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Markus Glaser/Martin Weber*

Momentum and Turnover: Evidence from the German Stock Market**

Abstract

This paper analyzes the relation between momentum strategies (strategies that buy stocks with high returns over the previous three to twelve months and sell stocks with low returns over the same period) and turnover (number of shares traded divided by the number of shares outstanding) for the German stock market. Our main finding is that momentum strategies are more profitable among high-turnover stocks. In contrast to U.S. evidence, this result is mainly driven by winners: high-turnover winners have higher returns than low-turnover winners. We present various robustness checks, long-horizon results, evidence on seasonality, and control for size-, book-to-market-, and industry-effects. We argue that our results are useful to empirically evaluate competing explanations for the momentum effect.

JEL-Classification: G10, G11, G12.

Keywords: Asset Pricing; Momentum; Momentum Strategies; Return Predictability; Turnover; Trading Volume.

1 Introduction

Recently, the interaction between momentum and measures of trading volume such as turnover (defined as the number of shares traded divided by the number of shares outstanding) has attracted attention for various reasons. The momentum effect, i.e., the effect that over intermediate horizons, winners continue to perform well and losers continue to perform poorly, is currently one of the most studied stock market anomalies. Momentum strategies that buy stocks with high returns over the last three to twelve months and sell stocks with low returns over the previous three to twelve months earn statistically significant profits in most of the world-wide equity markets. *Jegadeesh/Titman* (1993, 2001) and *Lee/Swaminathan* (2000) show that momentum strategies are successful in the U.S. stock market.

* Dipl-Volksw. *Markus Glaser*, Lehrstuhl für Bankbetriebslehre and Center for Doctoral Studies in Economics and Management (CDSEM), Universität Mannheim, L 13, 15, 68131 Mannheim; e-mail: glaser@bank.BWL.uni-mannheim.de. Prof. Dr. *Martin Weber*, Lehrstuhl für Bankbetriebslehre, Universität Mannheim, L 5, 2, 68131 Mannheim and CEPR, London;
e-mail: weber@bank.BWL.uni-mannheim.de.

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Rouwenhorst (1998) demonstrates the profitability of momentum strategies in eleven out of twelve European stock markets. *Schiereck/De Bondt/Weber* (1999) and *Liu/Strong/Xu* (1999) confirm this evidence for Germany and the UK, respectively. *Rouwenhorst* (1999) studies the momentum effect in 20 emerging stock markets in Latin America, Asia, Europe, Africa, and the Middle East and finds significant results in only six countries. However, when momentum strategies are implemented across all 20 countries, the profits are significantly positive. *Chui/Titman/Wei* (2000) and *Hameed/Yuanto* (2001) document the profitability of country-neutral momentum strategies in Asian stock markets when Japan is excluded.

In this study, we analyze the relation between momentum and turnover for the German stock market. Thus, we provide an out-of-sample test of the results of *Lee/Swaminathan* (2000) for a large European stock market with a different institutional environment. *Lee/Swaminathan* (2000) analyze the relation between momentum and turnover for the U.S. stock market. We also extend the *Lee/Swaminathan* (2000) analysis in various dimensions. We present size-, book-to-market-, and industry-adjusted returns, evidence on the seasonality of the returns, and several robustness checks of the results. Information on these issues is useful for discriminating between competing explanations for the momentum effect. Although the existence of the momentum effect is not controversial, the interpretation of this result is.

Theories that try to explain the momentum effect can be broadly categorized as risk-based or rational theories and non-risk-based or behavioral theories. *Barberis/Shleifer/Vishny* (1998), *Daniel/Hirshleifer/Subrahmanyam* (1998), and *Hong/Stein* (1999) present behavioral models that explain the momentum effect by cognitive biases in the way investors process information, or by the interaction between heterogeneous investors that leads to time-series predictability of stock returns. In contrast, *Conrad/Kaul* (1998) assume that expected stock returns are constant over time. They show that in using momentum strategies, investors buy stocks with high average mean returns and sell stocks with low average mean returns. They demonstrate that these differences reflect cross-sectional variations in expected returns and thus, risk. There are other rational explanations for the momentum effect. *Chordia/Shivakumar* (2002) show that macroeconomic variables can predict momentum profits. *Johnson* (2002) proposes a rational model with a time-varying expected dividend growth that produces a momentum effect. *Berk/Green/Naik* (1999) show that momentum effects can arise in a dynamic model when a firm's assets, systematic risk, and thus expected return, change over the life-cycle of a firm's chosen investment projects.

Those explanations have no explicit role for trading volume or turnover. Nevertheless it is possible to infer some directional predictions[1]. Recently, empirical and theoretical papers have analyzed the relation between the momentum effect and measures of trading volume such as turnover more directly. *Lee/Swaminathan* (2000) show that for the U.S. stock market, momentum is stronger among high-turnover stocks. In addition, they find that turnover predicts the magnitude and persistence of momentum profits over the long term, which helps us to

1 See *Lee/Swaminathan* (2000), pp. 2061-2063, and Section 4.1.

understand what drives long-horizon momentum return patterns. In contrast, *Nagel* (2002) argues that turnover has no special role in understanding long-term momentum returns. *Chui/Titman/Wei* (2000) find that in five out of eight Asian countries, momentum profits are higher in stocks with high turnover ratios. Momentum profits are five times larger among high-turnover stocks than for low-turnover stocks when country-neutral momentum strategies are implemented. *Hameed/Yuanto* (2001) show that low-turnover stocks in six Asian countries do not exhibit momentum, but momentum strategies are profitable among high-turnover stocks in two out of six countries. *Rouwenhorst* (1999) finds that winners have higher turnover measures than losers in 16 out of 20 emerging markets. *Chan/Hameed/Tong* (2000) analyze momentum strategies implemented on international stock market indexes. They find that momentum is stronger following an increase in trading volume. *Zuchel* (2001) proposes a theoretical model with heterogeneous investors that links momentum and trading volume. One group of investors is prone to the disposition effect, the tendency to sell winners too early and ride losers too long[2]. With no reinvestment opportunities, profit-taking after paper gains (increase of expected returns) and buying after paper losses (escalation of commitment; decrease in expected returns) imply, in equilibrium, strong momentum among high volume stocks. *Grinblatt/Han* (2001) present a similar model. In their model there are two groups of investors, rational investors and "disposition" investors. They find that stocks with aggregate unrealized capital gains (stocks that have appreciated in value) tend to outperform stocks with aggregate unrealized capital losses (stocks that have depreciated in value). They also find that stocks with high current volume (and low past volume) tend to have larger momentum.

In this paper, our main finding is that momentum is stronger among high-turnover stocks. In contrast to *Lee/Swaminathan* (2000), we find that this relation is more pronounced for *winners*. We extend the study of *Lee/Swaminathan* (2000) in our analysis of the seasonality of the relation between momentum and turnover. We show that large parts of the above-average performance of high-turnover momentum strategies come from poor performance of high-turnover losers in the last three months of the year. On the theoretical side, we are able to empirically test various explanations of the momentum effect. First, we are able to distinguish between rational and behavioral theories for the momentum effect. Trading volume should have no predictive power over and above risk. Second, we are able to distinguish between various explanations within the class of behavioral finance models.

Our study also has implications for investment management. Several studies show that "pure" momentum strategies are no longer profitable when transaction costs are considered[3]. If it is possible to find subgroups of stocks that show higher momentum than the average stock, momentum strategies might be exploitable after transaction costs. Compared to "pure" momentum strategies, we find higher

2 See *Shefrin/Statman* (1985), *Odean* (1998), and *Weber/Camerer* (1998) for empirical and experimental evidence on the disposition effect.

3 See, for example, *Alexander* (2000), *Grundy/Martin* (2001), *Lesmond/Schill/Zhou* (2001), and *Cochrane* (2001) for a discussion.

returns for high-turnover momentum strategies. However, when we focus on the one third of stocks with the largest market capitalization, this basic result almost completely disappears. Thus, our results indicate that turnover is unlikely to be a variable that can be used to optimize momentum strategies in a way exploitable by investment management on an institutional scale.

Our study contributes to the literature on stock market regularities in Germany. So far, no study is available that analyzes the relation between momentum profits and turnover for the German stock market. Using a sample of stocks from 1961 to 1991, *Schiereck/De Bondt/Weber* (1999) document significant momentum profits in Germany. This finding was confirmed by *August/Schiereck/Weber* (2000) for a sample of German stocks from 1974 to 1997. We study a larger sample of stocks and a more recent time period (1988–2001). The last point is important, since other stock markets anomalies, such as the small-firm effect (first documented by *Banz* (1981)), have disappeared over time[4]. In addition, we analyze data from a different database (Datastream) that, to our knowledge, has not yet been used to study security market regularities in Germany.

Last but not least, the relation between momentum and turnover is part of the huge literature on the relation between price changes and trading volume[5]. Thus, another contribution of our paper is that it adds to this literature. Why should we look at this price-volume relation? Theoretically, prices and trading volume are simultaneously determined in equilibrium. Technical analysts frequently use price/volume charts and believe that the relation between prices and trading volume provides valuable information about future price changes[6]. In surveying the literature on the relation between price changes and trading volume, *Karpoff* (1987) argues that looking at this relation is important for the following reasons: the relation provides insights into the structure of financial markets, it is useful for improving event studies that analyze a combination of price and volume data, it adds to the debate over the empirical distribution of stock returns, and it has implications for research into futures markets[7]. *Gervais/Kaniel/Mingelgrin* (2001) argue that the efficient market hypothesis can be tested by analyzing the informational role of trading volume in predicting stock returns. They say that "the efficient market hypothesis predicts that trading volume should not have any predictive power over and above an appropriate measure of risk"[8]. *Campbell/Grossman/Wang* (1993) note that "very different models can have similar implications for the time-series behavior of returns" and that stock market trading volume can "help solve this identification problem"[9]. Therefore, analyzing the relation between momentum and turnover is useful for empirically evaluating competing explanations for the momentum effect.

