). Thus, demand shocks are attenuated at the monthly frequency as compared to the weekly frequency, suggesting that turnover may be a poor proxy for the liquidity demands of non-informational traders at the monthly frequency.

III. Transaction Costs

Table I shows that the potential profits from a short-run contrarian strategy can be large. For instance, in the case of the extreme loser portfolio with high turnover and high illiquidity, the equally weighted (relative strength) contrarian strategy return is 1.16% (2.69%) per week. These returns are the profits that market makers (liquidity providers) earn from accommodating uninformed traders as per the CGW model. However, it is not clear that outside investors can earn incremental returns as well. We suspect that transactions costs may render any trading strategy unprofitable because the above zero-investment portfolio has the highest volatility (4.37% per week) and it also includes the most illiquid stocks.

We provide a detailed examination of transactions costs in this section. Specifically, we first provide descriptive statistics about the various trading strategies we consider here. We then use the transactions cost estimates of Keim and Madhavan (1997) (henceforth, KM) within a dynamic framework to estimate net returns based on a strategy that buys the losers and sells the winners, and we finally consider the market impact cost analysis of Korajczyk and Sadka (2004) (henceforth, KS).

A. Portfolio Characteristics

Table V, Panel A presents descriptive statistics about the various three-way sorted portfolios in Table I.[17] Controlling for turnover, the weekly dollar trading volume decreases monotonically with illiquidity, with the dollar trading volume for the lowest illiquidity portfolio in orders of magnitude larger than that of the highest illiquidity portfolio. For instance, for the extreme loser portfolio with the highest turnover, the dollar trading volume for the lowest (highest) illiquidity portfolio is $17.79 million ($0.13 million) per week. Consequently, the illiquidity measure in the lowest quartile is 0.03 and that for the highest quartile is 3.01, which is a 100 times higher. The differences in turnover are not as stark,

[17] These descriptive statistics are for the post-formation week. At least part of the round-trip trading costs are incurred in the formation week and it is perhaps more relevant to check the descriptive statistics in the formation period. However, by design, the differences in the high and low turnover or high and low liquidity portfolios are even more stark in the formation periods and, as such, we choose to be conservative in our estimates of the transactions costs by basing them on the statistics from the post-formation week.

Table V

Three-Way Sorted Portfolios: Descriptives

This table presents portfolio characteristics in the post-formation week. Equal-weighted portfolios are formed every week. The sorts are based on returns, turnover, and illiquidity. Turnover is measured as the ratio of the number of shares traded to the number of shares outstanding. Illiquidity is measured by the Amihud measure (ratio of absolute returns to dollar volume). Return breakpoints are determined by the median return for both positive and negative lagged returns. Breakpoints for turnover and illiquidity are based on quartile breakpoints. Return portfolio 1 is the extreme loser portfolio and return portfolio 4 is the extreme winner portfolio. Turnover (illiquidity) portfolio 1 has the lowest turnover (illiquidity), and portfolio 4 has the highest turnover (illiquidity). The sample period in Panel A is 1962 to 2002 and the portfolios include all NYSE and AMEX stocks that have data for all days of the week. Portfolio "Sz Rank" is the average size rank of the stocks in the portfolio, where the size rank (from 1 to 5) is determined from NYSE breakpoints. Portfolio "Turnover" is daily turnover in percent, "Volume" is dollar volume in millions of dollars, and "Illiquidity" is computed using the Amihud measure and is expressed as daily illiquidity (multiplied by 10^6). The sample period in Panel B is 1988 to 2002 and the portfolios include all NYSE stocks that have data for all days of the week. Portfolio "Depth" is the average depth, "QSPR" is the proportional quoted spread, and "PESPR" is the proportional effective spread. Depth is in thousands and proportional spreads are in percent.