The paper is organized as follows. In Section 2, we describe our data and methodology. Section 3 presents our key results and various robustness checks of these

4 See *Cochrane* (2001) and *Dimson/Marsh* (2000).
5 See, for example, *Karpoff* (1987) and *Gervais/Kaniel/Mingelgrin* (2001).
6 See *Lo/Mamaysky/Wang* (2000) and *Blume/Easley/O'Hara* (1994) for further references.
7 See *Karpoff* (1987), pp. 109-110.
8 *Gervais/Kaniel/Mingelgrin* (2001), p. 880.
9 *Campbell/Grossman/Wang* (1993), pp. 905–906.

results, size-, book-to-market-, and industry-adjusted returns, long-horizon results, and evidence on seasonality. Section 4 discusses our results and Section 5 concludes.

2 Data and Methodology

Our data set consists of 446 companies listed in the top segment of the Frankfurt Stock Exchange (*Amtlicher Handel*) for which we gather daily and monthly closing prices and the daily number of shares traded on a particular day. We also obtain other data, such as market capitalization and market-to-book value from Datastream. To be included in our sample, a stock must have past price and trading volume data for at least four months. For all eligible stocks we collect data, if available, from the beginning of June 1988 to the end of July 2001[10].

We define daily turnover as the number of shares traded on a particular day divided by the number of shares outstanding at the end of that day.

To analyze the profitability of momentum strategies we use the *Jegadeesh/Titman* (1993) methodology. However, due to the smaller number of stocks in our sample, unlike *Jegadeesh/Titman* (1993), we build only five portfolios based on past returns instead of ten portfolios. At the beginning of each month, we rank all stocks in ascending order based on past J months' cumulative raw returns and divide them into five equal-weighted, monthly rebalanced portfolios. If a stock is delisted during the test period, we assume that it was possible to sell the stock at the last trading day. After that, we assume a zero return until the end of the test period. Assuming the market return yields similar results. $R1$ represents the *loser* portfolio with the lowest returns, and $R5$ represents the *winner* portfolio with the highest returns during the previous J months. We analyze holding periods of three, six, nine, and twelve months. To increase the power of our tests, we construct overlapping portfolios. The winner (loser) portfolio is an overlapping portfolio that consists of winner (loser) portfolios in the previous J ranking months. For instance, a winner portfolio in t consists of the J winner portfolios formed in t, $t-1$, $t-2$ and so on up to $t-J+1$. Returns of the winner, loser, and intermediate portfolios in t are the average of J portfolio returns. These overlapping portfolios are equivalent to a composite portfolio in which each month $1/J$ of the holdings are revised. The momentum portfolio ($R5-R1$) is the zero-cost, winner minus loser portfolio.

To analyze the relation between momentum and turnover, we then independently sort all stocks based on the average daily turnover in the J ranking months[11]. $TO1$ represents the portfolio with the lowest turnover, $TO3$ represents the portfolio with the highest turnover in the ranking period. We group the stocks at the intersection of the two independent sorts into portfolios. We note that the number of

10 The daily number of shares traded is only available as of June 1988 in Datastream.

11 *Lee/Swaminathan* (2000) use the same methodology (independent sort), but they build ten portfolios based on past returns. We also use another methodology (conditional sort) in which we first sort stocks based on their past returns. Then we divide the stocks in three return-turnover portfolios *within* each return portfolio. Our results are robust to the choice of methodology.

stocks in the intersected portfolios need not to be constant across months. *Table 3* presents the average number of stocks in the various price-turnover portfolios. We compute monthly returns using the portfolio strategy described above.

3 Results for Turnover-Based Momentum Strategies

3.1 Results for "Pure" Momentum Strategies

Table 1 reports results for momentum strategies based on the methodology described in the previous section. $R1$ represents the *loser* portfolio with the lowest returns, and $R5$ represents the *winner* portfolio with the highest returns during the previous J months. K represents monthly holding periods where K = three, six, nine, or twelve months. The momentum portfolio ($R5 - R1$) is the zero-cost, winner minus loser portfolio. *Return* represents the geometric average monthly return in the ranking period. *Turnover* refers to the average daily turnover in the ranking period. Both are measured in percentages. *SizeDecile* represents the time-series average of the median size-decile of the portfolio on the portfolio formation date. The numbers in parentheses are t-statistics for monthly returns.

Our results are consistent with prior studies on price momentum. The last four columns of *Table 1* present equal-weighted average monthly returns in percentages for various price momentum portfolio strategies. All winner-minus-loser portfolio returns are statistically significant except for the $J = 3/K = 3$, $J = 3/K = 6$ and $J = 6/K = 3$ strategies. *Jegadeesh/Titman* (1993) find similar results for their $J = 3/K = 3$ strategy. However, we note that we do not skip a week or a month between ranking and test period, which, if anything, *reduces* the profitability of momentum strategies due to the profitability of short term contrarian investment srategies[12]. For example, the $J = 9/K = 6$ zero-cost strategy earns 0.96% per month

Table 1: Returns to Price Momentum Portfolios

This table presents average equal-weighted monthly returns in percentages for price momentum portfolio strategies involving stocks of Amtlicher Handel in Germany from June 1988 to July 2001. At the beginning of each month, all stocks are ranked in ascending order based on past J months' cumulative returns and divided into 5 equal-weighted, monthly-rebalanced portfolios. $R1$ represents the *loser* portfolio with the lowest returns, and $R5$ represents the *winner* portfolio with the highest returns during the previous J months. To increase the power of our tests, we construct overlapping portfolios. The winner (loser) portfolio is an overlapping portfolio that consists of winner (loser) portfolios in the previous J ranking months. For instance, a winner portfolio in t consists of the J winner portfolios formed in t, $t-1$, $t-2$ and so on up to $t-J+1$. Returns of the winner, loser, and intermediate portfolios in t are simply the average of J portfolio returns. This is equivalent to a composite portfolio in which each month $1/J$ of the holdings are revised. K represents monthly holding periods where K = three, six, nine, or twelve months. The momentum portfolio ($R5 - R1$) is the zero-cost, winner minus loser portfolio. *Return* represents the geometric average monthly return in the ranking period. *Turnover* refers to the average daily turnover in the ranking period. Both are measured in percentages. *SizeDecile* represents the time-series average of the median size-decile of the portfolio on the portfolio formation date. The numbers in parentheses are t-statistics for monthly returns.

12 See *Lehmann* (1990) and *Mase* (1999).

Table 1: Returns to Price Momentum Portfolios (continued)

J	Portfolio	Return	Turnover	SizeDecile	$K=3$	$K=6$	$K=9$	$K=12$
3	R1	-5.80	0.44	4.56	0.60	0.53	0.46	0.40
					(1.55)	(1.44)	(1.27)	(1.13)
	R2	-1.68	0.30	5.48	0.62	0.62	0.60	0.56
					(2.14)	(2.23)	(2.13)	(2.03)
	R3	0.24	0.33	5.70	0.56	0.59	0.60	0.62
					(2.11)	(2.18)	(2.25)	(2.35)
	R4	2.26	0.40	6.08	0.65	0.65	0.67	0.70
					(2.31)	(2.23)	(2.35)	(2.45)
	R5	7.05	0.55	5.80	0.80	0.84	0.89	0.93
					(2.57)	(2.67)	(2.85)	(2.92)
	R5-R1				0.21	0.31	0.44	0.52
					(0.92)	(1.53)	(2.50)	(3.31)
6	R1	-4.23	0.44	4.31	0.46	0.35	0.27	0.27
					(1.13)	(0.89)	(0.73)	(0.73)
	R2	-1.13	0.33	5.33	0.56	0.54	0.47	0.49
					(1.97)	(1.95)	(1.70)	(1.80)
	R3	0.28	0.35	5.80	0.50	0.53	0.55	0.57
					(1.84)	(1.93)	(2.03)	(2.07)
	R4	1.71	0.41	6.11	0.59	0.64	0.71	0.73
					(2.03)	(2.20)	(2.46)	(2.53)
	R5	4.99	0.51	6.13	0.91	0.95	0.98	0.94
					(2.82)	(2.98)	(3.07)	(2.91)
	R5-R1				0.46	0.61	0.71	0.67
					(1.53)	(2.31)	(3.01)	(3.05)
9	R1	-3.58	0.45	4.09	0.24	0.16	0.16	0.22
					(0.58)	(0.41)	(0.41)	(0.58)
	R2	-0.92	0.34	5.36	0.41	0.36	0.37	0.41
					(1.41)	(1.24)	(1.30)	(1.46)
	R3	0.27	0.34	5.75	0.41	0.43	0.48	0.48
					(1.54)	(1.63)	(1.77)	(1.80)
	R4	1.44	0.41	6.33	0.58	0.65	0.68	0.67
					(1.95)	(2.22)	(2.33)	(2.27)
	R5	4.11	0.50	6.26	1.09	1.12	1.07	0.99
					(3.35)	(3.36)	(3.17)	(2.87)
	R5-R1				0.85	0.96	0.92	0.77
					(2.86)	(3.40)	(3.47)	(3.05)
12	R1	-3.18	0.44	3.91	0.08	0.07	0.12	0.16
					(0.19)	(0.19)	(0.30)	(0.43)
	R2	-0.79	0.35	5.40	0.19	0.25	0.32	0.37
					(0.64)	(0.88)	(1.16)	(1.30)
	R3	0.25	0.36	5.81	0.41	0.43	0.42	0.43
					(1.46)	(1.54)	(1.52)	(1.55)
	R4	1.27	0.41	6.42	0.50	0.54	0.55	0.55
					(1.72)	(1.86)	(1.89)	(1.87)
	R5	3.63	0.50	6.30	1.16	1.07	0.96	0.88
					(3.41)	(3.10)	(2.73)	(2.46)
	R5-R1				1.07	1.00	0.84	0.71
					(3.53)	(3.37)	(3.01)	(2.71)

or about 12% per year (t-value 3.40). All monthly returns are slightly lower than the returns in *Lee/Swaminathan* (2000). This result can perhaps be explained by the reverse size effect in our sample. In Germany, small stocks, i.e., stocks with a low market capitalization, have a *lower* return than large stocks during our sample period. As do *Lee/Swaminathan* (2000), we equal-weight individual stock returns to calculate portfolio returns, which always biases portfolio returns towards the returns of small stocks, so our portfolio returns are downward-biased when compared to market returns. In contrast, the portfolio returns of *Lee/Swaminathan* (2000) are presumably biased upwards due to the positive size effect in the U.S. in their sample period. In addition, we only build five portfolios based on past returns. We do so because of the smaller number of stocks when compared to the U.S., which leads to lower momentum returns[13]. The turnover values are approximately twice as high as in *Lee/Swaminathan* (2000). This finding might be explained by different trading volume definitions. In contrast to *Lee/Swaminathan* (2000), we use a measure of trading volume (Umsatzstatistik) that includes both order book trades and trades that market participants have entered directly into the exchange settlement data system, in particular entries by the brokers as well as transactions between brokers. It includes both the buy and sell sides of transactions, henceforth double-counting any trade. *Lee/Swaminathan* (2000) exclude Nasdaq stocks from their study because of the double counting of dealer trades, because this would lead to an inconsistent treatment across stocks. We note that our study is *not* biased by an inconsistent treatment across stocks.

At the portfolio formation date, i.e., at the beginning of the test period, winner stocks are larger than loser stocks. This observation can be explained by the performance of the winners and losers in the formation (ranking) period. For the six-month formation period ($J = 6$) winners go up about 5% *per month* and losers go down by 4.23% *per month*. *Lee/Swaminathan* (2000) find similar results. *Table 1* shows the extreme performance differences in the ranking period that lead to small but significant return differences in the test period[14].

Turnover is positively correlated with absolute returns. We find the highest turnover values for extreme winners and extreme losers (see columns 3 and 4 of *Table 1*). These results are consistent with prior research on stock returns and turnover[15].

3.2 Momentum and Turnover

Table 2 presents monthly returns for portfolio strategies based on an independent two-dimensional sort on past returns and past average daily turnover. Each month, we sort all stocks independently based on the returns in the past J months and group them into five portfolios. $R5$ represents the *winner* portfolio, $R1$ the *loser* portfolio. The stocks are then independently sorted based on the average daily turnover in the J ranking months. $TO1$ represents the portfolio with the lowest

13 See *Cochrane* (2001).

14 See *Cochrane* (2001) for a discussion of this issue.

15 See *Lee/Swaminathan* (2000) and *Lakonishok/Smidt* (1986).

turnover, *TO*3 represents the portfolio with the highest turnover in the ranking period. The stocks at the intersection of the two independent sorts are grouped into portfolios. *K* represents monthly holding periods where K = three, six, nine, or twelve months. We compute monthly returns using the portfolio strategy described in the previous section.

The main result of *Table 2* can be summarized as follows: Momentum is stronger among high-turnover stocks. This result is consistent with *Lee/Swaminathan* (2000). The difference between the return of the zero-cost, winner minus loser ($R5 - R1$) portfolio for high-turnover stocks and for low-turnover stocks ($TO3 - TO1$) is always positive and in most cases significant. High-turnover losers have lower returns than low-turnover losers, and high-turnover winners have higher returns than low-turnover winners. This relation is more pronounced for winners. The above-average performance of momentum strategies among high turnover stocks is mainly driven by winners. For example, focusing on the $J = 6/K = 6$ cell shows that low-turnover winners have a return of 0.48% per month but high-turnover winners have a monthly return of 1.27%. The difference (0.78% per month) is significantly positive (t-statistic = 2.37). (We calculate the differences with exact, rather than rounded, values, which explains the difference of 0.01% per month.) High-turnover losers have a 0.27% per month lower return, which is not significant. So the difference of the monthly returns of high-turnover stocks and low-turnover stocks (1.16% per month − 0.11% per month = 1.05% per month = 0.78% per month − (−0.27% per month)) is mainly driven by the return differential of the winners. This result contradicts the results of *Lee/Swaminathan* (2000) for the U.S. stock market. *Lee/Swaminathan* (2000) find that the higher return of momentum strategies among high turnover stocks is completely driven by losers. High-turnover losers have significantly lower returns than low-turnover losers, but the results among winners are mixed. However, our results are consistent with *Hameed/Yuanto* (2001) who find that in Malaysia, Singapore, Thailand, Taiwan, and South Korea, high-turnover winners outperform low-turnover winners.

Table 2: Monthly Returns for Portfolios Based on Price Momentum and Turnover (Independent Sort)

This table presents monthly returns from portfolio strategies based on an independent two-dimensional sort based on past returns and past average daily turnover from 1988 to 2001. Each month all stocks of Amtlicher Handel are sorted independently based on the returns in the past *J* months and grouped into five portfolios. *R*5 represents the *winner* portfolio, *R*1 the *loser* portfolio. The stocks are then independently sorted based on the average daily turnover in the *J* ranking months. *TO*1 represents the portfolio with the lowest turnover, *TO*3 represents the portfolio with the highest turnover in the ranking period. The stocks at the intersection of the two independent sorts are grouped into portfolios. Monthly returns are computed using the portfolio strategy described in the previous table. The numbers in parentheses are t-statistics for monthly returns.

Table 2: Monthly Returns for Portfolios Based on Price Momentum and Turnover (Independent Sort) (continued)