		Return Portfolio = 1				Return Portfolio = 4			
		Illiquidity				Illiquidity			
Turnover		1	2	3	4	1	2	3	4
		Panel A: NYSE and AMEX Sample for 1962 to 2002							
1	Sz Rank	5.00	4.62	3.65	2.14	4.99	4.56	3.65	2.22
	Turnover	0.082	0.095	0.098	0.096	0.080	0.089	0.084	0.087
	Volume	15.120	1.574	0.410	0.073	14.849	1.436	0.353	0.074
	Illiquidity	0.022	0.088	0.360	5.190	0.034	0.092	0.341	4.481
2	Sz Rank	4.97	4.28	3.13	1.79	4.96	4.26	3.16	1.82
	Turnover	0.153	0.168	0.173	0.163	0.141	0.150	0.149	0.151
	Volume	19.330	1.955	0.476	0.089	19.400	1.825	0.446	0.089
	Illiquidity	0.021	0.099	0.445	3.989	0.026	0.101	0.414	3.652
3	Sz Rank	4.88	3.93	2.81	1.64	4.87	3.93	2.83	1.66
	Turnover	0.238	0.264	0.263	0.236	0.218	0.231	0.230	0.219
	Volume	17.130	2.188	0.545	0.101	16.774	2.070	0.518	0.107
	Illiquidity	0.022	0.114	0.464	3.342	0.026	0.115	0.421	3.072
4	Sz Rank	4.54	3.47	2.45	1.48	4.48	3.39	2.39	1.45
	Turnover	0.597	0.543	0.507	0.404	0.595	0.537	0.479	0.397
	Volume	17.791	2.646	0.644	0.125	16.930	2.557	0.657	0.138
	Illiquidity	0.027	0.133	0.464	3.006	0.029	0.119	0.436	2.572
		Panel B: TAQ Sample for 1988 to 2002							
1	Depth	7.97	3.84	3.05	3.67	8.37	3.50	2.55	3.13
	PQSPR	0.355	0.623	1.001	2.676	0.364	0.588	0.926	2.328
	PESPR	0.238	0.409	0.660	1.828	0.247	0.385	0.608	1.569
2	Depth	8.06	4.91	4.41	5.29	7.37	4.16	3.62	4.32
	PQSPR	0.405	0.666	1.129	2.801	0.376	0.618	1.025	2.463
	PESPR	0.270	0.439	0.761	1.951	0.251	0.404	0.684	1.701
3	Depth	8.36	6.02	5.87	6.37	7.41	5.11	4.59	5.24
	PQSPR	0.437	0.734	1.284	2.979	0.395	0.674	1.126	2.616
	PESPR	0.291	0.489	0.883	2.100	0.260	0.446	0.759	1.805
4	Depth	9.04	7.66	7.22	8.28	8.36	7.03	6.17	6.77
	PQSPR	0.493	0.847	1.475	3.300	0.456	0.784	1.313	2.855
	PESPR	0.332	0.575	1.029	2.354	0.305	0.529	0.902	2.008

especially for the higher turnover portfolios. In sum, the high illiquidity portfolios have trading volumes that are, in general, orders of magnitude smaller than those of the low illiquidity portfolios. The high illiquidity portfolios have stocks in the lowest size quintiles, as opposed to the low illiquidity portfolios that have high trading volumes and stocks in the fourth- or fifth-highest size quintiles as per NYSE breakpoints.[18]

Panel B of Table V presents the bid–ask spread and the depths of the various three-way sorted portfolios of NYSE stocks over the period 1988 through 2002. Focusing once again on the extreme loser portfolios with the highest turnover, we note that the proportional effective spread increases from 0.33% for the lowest illiquidity portfolio to 2.35% for the highest illiquidity portfolio. The quoted depth is always lower for the high illiquidity portfolios and the difference is the largest for the highest turnover portfolios. Except for the lowest illiquidity portfolio, the effective spread is larger than the potential trading profits from a contrarian strategy. For instance, the potential profit of 1.16% for the loser portfolio with the highest turnover and illiquidity seems to be swamped by the proportional effective spread of 2.35%.

Table VI documents the portfolio characteristics for the relative strength strategies with the weighting scheme as in equation (3). The difference between the illiquidity measure between the high and the low liquidity portfolios is far greater than that of Table V. This is consistent with the evidence that the relative strength strategies place greater weights on stocks that are extreme in terms of returns, liquidity, and turnover. Also, note in Panel B that the proportional spread is larger with the relative strength strategies than with the equally weighted strategies. Recall from Table III that the returns from buying losers and selling winners are 2.69%. The loser minus winner relative strength portfolio with high turnover and high liquidity has a proportional effective spread of 3.03%, suggesting that any potential profits are swamped by the round-trip costs of 6.06%. However, institutional investors carefully watch transactions costs. They choose trade size and spread their trades out over days so as to minimize trading costs. Therefore, the proportional spread of 3.03% may be an overstatement.

To obtain more precise estimates of institutional trading costs, we turn to KM estimates of transactions costs.