		K = 3				K = 6				K = 9				K = 12			
J	Portfolio	TO1	TO2	TO3	TO3-TO1	TO1	TO2	TO3	TO3-TO1	TO1	TO2	TO3	TO3-TO1	TO1	TO2	TO3	TO3-TO1
3	R1	0.67	0.53	0.57	-0.10	0.55	0.37	0.46	-0.09	0.51	0.41	0.29	-0.21	0.42	0.42	0.29	-0.13
		(2.10)	(1.27)	(0.95)	(-0.21)	(1.85)	(0.92)	(0.85)	(-0.24)	(1.72)	(1.01)	(0.58)	(-0.60)	(1.46)	(1.07)	(0.59)	(-0.39)
	R2	0.50	0.65	0.46	-0.04	0.50	0.60	0.50	0.01	0.55	0.51	0.48	-0.07	0.50	0.47	0.51	0.01
		(2.20)	(1.96)	(1.09)	(-0.15)	(2.30)	(1.85)	(1.23)	(0.02)	(2.62)	(1.57)	(1.19)	(-0.27)	(2.41)	(1.49)	(1.26)	(0.03)
	R3	0.54	0.65	0.35	-0.19	0.52	0.71	0.47	-0.05	0.55	0.65	0.54	0.00	0.56	0.65	0.58	0.02
		(2.71)	(2.05)	(0.88)	(-0.68)	(2.71)	(2.28)	(1.19)	(-0.18)	(2.84)	(2.10)	(1.39)	(-0.01)	(2.95)	(2.12)	(1.50)	(0.09)
	R4	0.47	0.76	0.73	0.27	0.48	0.71	0.73	0.25	0.51	0.73	0.72	0.22	0.54	0.72	0.73	0.19
		(2.32)	(2.44)	(1.80)	(0.91)	(2.45)	(2.27)	(1.80)	(0.87)	(2.62)	(2.36)	(1.83)	(0.78)	(2.80)	(2.33)	(1.85)	(0.71)
	R5	0.29	0.65	1.15	0.86	0.43	0.82	1.13	0.70	0.54	0.89	1.13	0.59	0.63	0.91	1.11	0.48
		(1.13)	(1.99)	(2.91)	(2.71)	(1.68)	(2.56)	(2.80)	(2.42)	(2.12)	(2.82)	(2.82)	(2.19)	(2.50)	(2.84)	(2.76)	(1.86)
	R5-R1	-0.37	0.13	0.58	0.96	-0.13	0.44	0.67	0.80	0.03	0.48	0.83	0.80	0.21	0.48	0.82	0.61
		(-1.43)	(0.46)	(1.35)	(2.00)	(-0.62)	(1.83)	(1.90)	(2.22)	(0.17)	(2.25)	(2.92)	(2.70)	(1.25)	(2.45)	(3.13)	(2.41)
6	R1	0.33	0.32	0.34	0.01	0.37	0.13	0.10	-0.27	0.34	0.15	0.07	-0.27	0.31	0.17	0.13	-0.18
		(0.97)	(0.68)	(0.55)	(0.01)	(1.11)	(0.30)	(0.18)	(-0.63)	(1.05)	(0.34)	(0.13)	(-0.70)	(1.01)	(0.38)	(0.26)	(-0.50)
	R2	0.64	0.43	0.26	-0.38	0.50	0.47	0.40	-0.10	0.43	0.35	0.46	0.02	0.43	0.40	0.48	0.05
		(2.84)	(1.31)	(0.61)	(-1.24)	(2.29)	(1.39)	(0.98)	(-0.35)	(2.04)	(1.04)	(1.13)	(0.09)	(2.07)	(1.23)	(1.20)	(0.19)
	R3	0.51	0.48	0.44	-0.06	0.51	0.49	0.49	-0.02	0.52	0.52	0.54	0.02	0.55	0.50	0.57	0.02
		(2.59)	(1.52)	(1.11)	(-0.23)	(2.65)	(1.59)	(1.21)	(-0.05)	(2.78)	(1.69)	(1.35)	(0.08)	(2.94)	(1.62)	(1.43)	(0.06)
	R4	0.41	0.78	0.65	0.24	0.52	0.79	0.63	0.11	0.57	0.75	0.67	0.10	0.56	0.79	0.70	0.14
		(1.84)	(2.37)	(1.67)	(0.87)	(2.41)	(2.49)	(1.61)	(0.40)	(2.75)	(2.41)	(1.73)	(0.37)	(2.71)	(2.56)	(1.82)	(0.56)
	R5	0.30	0.84	1.32	1.02	0.48	0.96	1.27	0.78	0.64	0.94	1.22	0.58	0.65	0.87	1.12	0.47
		(1.03)	(2.44)	(3.04)	(2.66)	(1.70)	(2.91)	(2.99)	(2.37)	(2.33)	(2.89)	(2.89)	(1.89)	(2.43)	(2.64)	(2.66)	(1.58)
	R5-R1	-0.03	0.51	0.98	1.01	0.11	0.82	1.16	1.05	0.30	0.79	1.15	0.85	0.34	0.70	0.99	0.65
		(-0.08)	(1.34)	(1.99)	(1.98)	(0.38)	(2.52)	(2.87)	(2.44)	(1.16)	(2.69)	(3.22)	(2.34)	(1.51)	(2.58)	(3.04)	(2.08)
9	R1	0.43	0.08	-0.18	-0.61	0.31	-0.02	-0.08	-0.39	0.29	0.03	-0.05	-0.34	0.33	0.10	0.03	-0.29
		(1.16)	(0.16)	(-0.28)	(-1.17)	(0.85)	(-0.04)	(-0.14)	(-0.82)	(0.84)	(0.06)	(-0.09)	(-0.80)	(1.00)	(0.23)	(0.07)	(-0.77)
	R2	0.42	0.26	0.34	-0.08	0.37	0.19	0.38	0.01	0.39	0.17	0.45	0.07	0.38	0.24	0.50	0.12
		(1.85)	(0.75)	(0.77)	(-0.29)	(1.73)	(0.56)	(0.87)	(0.04)	(1.84)	(0.49)	(1.06)	(0.23)	(1.82)	(0.70)	(1.19)	(0.43)
	R3	0.38	0.31	0.44	0.06	0.37	0.37	0.47	0.09	0.42	0.43	0.51	0.09	0.46	0.41	0.52	0.06
		(1.88)	(0.98)	(1.06)	(0.21)	(1.93)	(1.18)	(1.14)	(0.33)	(2.18)	(1.37)	(1.26)	(0.33)	(2.46)	(1.28)	(1.29)	(0.22)
	R4	0.46	0.65	0.59	0.13	0.58	0.67	0.64	0.06	0.60	0.68	0.66	0.06	0.56	0.68	0.66	0.11
		(1.99)	(1.99)	(1.47)	(0.45)	(2.56)	(2.09)	(1.59)	(0.22)	(2.68)	(2.13)	(1.64)	(0.21)	(2.51)	(2.17)	(1.65)	(0.41)
	R5	0.75	1.08	1.38	0.63	0.93	1.11	1.32	0.40	0.94	1.04	1.19	0.25	0.87	0.96	1.07	0.20
		(2.32)	(3.16)	(3.21)	(1.74)	(2.99)	(3.20)	(3.05)	(1.18)	(3.17)	(3.01)	(2.74)	(0.82)	(2.89)	(2.73)	(2.44)	(0.67)
	R5-R1	0.32	1.00	1.56	1.24	0.62	1.12	1.41	0.79	0.65	1.02	1.24	0.59	0.54	0.86	1.03	0.50
		(0.86)	(2.55)	(3.26)	(2.27)	(1.82)	(3.13)	(3.23)	(1.71)	(2.19)	(3.05)	(3.25)	(1.51)	(1.94)	(2.65)	(2.97)	(1.44)
12	R1	0.20	-0.05	-0.21	-0.40	0.17	-0.04	-0.14	-0.31	0.23	0.04	-0.08	-0.31	0.28	0.07	0.01	-0.27
		(0.52)	(-0.10)	(-0.32)	(-0.75)	(0.49)	(-0.09)	(-0.22)	(-0.63)	(0.67)	(0.08)	(-0.13)	(-0.72)	(0.85)	(0.15)	(0.01)	(-0.70)
	R2	0.26	0.06	0.16	-0.10	0.30	0.04	0.29	-0.01	0.36	0.11	0.38	0.01	0.40	0.21	0.41	0.01
		(1.11)	(0.15)	(0.36)	(-0.33)	(1.32)	(0.11)	(0.68)	(-0.03)	(1.65)	(0.32)	(0.89)	(0.05)	(1.81)	(0.61)	(0.99)	(0.05)
	R3	0.39	0.32	0.52	0.12	0.39	0.29	0.55	0.16	0.38	0.32	0.53	0.15	0.43	0.34	0.51	0.08
		(1.81)	(1.00)	(1.21)	(0.40)	(1.83)	(0.89)	(1.30)	(0.54)	(1.84)	(1.00)	(1.28)	(0.51)	(2.09)	(1.04)	(1.23)	(0.28)
	R4	0.48	0.54	0.55	0.07	0.51	0.63	0.55	0.03	0.47	0.59	0.60	0.13	0.43	0.57	0.60	0.17
		(1.98)	(1.75)	(1.31)	(0.21)	(2.20)	(2.00)	(1.31)	(0.11)	(2.11)	(1.86)	(1.44)	(0.43)	(1.97)	(1.82)	(1.46)	(0.59)
	R5	0.99	1.17	1.17	0.17	0.98	1.10	1.07	0.09	0.90	1.02	0.90	0.00	0.78	0.92	0.82	0.04
		(2.78)	(3.27)	(2.68)	(0.42)	(2.99)	(3.09)	(2.39)	(0.26)	(2.79)	(2.88)	(1.99)	(0.01)	(2.45)	(2.59)	(1.79)	(0.11)
	R5-R1	0.80	1.22	1.38	0.58	0.80	1.14	1.21	0.40	0.67	0.98	0.98	0.31	0.50	0.86	0.81	0.31
		(2.01)	(3.13)	(2.71)	(1.07)	(2.28)	(3.05)	(2.60)	(0.84)	(2.07)	(2.73)	(2.42)	(0.73)	(1.68)	(2.46)	(2.22)	(0.82)

3.3 Portfolio Characteristics

Table 3 presents various characteristics of the return-turnover portfolios presented in *Table 2*. *J* represents the number of months in the ranking period. *R*5 represents the *winner* portfolio, *R*1 the *loser* portfolio. *TO*1 represents the portfolio with the lowest turnover, *TO*3 represents the portfolio with the highest turnover in the ranking period. *Return* represents the geometric average monthly return in the ranking period. *Turnover* refers to the average daily turnover in the ranking period. Both are measured in percentages. *SizeDecile* represents the time-series average of the median size-decile of the portfolio on the portfolio formation date. *N* is the average number of stocks in the respective portfolio.

The results in this table are similar to the results of *Lee/Swaminathan* (2000), Table IV, Panel A. Winners are larger than losers. High-turnover (*TO*3-)stocks are larger than low-turnover (*TO*1-)stocks. Surprisingly, the time-series average of the median size-decile of *TO*2-stocks is even lower than *SizeDecile* of *TO*1-stocks. The difference of the geometric average monthly return of winners and losers in the ranking period is larger for *TO*3-stocks than for *TO*1 stocks. The portfolio with the lowest average number of stocks is the *R*5*TO*1-portfolio with values of *N* from 13.75 to 15.05. *Lee/Swaminathan* (2000) also find that winners with low turnover are quite rare: The average number of low-turnover winners (*R*10*V*1) in *Lee/Swaminathan* (2000) is 35, which is the lowest value of *N* in Table IV, Panel A.

3.4 Robustness Checks

So far, we have analyzed the returns of the 5 × 3-partitioning. This partitioning is, of course, somewhat arbitrary. In *Table 4*, we present several robustness checks of our results. We especially test whether changes to our benchmark partitioning (five return portfolios and three turnover portfolios, i.e., 5 × 3) and to the methodology of independent sort alter our results. We focus on a six-months formation period and a six-months holding period to conserve space ($J = 6$, $K = 6$). (The results for three, nine, and twelve months formation and holding period are similar.) Panel A in *Table 4* once again states our benchmark results (5 × 3).

Table 3: Characteristics of Portfolios Based on Price Momentum and Turnover (Independent Sort)

This table presents characteristics of the portfolios in *Table 2*. The sample period is 1988 to 2001. *J* represents the number of months in the ranking period. *R*5 represents the *winner* portfolio, *R*1 the *loser* portfolio. *TO*1 represents the portfolio with the lowest turnover, *TO*3 represents the portfolio with the highest turnover in the ranking period. *Return* represents the geometric average monthly return in the ranking period. *Turnover* refers to the average daily turnover in the ranking period. Both are measured in percentages. *SizeDecile* represents the time-series average of the median size-decile of the portfolio on the portfolio formation date. *N* is the average number of stocks in the respective portfolio.

Table 3: Characteristics of Portfolios Based on Price Momentum and Turnover (Independent Sort) (continued)

		TO1				TO2				TO3			
J	Portfolio	Return	Turnover	SizeDecile	*N*	Return	Turnover	SizeDecile	*N*	Return	Turnover	SizeDecile	*N*
3	R1	-5.28	0.03	4.56	20.37	-5.54	0.21	4.09	22.63	-6.76	1.24	5.47	19.84
	R2	-1.67	0.03	5.60	24.18	-1.69	0.21	4.94	20.51	-1.69	0.84	6.87	16.73
	R3	0.23	0.03	5.78	23.27	0.23	0.21	5.09	19.63	0.25	0.86	7.17	17.18
	R4	2.20	0.03	6.18	20.05	2.28	0.22	5.41	19.94	2.30	0.90	7.36	21.64
	R5	7.06	0.03	5.79	15.05	6.71	0.22	5.40	19.99	7.13	1.10	6.77	26.39
6	R1	-3.83	0.04	4.46	20.50	-4.04	0.23	3.99	21.32	-5.05	1.19	5.26	19.48
	R2	-1.11	0.03	5.58	23.42	-1.15	0.23	4.96	20.46	-1.11	0.89	6.79	16.19
	R3	0.26	0.03	5.97	22.41	0.27	0.23	5.14	18.97	0.29	0.90	7.27	17.34
	R4	1.66	0.03	6.40	19.54	1.71	0.23	5.38	19.24	1.76	0.91	7.49	20.93
	R5	4.75	0.04	6.13	14.50	4.80	0.23	5.64	20.07	5.08	1.00	7.14	25.31
9	R1	-3.18	0.04	4.18	19.98	-3.37	0.25	3.88	21.18	-4.30	1.12	5.00	19.30
	R2	-0.90	0.04	5.66	22.58	-0.94	0.25	4.85	19.93	-0.93	0.91	6.70	16.45
	R3	0.25	0.03	6.03	22.43	0.27	0.24	5.07	18.45	0.29	0.88	7.39	16.35
	R4	1.40	0.04	6.56	19.56	1.46	0.24	5.46	18.75	1.47	0.91	7.84	20.39
	R5	3.83	0.04	6.29	13.86	3.99	0.24	5.75	19.73	4.22	0.95	7.33	24.80
12	R1	-2.83	0.04	4.10	19.06	-3.03	0.26	3.69	21.60	-3.80	1.05	4.76	18.83
	R2	-0.78	0.04	5.74	22.77	-0.80	0.26	4.65	18.94	-0.80	0.92	6.83	16.24
	R3	0.25	0.04	6.18	21.74	0.26	0.25	5.12	18.17	0.25	0.89	7.53	16.41
	R4	1.23	0.04	6.59	19.23	1.27	0.24	5.49	18.31	1.29	0.92	8.11	19.89
	R5	3.36	0.04	6.49	13.75	3.59	0.25	5.87	19.27	3.73	0.94	7.57	24.17

Panels B, C, and D present results for the 3 × 3-, 5 × 5-, and 3 × 5-partitioning. Momentum is always stronger among high turnover stocks, although this relation is not monotonic for 5 × 5 and 3 × 5. *TO*4-stocks exhibit the highest momentum returns.

In addition, the methodology of independent sort does not bias the results. When we use a conditional sort, as described above, the results are similar.

3.5 *Momentum, Turnover, and Firm Size*

Table 5 shows how our results are related to firm size or market capitalization. Panel A again states our benchmark results.

To create Panel B, we first rank all stocks by market capitalization on a particular portfolio formation date. We then use the methodology described in Section 2 each month for the largest 50 percent of all stocks. Our results hold for the largest 50 percent of stocks in our sample, although the returns are smaller in magnitude. To generate Panels C, D, and E we once again rank all stocks in ascending order of their market capitalization and build three groups at each portfolio formation date. For each tercile we then proceed as described in Section 2. Panels C, D, and E show that our results are almost completely driven by the middle tercile. We note that *Hong/Lim/Stein* (2000) also find that momentum is mainly driven by mid-cap stocks. These results show that once we move away from the stocks with the lowest market capitalization, momentum declines sharply with size. This finding is no surprise. The first-order autocorrelation coefficient of the monthly returns of the equal-weighted index of all stocks in our sample is 0.21 (*t*-value 2.65), but the first-order autocorrelation coefficient of the monthly returns of the equal-weighted index of the largest 30% of the stocks in our sample is 0.065 (*t*-value 0.81). Our results are similar to those of the U.S. stock market. *Campbell/Lo/MacKinlay* (1997), p. 67, report a first-order autocorrelation coefficient of the monthly returns of the CRSP Equal-Weighted Index of 0.15 in the most recent period from 1978 to 1994, but the respective number for the CRSP Value-Weighted Index is 0.013. The CRSP Value-Weighted Index is comparable to our equal-weighted index of the largest 30% of the stocks in our sample. When we focus on

Table 4: Robustness Checks

This table presents average monthly returns in percentages for price momentum portfolio strategies involving stocks of Amtlicher Handel in Germany from June 1988 to July 2001. The portfolio strategies are based on a six-month-ranking and a six-month test period ($J = 6$, $K = 6$). Panel A presents the results for the benchmark partitioning which is based on 5 price momentum and 3 turnover portfolios, where all stocks are sorted independently (5 × 3, independent sort). Panel B presents results for 3 price momentum and 3 turnover portfolios, Panel C presents results for 5 price momentum and 5 turnover portfolios, and Panel D reports results for 3 price momentum and 5 turnover portfolios. Panel E presents results for 5 price momentum and 3 turnover portfolios based on conditional sort. We first sort stocks based on their past returns. Then we divide the stocks in 3 return-turnover portfolios *within* each return portfolio. HTO-LTO is the difference between the returns of high-turnover and low-turnover portfolios. The numbers in parentheses are *t*-statistics for monthly returns.

Table 4: Robustness Checks (continued)

		Portfolio	TO1	TO2	TO3	TO4	TO5	HTO-LTO
Panel A:	5 × 3	R1	0.37	0.13	0.10	-	-	-0.27
	(Benchmark)		(1.11)	(0.30)	(0.18)	-	-	(-0.63)
		R2	0.50	0.47	0.40	-	-	-0.10
			(2.29)	(1.39)	(0.98)	-	-	(-0.35)
		R3	0.51	0.49	0.49	-	-	-0.02
			(2.65)	(1.59)	(1.21)	-	-	(-0.05)
		R4	0.52	0.79	0.63	-	-	0.11
			(2.41)	(2.49)	(1.61)	-	-	(0.40)
		R5	0.48	0.96	1.27	-	-	0.78
			(1.70)	(2.91)	(2.99)	-	-	(2.37)
		R5-R1	0.11	0.82	1.16	-	-	1.05
			(0.38)	(2.52)	(2.87)	-	-	(2.44)
Panel B:	3 × 3	R1	0.42	0.30	0.23	-	-	-0.19
			(1.51)	(0.75)	(0.46)	-	-	(-0.55)
		R2	0.51	0.46	0.47	-	-	-0.04
			(2.66)	(1.47)	(1.18)	-	-	(-0.13)
		R3	0.54	0.95	1.08	-	-	0.54
			(2.14)	(2.93)	(2.66)	-	-	(1.91)
		R3-R1	0.12	0.64	0.85	-	-	0.73
			(0.55)	(2.64)	(2.91)	-	-	(2.52)
Panel C:	5 × 5	R1	0.45	0.23	0.40	-0.13	0.14	-0.31
			(1.32)	(0.59)	(0.82)	(-0.26)	(0.19)	(-0.46)
		R2	0.47	0.58	0.54	0.22	0.54	0.07
			(2.21)	(2.03)	(1.54)	(0.58)	(1.15)	(0.19)
		R3	0.51	0.64	0.57	0.27	0.53	0.02
			(2.92)	(2.34)	(1.78)	(0.71)	(1.20)	(0.06)
		R4	0.52	0.76	0.69	0.68	0.69	0.17
			(2.62)	(2.49)	(2.14)	(1.80)	(1.62)	(0.50)
		R5	0.33	0.73	1.09	1.10	1.27	0.94
			(1.11)	(2.31)	(3.17)	(2.77)	(2.69)	(2.44)
		R5-R1	-0.12	0.50	0.69	1.23	1.13	1.25
			(-0.35)	(1.52)	(1.83)	(3.36)	(1.85)	(2.01)
Panel D:	3 × 5	R1	0.48	0.32	0.48	-0.05	0.38	-0.10
			(1.80)	(0.98)	(1.13)	(-0.12)	(0.62)	(-0.20)
		R2	0.48	0.59	0.53	0.28	0.49	0.01
			(2.91)	(2.19)	(1.69)	(0.74)	(1.15)	(0.04)
		R3	0.41	0.79	1.00	0.99	1.08	0.67
			(1.70)	(2.63)	(3.10)	(2.63)	(2.48)	(2.00)
		R3-R1	-0.07	0.47	0.54	1.04	0.70	0.77
			(-0.31)	(1.93)	(2.16)	(3.91)	(1.65)	(1.85)
Panel E:	5 × 3	R1	0.37	0.35	0.01	-	-	-0.35
	Conditional		(1.15)	(0.79)	(0.03)	-	-	(-0.91)
	Sort	R2	0.51	0.57	0.39	-	-	-0.12
			(2.47)	(1.83)	(0.98)	-	-	(-0.41)
		R3	0.57	0.51	0.45	-	-	-0.12
			(3.11)	(1.65)	(1.15)	-	-	(-0.43)
		R4	0.58	0.67	0.65	-	-	0.07
			(2.52)	(2.08)	(1.67)	-	-	(0.28)
		R5	0.65	1.04	1.16	-	-	0.51
			(2.34)	(2.98)	(2.64)	-	-	(1.61)
		R5-R1	0.28	0.69	1.14	-	-	0.86
			(1.04)	(2.12)	(2.88)	-	-	(2.24)

Table 5: Momentum, Turnover, and Firm Size

This table presents average monthly returns in percentages for price momentum portfolio strategies involving stocks of Amtlicher Handel in Germany from June 1988 to July 2001. The portfolio strategies are based on a six-month-ranking and a six-month test period ($J = 6$, $K = 6$). Panel A states our benchmark results once again. To create Panel B, we first rank all stocks on market capitalization on a particular portfolio formation date. We then use the methodology described in Section 2 each month for the largest 50 percent of all stocks. To generate Panel C to Panel E we once again rank all stocks in ascending order of their market capitalization and build three groups at each portfolio formation date. For each tercile we then proceed as described in Section 2. The numbers in parentheses are *t*-statistics for monthly returns.

the time period from 1962 to 1994 the numbers are even more close (0.17 and 0.043, respectively). As *Cochrane* (2001) points out, momentum exploits the small, but significant, predictability of monthly returns. If there is no predictability, such as among the largest stocks in our sample, there is no momentum.