B. KM Estimates of Transactions Costs

First, we present some back-of-the-envelope calculations. KM provide estimates of market impact as well as commission costs for buy and sell trades for NYSE–AMEX stocks (as well as NASDAQ stocks) traded by 21 large institutions during 1991 to 1993. Their transactions cost data are categorized by trade size as well as by firm size. We focus on the smallest trade sizes to minimize trading costs. We also use the various size classifications from Table V.

[18] NYSE breakpoints come from the data library at Ken French's website. See http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/.

Once again, we focus on the extreme loser portfolio because the potential profits are the highest for these portfolios. Consider the lowest turnover, lowest illiquidity portfolio that has a contrarian trading profit of 0.31% per week (see Table I). The stocks in this portfolio belong to the largest size quintile. According

Table VI

Relative Strength Portfolios: Descriptives

This table presents portfolio characteristics in the post-formation week. Portfolios are formed every week. The sorts are based on returns, turnover, and illiquidity. Turnover is measured as the ratio of the number of shares traded to the number of shares outstanding. Illiquidity is measured by the Amihud measure (ratio of absolute returns to dollar volume). Return breakpoints are determined by the median return for both positive and negative lagged returns. Breakpoints for turnover and illiquidity are based on quartile breakpoints. Weights on stock i in week t are based on

$$w_{pit} = \frac{R_{it-1}T_{it-1}L_{it-1}}{\sum_{i=1}^{N_p} R_{it-1}T_{it-1}L_{it-1}},$$
$$p = WHH, WHL, WLH, WLL, LHH, LHL, LLH, LLL,$$

where $T_{it-1}(L_{it-1})$ represents the turnover (illiquidity) of stock i in week $t-1$ and N_p is the number of stocks in each of the eight portfolios formed by the three-way sort between winners (W) and losers (L) and high (H) and low (L) turnover and illiquidity. The results are presented only for the weighting criteria that utilizes return, turnover, and illiquidity. The sample period in Panel A is 1962 to 2002 and the portfolios include all NYSE and AMEX stocks that have data for all days of the week. Portfolio "Sz Rank" is the weighted average size rank of the stocks in the portfolio, where the size rank (from 1 to 5) is determined from NYSE breakpoints. Portfolio "Turnover" is daily turnover in percent, "Volume" is dollar volume in millions of dollars, and "Illiquidity" is computed using the Amihud measure and is expressed as daily illiquidity (multiplied by 10^6). The sample period in Panel B is 1988 to 2002 and the portfolios include all NYSE stocks that have data for all days of the week. Portfolio "Depth" is the weighted average depth, "QSPR" is the proportional quoted spread, and "PESPR" is the proportional effective spread. Depth is in thousands and proportional spreads are in percent.

Panel A: NYSE and AMEX Sample for 1962 to 2002						
Sorting Criterion			Descriptives			
Return	Turnover	Illiquidity	Sz Rank	Turnover	Volume	Illiquidity
W	H	H	1.26	0.503	0.145	5.315
W	H	L	3.94	0.881	13.613	0.052
W	L	H	1.63	0.097	0.037	10.551
W	L	L	4.75	0.114	10.736	0.047
L	H	H	1.35	0.444	0.145	6.313
L	H	L	4.09	0.768	13.848	0.057
L	L	H	1.63	0.101	0.036	10.988
L	L	L	4.74	0.121	10.449	0.049
L−W	H	H	1.30	0.473	0.145	5.815
L−W	H	L	4.01	0.825	13.731	0.055
L−W	L	H	1.63	0.099	0.036	10.769
L−W	L	L	4.74	0.117	10.593	0.048

(continued)

Table VI—*Continued*

Panel B: TAQ Sample for 1988 to 2002					
Sorting Criterion			Descriptives		
Return	Turnover	Illiquidity	Depth	PQSPR	PESPR
W	H	H	8.494	3.940	2.795
W	H	L	9.502	0.597	0.408
W	L	H	4.625	3.964	2.734
W	L	L	5.884	0.467	0.310
L	H	H	9.591	4.501	3.256
L	H	L	9.472	0.639	0.436
L	L	H	4.841	4.226	2.968
L	L	L	6.017	0.501	0.332
L−W	H	H	9.043	4.220	3.025
L−W	H	L	9.487	0.618	0.422
L−W	L	H	4.733	4.095	2.851
L−W	L	L	5.950	0.484	0.321

to KM, the cost of a small buy trade in the largest size quintile is 0.31%, and the cost of a small sell trade in the same size quintile is 0.21% for a total round-trip cost of 0.52%. This cost is larger than the potential profit of 0.31%. Since most of the potential trading profits in the low illiquidity portfolios are lower than 0.52%, we now turn to the high illiquidity, high turnover portfolio. The average size quintile that corresponds to this portfolio is 1.48. Interpolating between the two lowest size quintiles we find that the cost of a small buy trade is 0.38%, and the cost of a small sell trade is 0.88%, for a total round-trip cost of 1.26%. This cost, once again, is larger than the potential profit of 1.16%.

The caveat with the above analysis is that the data in KM pertain to institutional trades during 1991 to 1993. Trading costs are likely to be higher during the early part of the sample. Also, trading costs have not declined over the latter part of the sample.[19] Given these caveats, it is important to conduct a dynamic analysis of the trading costs by using the methodology of Cooper, Gutierrez, and Marcum (2005). This methodology applies the trading cost estimates from Stoll (1995) to the sample-specific estimates of KM.[20] In order to be conservative, we estimate costs for value traders since they have the lowest trading costs, we set the trade size to zero, and we place a cap of 2.5% on the trading costs for each stock. The results are presented in Tables VII and VIII for the equally weighted portfolios and the relative strength portfolios, respectively.

Consider the equally weighted portfolio strategies in Table VII. The highest potential profits occur in the high turnover, high illiquidity portfolios. The loser minus winner long–short strategy results in raw weekly returns of 1.33%. However, due to low liquidity, the net return after accounting for transactions costs

[19] Personal communication with Don Keim.

[20] For details, see the appendix in Cooper et al. (2005).

Table VII

Three-Way Sorted Portfolios: Net Returns

This table presents returns net of cost in the post-formation week. Equal-weighted portfolios are formed every week. The sorts are based on returns, turnover, and illiquidity. Turnover is measured as the ratio of the number of shares traded to the number of shares outstanding. Illiquidity is measured by the Amihud measure (ratio of absolute returns to dollar volume). Return breakpoints are determined by the median return for both positive and negative lagged returns. Breakpoints for turnover and illiquidity are based on quartile breakpoints. Return portfolio 1 is the extreme loser portfolio and return portfolio 4 is the extreme winner portfolio. Turnover (illiquidity) portfolio 1 has the lowest turnover (illiquidity), and portfolio 4 has the highest turnover (illiquidity). Portfolio returns are in percent per week and are based on skip-day methodology in which the return on the last day of the week is not used in computations. The returns are presented for a long position in return portfolio 1 (loser), a long position in return portfolio 4 (winner), and a combined long position in return portfolio 1 and a short position in return portfolio 4. Net returns are calculated by subtracting Keim and Madhavan (1997) and Korajyzck and Sadka (2004) (with a starting dollar amount of $10,000 dollars) cost estimates. These are indicated by the mnemonics "KM" and "KS", respectively. The sample period is 1962 to 2002 and the portfolios include all NYSE and AMEX stocks that have data for all days of the week.

Turnover Portfolio	4	4	1	1
Illiquidity Portfolio	4	1	4	1
	Return Portfolio = 1 (Loser)			
Raw Return	1.16	0.42	0.48	0.31
Net Return (KM)	−2.26	−0.00	−2.22	0.18
Net Return (KS)	−0.18	−0.18	−0.54	0.04
	Return Portfolio = 4 (Winner)			
Raw Return	−0.17	−0.02	0.14	−0.01
Net Return (KM)	−3.34	−0.40	−2.31	−0.14
Net Return (KS)	−1.24	−0.54	−0.79	−0.32
	Return Portfolio = 1–4 (Loser−Winner)			
Raw Return	1.33	0.44	0.34	0.40
Net Return (KM)	−5.26	−0.36	−4.81	0.11
Net Return (KS)	−1.09	−0.68	−1.61	−0.18

is −5.26%. Transactions costs overwhelm the potential profits. This is true of all the turnover, illiquidity portfolios except for the low turnover, low illiquidity portfolio. Even for this portfolio the weekly returns after transactions costs is only 11 basis points. Similarly, from Table VIII we see that the trading costs for all turnover, illiquidity portfolios are far larger than the potential profits for the relative strength strategies. The potential weekly return of 2.69% for the high turnover, high illiquidity portfolio turns into a net return of −4.48% after accounting for transactions costs.

While it seems that the above transactions costs are large, the costs may actually be understated for two reasons. First, KM use data for trades that were actually consummated. If some trades were abandoned due to high transactions costs, then the KM estimates of trading costs would be biased downward. Second, the transaction cost estimates in KM do not include short-selling costs.