3.6 Size-, Book-to-Market, and Industry-Adjusted Returns

Table 6 presents results for size-, book-to-market, and industry-adjusted returns. Panel A reports our benchmark results. To create Panel B, we rank all stocks in ascending order of their market capitalization at the end of each month and assign each stock to one of ten groups (size deciles). To calculate monthly portfolio returns we proceed as described in Section 2 except that we do not use raw returns, but instead use adjusted returns. Prior *raw* returns are used to build portfolios, so the stocks in the respective portfolios are the same as in Panel A. We calculate each firm's monthly adjusted return by subtracting the monthly return of the appropriate benchmark portfolio. This benchmark portfolio is the portfolio that corresponds to the size-, book-to-market (B/M), size-and-B/M, or industry grouping of the stock at the respective portfolio formation date. We define the book value of equity as net tangible assets, which is the difference between ordinary shareholder's equity and intangible assets minus total intangible assets.

Table 6: Momentum and Turnover: Adjusted Returns

This table presents average monthly adjusted returns in percentages for price momentum portfolio strategies involving stocks of Amtlicher Handel in Germany from June 1988 to July 2001. Panel A reports our benchmark results. To create, for example, panel B, we rank all stocks in ascending order of their market capitalization at the end of each month and assign each stock to one of ten groups (size deciles). To calculate monthly portfolio returns we proceed as described in Section 2 except for the fact that we do not use raw returns but adjusted returns. Returns in each portfolio are equal-weighted. Portfolios are rebalanced at the end of each month. Prior *raw* returns are used to build portfolios, so the stocks in the respective portfolios are the same as in Panel A. Book value of equity is defined as net tangible assets which is the difference between ordinary shareholder's equity and intangible assets minus total intangible assets. To generate the results in Panel D we build 25 size-B/M reference portfolios that are based on an independent two-dimensional sort. The portfolio strategies are based on a six-month-ranking and a six-month test period ($J = 6$, $K = 6$). The numbers in parentheses are *t*-statistics for monthly returns.

Table 5: Momentum, Turnover, and Firm Size (continued)

		Portfolio	TO1	TO2	TO3	TO3-TO1
Panel A:	5 × 3	R1	0.37	0.13	0.10	-0.27
	(Benchmark)		(1.11)	(0.30)	(0.18)	(-0.63)
		R5	0.48	0.96	1.27	0.78
			(1.70)	(2.91)	(2.99)	(2.37)
		R5-R1	0.11	0.82	1.16	1.05
			(0.38)	(2.52)	(2.87)	(2.44)
Panel B:	5x3	R1	0.69	0.44	0.45	-0.23
	Largest		(2.17)	(1.03)	(0.87)	(-0.60)
	50%	R2	0.64	0.51	0.72	0.07
	5 × 3		(3.04)	(1.34)	(1.59)	(0.21)
		R3	0.37	0.62	0.59	0.22
			(1.87)	(1.73)	(1.39)	(0.71)
		R4	0.62	0.95	0.68	0.06
			(2.50)	(2.68)	(1.60)	(0.19)
		R5	0.59	1.22	1.18	0.59
			(1.72)	(2.96)	(2.57)	(1.50)
		R5-R1	-0.10	0.77	0.73	0.83
			(-0.31)	(2.29)	(1.93)	(1.87)
Panel C:	5 × 3	R1	0.92	0.69	0.76	-0.16
	highest		(2.88)	(1.50)	(1.45)	(-0.40)
	Tercile	R2	0.57	0.87	0.85	0.28
			(2.51)	(2.21)	(1.78)	(0.78)
		R3	0.39	0.77	0.83	0.44
			(1.88)	(2.04)	(1.81)	(1.27)
		R4	0.76	0.89	0.98	0.22
			(2.82)	(2.34)	(2.19)	(0.65)
		R5	0.90	1.07	1.14	0.24
			(2.16)	(2.44)	(2.28)	(0.54)
		R5-R1	-0.02	0.38	0.38	0.40
			(-0.06)	(1.10)	(0.92)	(0.83)
Panel D:	5 × 3	R1	0.21	0.14	-0.30	-0.51
	middle		(0.58)	(0.27)	(-0.56)	(-1.18)
	Tercile	R2	0.46	0.33	0.10	-0.36
			(1.88)	(0.87)	(0.22)	(-1.07)
		R3	0.34	0.58	0.20	-0.15
			(1.61)	(1.73)	(0.48)	(-0.46)
		R4	0.47	0.75	0.47	-0.01
			(1.82)	(1.95)	(1.16)	(-0.02)
		R5	-0.02	1.32	1.56	1.59
			(-0.07)	(3.39)	(3.52)	(3.88)
		R5-R1	-0.23	1.18	1.87	2.10
			(-0.62)	(2.88)	(4.87)	(4.28)
Panel E:	5 × 3	R1	0.52	0.18	0.05	-0.46
	lowest		(1.07)	(0.31)	(0.06)	(-0.61)
	Tercile	R2	0.29	0.51	0.17	-0.12
			(0.91)	(1.30)	(0.37)	(-0.34)
		R3	0.20	0.51	0.00	-0.19
			(0.76)	(1.46)	(0.01)	(-0.57)
		R4	0.92	0.60	0.09	-0.83
			(3.02)	(1.71)	(0.23)	(-2.59)
		R5	0.91	0.77	1.02	0.11
			(2.06)	(2.08)	(1.91)	(0.20)
		R5-R1	0.39	0.57	0.96	0.58
			(0.70)	(1.10)	(1.20)	(0.63)

Table 6: Momentum and Turnover: Adjusted Returns (continued)

		Portfolio	TO1	TO2	TO3	TO3-TO1
Panel A:	5 × 3	R1	0.37	0.13	0.10	-0.27
	(Benchmark)		(1.11)	(0.30)	(0.18)	(-0.63)
		R5	0.48	0.96	1.27	0.78
			(1.70)	(2.91)	(2.99)	(2.37)
		R5-R1	0.11	0.82	1.16	1.05
			(0.38)	(2.52)	(2.87)	(2.44)
Panel B:	5 × 3	R1	-0.03	-0.15	-0.32	-0.29
	Size-Adjusted-		(-0.13)	(-0.69)	(-0.93)	(-0.68)
	Returns	R2	-0.11	-0.08	-0.40	-0.29
	(10 Portfolios)		(-0.68)	(-0.84)	(-2.90)	(-1.18)
		R3	-0.15	-0.06	-0.41	-0.27
			(-0.95)	(-0.67)	(-3.09)	(-1.05)
		R4	-0.16	0.17	-0.32	-0.16
			(-1.07)	(1.75)	(-2.71)	(-0.69)
		R5	-0.19	0.28	0.37	0.56
			(-1.01)	(1.89)	(1.89)	(1.84)
		R5-R1	-0.17	0.43	0.69	0.85
			(-0.59)	(1.44)	(1.83)	(1.97)
Panel C:	5 × 3	R1	-0.09	-0.33	-0.21	-0.12
	B/M-Adjusted-		(-0.38)	(-1.41)	(-0.59)	(-0.26)
	Returns	R2	-0.04	-0.14	-0.07	-0.03
	(10 Portfolios)		(-0.20)	(-1.37)	(-0.47)	(-0.12)
		R3	-0.11	-0.14	0.02	0.13
			(-0.63)	(-1.54)	(0.13)	(0.47)
		R4	-0.11	0.10	0.04	0.15
			(-0.64)	(0.88)	(0.27)	(0.56)
		R5	-0.06	-0.01	0.34	0.40
			(-0.26)	(-0.10)	(1.63)	(1.16)
		R5-R1	0.03	0.32	0.55	0.52
			(0.08)	(1.03)	(1.34)	(1.04)
Panel D:	5 × 3	R1	0.03	-0.18	-0.19	-0.23
	Size- and		(0.16)	(-0.84)	(-0.59)	(-0.54)
	B/M-Adjusted-	R2	0.03	-0.10	-0.26	-0.30
	Returns		(0.21)	(-1.06)	(-2.03)	(-1.25)
	(5 × 5)	R3	-0.02	-0.13	-0.26	-0.24
			(-0.10)	(-1.51)	(-2.25)	(-1.03)
		R4	-0.08	0.12	-0.21	-0.13
			(-0.49)	(1.13)	(-1.90)	(-0.55)
		R5	-0.04	0.01	0.15	0.20
			(-0.19)	(0.08)	(0.85)	(0.61)
		R5-R1	-0.08	0.19	0.34	0.42
			(-0.24)	(0.68)	(0.94)	(0.87)
Panel E:	5 × 3	R1	-0.16	-0.37	-0.42	-0.26
	Industry-		(-0.79)	(-1.68)	(-1.34)	(-0.65)
	Adjusted-	R2	-0.17	-0.08	-0.07	0.11
	Returns		(-1.27)	(-0.79)	(-0.47)	(0.44)
		R3	-0.15	-0.08	-0.09	0.06
			(-1.11)	(-0.86)	(-0.61)	(0.24)
		R4	-0.15	0.16	0.03	0.19
			(-1.18)	(1.70)	(0.24)	(0.79)
		R5	-0.14	0.31	0.49	0.64
			(-0.79)	(2.13)	(2.60)	(2.26)
		R5-R1	0.02	0.69	0.91	0.89
			(0.08)	(2.37)	(2.54)	(2.26)

The intuition behind size- and book-to-market adjusted returns is as follows. Size and B/M are known to predict the cross-section of returns as risk factors or measures of mispricing[16]. Whatever interpretation is correct, adjusted returns measure the part of the returns that can be explained by turnover *in addition* to size- or B/M-effects. Industry-adjusted returns are motivated by the work of *Moskowitz/ Grinblatt* (1999), who find that momentum profits are related to returns of portfolios formed by industry.

Panel B shows size-adjusted returns using ten size-deciles. The momentum returns are substantially lower than in Panel A. Panel C reports B/M-adjusted returns based on ten B/M-portfolios. To create Panel C, we proceed as described above, except that we use B/M instead of size to build the portfolio returns. The momentum returns are reduced even more when compared to Panel A. The momentum returns are even lower in Panel D. To generate the results in Panel D, we build 25 size-B/M reference portfolios that are based on an independent two-dimensional sort.

In Panel E, we calculate industry-adjusted returns using the industry classification reported in *Table 7*. Again, compared to the results in Panel A, momentum returns are reduced. However, the results remain significant.

Table 7: Industry Classification

This table presents the distribution of the number of firm months in Datastream's industry-classification (datatype INDC3) of the 446 stocks in our sample. Time period is June 1988 to July 2001.

Industry	Firm months	Percent
Resources	11377	16.51
Basic Industries	9164	13.3
General Industries	6794	9.86
Cyclical Consumer Goods	15484	22.48
Non-Cyclical Consumer Goods	1106	1.61
Cyclical Services	8532	12.39
Non-Cyclical Services	2212	3.21
Utilities	632	0.92
Information Technology	10902	15.83
Financials	2686	3.9
Total	68889	100

To summarize, our basic effects hold even when we use adjusted returns: momentum is stronger among high-turnover stocks, but the magnitude of the returns and the significance of the results are reduced. Our basic result is, to some extent, a size-, B/M-, and industry-effect.

16 See *Fama/French* (1992) and *Lakonishok/Shleifer/Vishny* (1994).

3.7 CAPM-Time-Series Regressions

Table 8 presents CAPM-time-series regression results of various portfolios. We estimate these results by regressing the monthly portfolio returns r_t^i in excess of the risk-free r_t^f (except for the zero-cost portfolios) on the equal-weighted index of all stocks in our sample r_t^m minus the risk-free rate. We focus on a six-month formation period and a six-month test period. Thus, the time period for the time-series regression is January 1989 to July 2001 (151 months):

Table 8: Momentum and Turnover: CAPM-Time-Series Regressions

Table 8 presents CAPM-time-series regression results of various portfolios estimated by regressing the monthly portfolio returns r_t^i in excess of the risk free r_t^f (except for the zero-cost portfolios) on the equal-weighted index of all stocks in our sample r_t^m minus the risk free rate:

$$r_t^i - r_t^f = \alpha_i + \beta_i (r_t^m - r_t^f) + \varepsilon_t^i, \quad t = 1,\ldots,151$$

We focus on a six-month formation period and a six-month test period. Time period is January 1989 to July 2001 (151 months). As risk free rate we use the three-month-FIBOR. *t*-values are in parentheses.

	α	β	$\bar{R}^2$		α	β	$\bar{R}^2$
R1	-0.003	1.201	0.835	TO1	-0.002	0.861	0.573
	(-1.88)	(27.54)			(-1.03)	(14.22)	
				TO2	-0.005	1.346	0.763
					(-2.35)	(21.99)	
				TO3	-0.006	1.587	0.711
					(-1.97)	(19.23)	
R5	0.003	1.011	0.862	TO1	-0.001	0.772	0.628
	(2.85)	(30.67)			(-0.35)	(15.94)	
				TO2	0.003	0.983	0.777
					(2.19)	(22.89)	
				TO3	0.006	1.231	0.741
					(2.84)	(20.74)	
R5-R1	0.006	-0.189	0.046	TO1	0.002	-0.090	0.002
	(2.50)	(-2.69)			(0.57)	(-1.12)	
				TO2	0.009	-0.363	0.103
					(2.80)	(-4.27)	
				TO3	0.012	-0.036	0.062
					(3.08)	(-3.31)	

$$r_t^i - r_t^f = \alpha_i + \beta_i(r_t^m - r_t^f) + \varepsilon_t^i, \quad t = 1,\ldots,151 \qquad (1)$$

We use the three-month FIBOR as the risk-free rate. Focusing on the first four columns, the results indicate that losers have a higher β than winners, which contradicts a CAPM-based explanation of momentum returns. The CAPM alpha estimates for the winner minus loser portfolios are about the same as the raw return differences in *Table 1* and in *Table 2*.

The last four columns show that our results hold even if we adjust the returns for β-risk. We also find that high-turnover stocks have higher β-estimates than do low-turnover stocks.

3.8 Seasonality

Table 9 reports results on the seasonality of the returns. We confirm prior results on seasonality and momentum. Momentum returns are negative in Januaries. We note that *all* returns (except for the returns of the zero-cost portfolios) are above average in January. This finding is evidence of a January or turn-of-the-year effect, the tendency that stock returns in January are higher on average than during the rest of the year[17]. *Table 9* shows that these results are always stronger for high-turnover stocks.

Hvidkjaer (2002) finds strongest selling pressure for losers, especially among small trades in the last three months of the year. Therefore, we analyze January–September (Panel D) and October–December (Panel E) returns of various price momentum portfolios. We find that large parts of the above-average performance of high-turnover stocks comes from short positions in loser stocks in the last three months of the year.

3.9 Long-Horizon Results

We now study the long-horizon returns of the benchmark momentum strategy and also the high- and low-turnover momentum strategy. We use a six-month formation period. This event study analysis tracks cumulative returns over the 36 months following the portfolio formation date of the three momentum strategies mentioned above. We define the event date as the respective portfolio's formation

Table 9: Momentum and Turnover: Seasonality

This table presents average monthly returns in percentages for price momentum portfolio strategies involving stocks of Amtlicher Handel in Germany from June 1988 to July 2001 within and outside January as well as January-September and October-December returns. The portfolio strategies are based on a six-month-ranking and a six-month test period ($J = 6$, $K = 6$). The numbers in parentheses are t-statistics for monthly returns.

17 See *Hawawini/Keim* (1995) for international evidence on this issue.

Table 9: Momentum and Turnover: Seasonality (continued)

		Portfolio	TO1	TO2	TO3	TO3-TO1
Panel A:	5 × 3 (Benchmark)	R1	0.37	0.13	0.10	-0.27
			(1.11)	(0.3)	(0.18)	(-0.63)
		R5	0.48	0.96	1.27	0.78
			(1.7)	(2.91)	(2.99)	(2.37)
		R5-R1	0.11	0.82	1.16	1.05
			(0.38)	(2.52)	(2.87)	(2.44)
Panel B:	5 × 3 January-Returns	R1	1.39	3.40	5.15	3.76
			(1.34)	(1.74)	(2.69)	(2.76)
		R2	1.10	1.93	2.66	1.56
			(1.24)	(1.46)	(1.82)	(1.75)
		R3	0.56	2.07	2.45	1.89
			(0.69)	(2.09)	(1.71)	(2.14)
		R4	0.39	1.77	2.37	1.98
			(0.42)	(1.51)	(1.85)	(2.14)
		R5	0.56	1.93	2.84	2.28
			(0.57)	(1.76)	(2.71)	(2.27)
		R5-R1	-0.83	-1.47	-2.31	-1.48
			(-0.95)	(-0.90)	(-1.47)	(-0.89)
Panel C:	5 × 3 February-December-Returns	R1	0.28	-0.16	-0.36	-0.64
			(0.78)	(-0.35)	(-0.64)	(-1.45)
		R2	0.44	0.33	0.20	-0.24
			(1.93)	(0.95)	(0.46)	(-0.83)
		R3	0.51	0.35	0.31	-0.19
			(2.58)	(1.08)	(0.74)	(-0.67)
		R4	0.55	0.70	0.47	-0.08
			(2.46)	(2.12)	(1.15)	(-0.29)
		R5	0.52	0.87	1.12	0.60
			(1.72)	(2.52)	(2.48)	(1.75)
		R5-R1	0.25	1.03	1.49	1.24
			(0.79)	(3.22)	(3.62)	(2.82)
Panel D:	5 × 3 January-September-Returns	R1	0.65	0.58	0.59	-0.07
			(1.58)	(1.04)	(0.86)	(-0.13)
		R2	0.65	0.69	0.62	-0.03
			(2.37)	(1.69)	(1.27)	(-0.08)
		R3	0.63	0.67	0.64	0.01
			(2.67)	(1.80)	(1.30)	(0.03)
		R4	0.61	0.92	0.71	0.10
			(2.32)	(2.35)	(1.51)	(0.32)
		R5	0.61	1.09	1.44	0.83
			(1.76)	(2.71)	(2.88)	(2.08)
		R5-R1	-0.05	0.51	0.85	0.90
			(-0.13)	(1.29)	(1.69)	(1.65)
Panel E:	5 × 3 October-December-Returns	R1	-0.53	-1.24	-1.41	-0.88
			(-1.10)	(-1.80)	(-1.65)	(-1.31)
		R2	0.00	-0.23	-0.28	-0.28
			(-0.01)	(-0.42)	(-0.40)	(-0.53)
		R3	0.14	-0.04	0.04	-0.10
			(0.50)	(-0.08)	(0.06)	(-0.19)
		R4	0.31	0.39	0.39	0.08
			(0.83)	(0.81)	(0.58)	(0.18)
		R5	0.27	0.56	0.73	0.47
			(0.52)	(1.06)	(0.92)	(0.92)
		R5-R1	0.79	1.81	2.14	1.34
			(2.02)	(3.43)	(3.98)	(2.91)

date. Monthly returns are averaged in event time. This method provides information about the persistence of the momentum effect. This information is often used to distinguish between various explanations for the momentum effect that make different predictions about the long-horizon returns of momentum strategies.