Table VIII

Relative Strength Portfolios: Net Returns

This table presents returns net of cost in the post-formation week. Portfolios are formed every week. The sorts are based on returns, turnover, and illiquidity. Turnover is measured as the ratio of the number of shares traded to the number of shares outstanding. Illiquidity is measured by the Amihud measure (ratio of absolute returns to dollar volume). Return breakpoints are determined by the median return for both positive and negative lagged returns. Breakpoints for turnover and illiquidity are based on quartile breakpoints. Weights on stock i in week t are based on

$$w_{pit} = \frac{R_{it-1}T_{it-1}L_{it-1}}{\sum_{i=1}^{N_p} R_{it-1}T_{it-1}L_{it-1}},$$

$$p = WHH, WHL, WLH, WLL, LHH, LHL, LLH, LLL,$$

where $T_{it-1}(L_{it-1})$ represents the turnover (illiquidity) of stock i in week $t-1$ and N_p is the number of stocks in each of the eight portfolios formed by the three-way sort between winners (W) and losers (L) and high (H) and low (L) turnover and illiquidity. The results are presented only for the weighting criteria that utilizes return, turnover, and illiquidity. Portfolio returns are in percent per week and are based on skip-day methodology in which the return on the last day of the week is not used in computations. The returns are presented for a long position in return portfolio 1 (loser), a long position in return portfolio 4 (winner), and a combined long position in return portfolio 1 and a short position in return portfolio 4. Net returns are calculated by subtracting Keim and Madhavan (1997) and Korajyzck and Sadka (2004) (with a starting dollar amount of $10,000) cost estimates. These are indicated by the mnemonics "KM" and "KS", respectively. The sample period is 1962 to 2002 and the portfolios include all NYSE and AMEX stocks that have data for all days of the week.

Turnover Portfolio	H	H	L	L
Illiquidity Portfolio	H	L	H	L
	Return Portfolio = L (Loser)			
Raw Return	1.83	0.33	0.94	0.24
Net Return (KM)	−1.77	−0.39	−2.27	−0.02
Net Return (KS)	0.24	−0.34	−0.29	−0.24
	Return Portfolio = W (Winner)			
Raw Return	−0.85	−0.07	0.15	−0.04
Net Return (KM)	−4.42	−0.78	−3.02	−0.26
Net Return (KS)	−2.15	−0.66	−0.80	−0.49
	Return Portfolio = L − W (Loser − Winner)			
Raw Return	2.69	0.40	0.78	0.28
Net Return (KM)	−4.48	−1.03	−5.59	−0.21
Net Return (KS)	−0.20	−0.85	−1.39	−0.65

C. KS Estimates of Market Impact Costs

KS use intraday transactions data to estimate market impact costs. These costs are estimated each month for each stock over the period January 1993 through May 1997. Using cross-sectional relationships between these market impact costs and firm characteristics, the costs are then estimated for the entire sample period.[21] Since KS estimate costs for each stock–each month, we keep

[21] We thank Ronnie Sadka for providing us this data.

these costs constant for all the weeks in that month in our weekly analysis. The estimated market impact costs are then used to compute the cost of taking positions in the extreme winner or loser stocks each week.[22] The costs also depend on the value of the investment portfolio at any given point in time. We set our initial portfolio value in 1962 to $10,000 (this is roughly equivalent to $60,000 in 2002 dollars). The results are presented in Tables VII and VIII for the equally weighted portfolios and the relative strength portfolios, respectively.

From Table VII we see that the highest potential weekly return of 1.33% from the high turnover, high illiquidity, loser minus winner strategy turns into a net return of −1.09% when the market impact costs are taken into account. In fact, all the net returns are negative. The same result obtains for the relative strength strategies in Table VIII. The high turnover, high illiquidity, loser minus winner portfolios have the highest potential returns of 2.69% and net returns of −0.20%. Thus, an investment portfolio as small as $60,000 in 2002 dollars has enough market impact costs to swamp all potential profits from a strategy that exploits the short-term reversal phenomenon in individual stock returns. While it is important to consider long–short trading strategies to eliminate market risk, it should be pointed out that market impact costs (with a $10,000 initial investment) are not sufficient to eliminate all the potential profits from going long the high turnover, high illiquidity stocks. A net return of 24 basis points obtains after accounting for market impact costs.

Similar to the caveat about KM costs, the KS costs understate the true transactions costs because they do not account for commissions. In Table II of their paper, KM show that commissions for institutional investors can be more than 60% of the market impact costs. Note also that the analysis of KS does not account for short-sale costs.

D. Summary of Transactions Costs

This paper analyzes trading costs from a number of different perspectives, including proportional effective bid–ask spreads, dynamic institutional trading costs, and market impact costs. Consider the relative strength strategy, loser minus winner portfolio with the highest turnover and the highest illiquidity. The round-trip proportional bid–ask spread cost for this portfolio calculated over the sample period 1988 through 2002 is 6.06%. The dynamic cost analysis of institutional trading costs using the methodology of Cooper et al. (2005) suggests that transactions costs including commissions are 7.17%. The market impact costs (not including commission costs) using the KS methodology amount to 2.89% for an investment portfolio as small as $10,000. All these costs are larger than the potential contrarian trading strategy profits.

The overall conclusion from this analysis is that the potential contrarian trading profits are not attainable after accounting for trading costs. The main reason is that the largest potential profits obtain in the highly illiquid stocks that have high trading costs.

[22] For details, see Appendix A in Korajczyk and Sadka (2004).

We emphasize that the analysis in this section is from the perspective of money managers and not market makers. Market makers receive a return for being available to accommodate demands for liquidity. Thus, market makers can profit from accommodating the trading demands from uninformed investors. On the other hand, we show that money managers who devise contrarian trading strategies to profit from short-horizon reversals face transactions costs that overwhelm any potential profits.

IV. Conclusions

Stock return predicatablity at low frequencies that is due to time variation in expected returns is consistent with rational asset pricing. However, predictability at high frequencies, such as stock return reversals, poses a serious challenge to the efficient market hypothesis because stock prices are likely to follow a martingale process over short horizons. The notion is that short-run changes in fundamental values should be negligible in efficient markets with random information arrival. High frequency price reversals have been explained within a rational equilibrium paradigm by CGW (1993). The CGW model is analogous to the inventory cost models of market making. The idea is that demand shocks from non-informational traders are absorbed by market makers who require compensation for holding non-optimal inventories. This compensation is provided in the form of short-run reversals. In the model, trading volume plays an important role in identifying price changes due to either public information or exogenous selling pressure by non-informational trades. Non-informed trading is accompanied by high trading volume, whereas informed trading, which does not lead to reversals, is accompanied by little trading volume. Thus, price changes accompanied by high (low) trading volume should (should not) revert.

The CGW paradigm assumes downward-sloping demand curves for stocks. If demand curves were perfectly elastic, there would be no trade-induced price impact and subsequent price reversals would not occur. With downward-sloping demand curves, however, price reversals should follow liquidity or non-informational trading. Stocks that are more illiquid should experience stronger reversals. Consequently, this paper incorporates the unexplored dimension of illiquidity into the empirical investigation of the serial correlation patterns of individual stock returns. Indeed, we show that liquidity plays an important role in understanding the autocorrelation patterns in stock returns.

Our main findings are as follows: (i) There is reversal in weekly and monthly stock returns, but it is mainly confined to the loser stocks. (ii) At the weekly frequency, high turnover stocks exhibit higher negative serial correlation than low turnover stocks. (iii) At the monthly frequency, the impact of turnover on autocorrelations is the opposite of that at the weekly frequency with low turnover stocks exhibiting more reversals than high turnover stocks. (iv) Controlling for turnover, there is more reversal in stocks with low liquidity than in the highly liquid stocks, and this pattern is the same across the weekly and the monthly frequency. (v) The high turnover, low liquidity stocks have more negative serial correlations in cross-sectional regressions, and the potential contrarian trading strategy profits are the highest for these stocks. (vi) The largest potential profits before accounting for transactions costs obtain in the high turnover, high illiquidity, loser minus winner portfolio.

These findings are consistent with the hypothesis that extreme price changes occur in stocks with low liquidity and in high turnover stocks, for which the demand for liquidity from uninformed traders is high. The largest price reversals occur in precisely these high volume, low liquidity stocks as the initial price changes are reversed. Thus, the high frequency negative autocorrelations are more likely to result from stresses in the market for liquidity. A high frequency trading strategy that attempts to profit from the negative serial correlations has high transactions costs and substantial price impact. Consequently, while the presence of negative autocorrelations in individual security returns is undeniable, it is not possible to profit from this short-run predictability. This lack of profitability and the fact that the overall findings are consistent with the rational paradigm of CGW (1993) suggest that the violation of the efficient market hypothesis due to short-term reversals is not so egregious after all.

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