One explanation for the momentum effect is that momentum arises because of a conservatism bias (*Edwards* (1968)). Information is gradually incorporated into prices, which leads to momentum. Once the information is incorporated into prices, stock returns are unpredictable. Three recent behavioral models (*Barberis/Shleifer/Vishny* (1998), *Daniel/Hirshleifer/Subrahmanyam* (1998), and *Hong/Stein* (1999)) explain momentum by delayed overreaction that drives prices above fundamental value. In the long run we see price corrections.

Another explanation argues that the momentum effect is due to cross-sectional dispersion in mean returns that are constant over time (*Conrad/Kaul* (1998)). The prediction of this hypothesis is that momentum will continue in *any* post-ranking period.

Figure 1 plots cumulative returns of our benchmark momentum strategy (Momentum), the high-turnover winner minus high-turnover loser (HTOW-HTOL), and the low-turnover winner minus low-turnover loser (LTOW-LTOL) momentum strategies. Our first observation is the remarkable similarity between cumulative returns over the first 36 months following the portfolio formation date of our benchmark momentum strategy and the momentum strategy in the U.S. in the most recent period[18]. The long-run performance of the benchmark strategy is consistent with the underreaction hypothesis, but the long-run performance of the high-turnover momentum strategy (HTOW-HTOL) shows delayed overreaction and correction. As in *Lee/Swaminathan* (2000), the magnitude and persistence of momentum over the long term seems to be a function of past turnover. The behavioral models of *Barberis/Shleifer/Vishny* (1998), *Daniel/Hirshleifer/Subrahmanyam* (1998), and *Hong/Stein* (1999) predict, as *Hirshleifer* (2001) stresses, that if there is market segmentation, stocks with a strong price momentum will show the largest return reversals, because the mistaken beliefs that are responsible for the momentum effect are also responsible for the long-term reversal[19]. If we interpret our sort on turnover as market segmentation, then *Figure 1* is a clear evidence in favor of these behavioral models.

4 Discussion

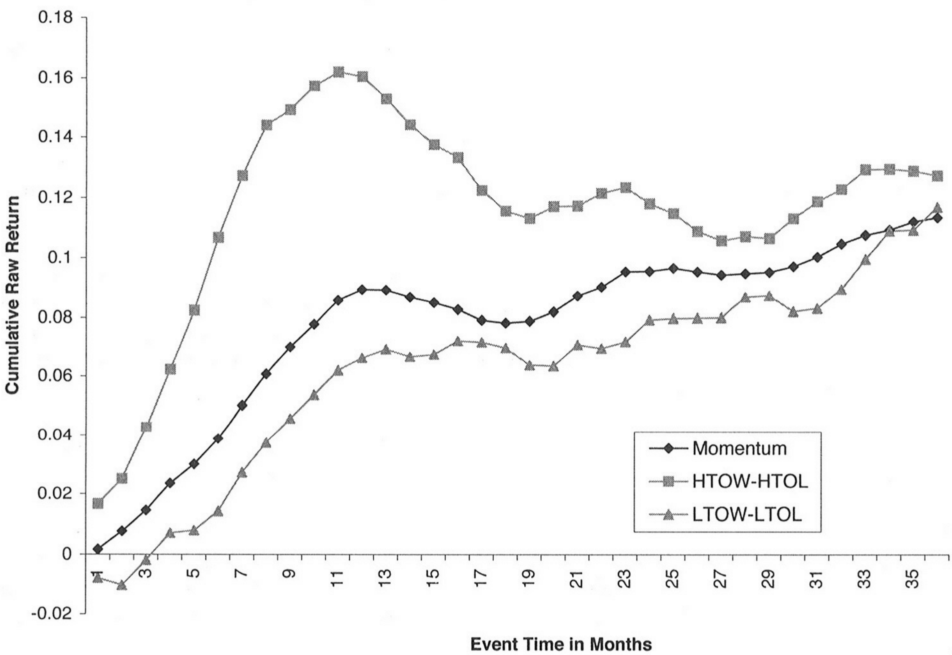
4.1 Momentum and Turnover

Our results demonstrate that momentum is stronger among high-turnover stocks. We examine this result in light of existing models that try to explain the momentum effect.

18 See *Jegadeesh/Titman* (2001b), p. 713, *Figure 3*.
19 *Hirshleifer* (2001), p. 1575.

Figure 1: Long-Horizon Results

This figure plots cumulative long-horizon returns of the benchmark momentum strategy (Momentum), the high-turnover winner minus high-turnover loser (HTOW-HTOL), and the low-turnover winner minus low-turnover loser (LTOW-LTOL) momentum strategies with a six-month formation period each. This event study analysis tracks cumulative returns over the 36 months following the portfolio formation date of the three momentum strategies mentioned above. Stocks are assigned to portfolios as described in Section 2. Event date is the respective portfolio formation date. Monthly returns are averaged in event time. The time period is 1988-2001.



Hong/Stein (1999) present a model with two groups of boundedly rational traders, news watchers and momentum traders. News watchers trade on firm-specific private signals; momentum traders condition their forecasts on past price movements. *Hong/Stein*'s (1999) main finding is that in the case of gradual firm-specific information diffusion prices initially underreact to information. One implication of this finding is a stronger momentum effect among stocks with slower diffusion of firm-specific information. If low turnover is a proxy for slow information diffusion, then our results contradict this theory of the momentum effect because we do not find stronger momentum among low-turnover stocks.

Daniel/Hirshleifer/Subrahmanyam (1998) build a model with overconfident investors. Overconfidence is modeled as overestimation of the precision of an investor's private information. One implication of their model is that overconfidence should be greater among stocks that are difficult to evaluate. *If* turnover is a proxy for the trading activity of overconfident investors, then mispricing and thus momentum should be stronger among high-turnover stocks. Our data support this prediction.

One problem of these models is that they have no explicit role for trading volume and thus do not make precise predictions about the relation between momentum and turnover. Therefore, our arguments are speculation.

Zuchel (2001) proposes a model with heterogeneous investors that studies the relation between momentum and trading volume. One type of investors, the disposition investors, has, all else equal, higher demand for losers than for winners. With no reinvestment opportunities, profit-taking after paper gains and buying after paper losses imply, in equilibrium, strong momentum among high-volume stocks. This result is consistent with our data.

This discussion shows that our results are consistent with behavioral models. The long-term results presented in Section 3.9 do not support the *Conrad/Kaul* (1998) conjecture. However, our results show that our discussion so far is only one part of the story. The turnover effect is, to a large extent, a size-, B/M-, and industry-effect. In addition, the turnover effect is substantially reduced when we exclude October-December returns. Our results can, at least in part, be explained by the selling pressure of high-turnover losers at the end of the year and thus, by tax-loss selling (see *Hvidkjaer* (2002)). High-turnover stocks also have a higher β-risk than low-turnover stocks. However, the CAPM risk-adjusted high-turnover momentum returns are significantly positive (t-value 3.08). In summary, turnover seems to have predictive power over and above risk. According to *Gervais/Kaniel/Mingelgrin* (2001), this finding is a sign of market inefficiency.

The turnover effect almost completely disappears when we consider the largest and presumably most liquid stocks, so doubts remain as to whether our results have any practical investment value. All in all, there are a lot of unresolved questions. Clearly, more sophisticated models with an explicit role for turnover are needed to better understand our results.

In future research, it would be interesting to analyze other measures of trading volume, such as raw trading volume or the number of trades[20]. If turnover is a measure of a stock's visibility (see *Gervais/Kaniel/Mingelgrin* (2001)), measures such as changes in turnover (see *Lee/Swaminathan* (2000)), abnormal turnover (see *Ajinkya/Jain* (1989)), or volatility of turnover (see *Chordia/Subrahmanyam/Anshuman* (2001)) could be more appropriate than turnover for optimizing momentum strategies. Another suggestion for future research is to study to what extent our results are related to the skewness and liquidity literature[21]. *Chen/Hong/Stein* (2001) find that negative skewness is most pronounced in stocks that have experienced an increase in trading volume relative to trend over the previous six months. *Ang/Chen/Xing* (2002) find that parts of the profitability of momentum strategies is compensation for bearing downside risk. *Harvey/Siddique* (2000) show that a momentum investor must accept substantial negative skewness of returns. *Franke/Weber* (2001) propose a model that is consistent with these

20 See *Karpoff* (1987) and *Lo/Wang* (2000) for surveys on trading volume and price changes, and definitions of measures of trading volume.

21 See *Chen/Hong/Stein* (2001), *Ang/Chen/Xing* (2002) and *Harvey/Siddique* (2000) for the relation between skewness and stock returns.

empirical findings. *Baker/Stein* (2001) find that an increase in liquidity, such as high turnover, leads to low subsequent stock returns.

In addition, momentum seems to be related to the ownership structure of firms. *Chui/Titman/Wei* (2000) show that momentum is stronger for independent firms than for group-affiliated firms. *Chen/Hong/Stein* (2002) find that changes in breadth of ownership forecast stock returns. Since we have not considered the fact that some firms have only a small percentage of free floating stocks, our turnover measure could be a proxy for ownership structure. These firms have a low-turnover measure even if the turnover of the free floating stocks is high.

4.2 *Other Stylized Momentum Facts*

This paper confirms most of the results of *Lee/Swaminathan* (2000) concerning momentum and turnover. In addition, our analysis is consistent with other stylized momentum facts[22]. Consequently, the big picture seems to emerge.

Momentum seems to be related to firm size or market capitalization. *Jegadeesh/Titman* (1993) analyze the profitability of momentum strategies in three subsamples based on firm size, using NYSE and AMEX stocks from 1965 to 1989. Medium-sized firms show the largest momentum effect and stocks with the highest market capitalization show the lowest momentum effect[23]. *Hong/Lim/Stein* (2000) analyze the profitability of momentum strategies in ten subgroups (size deciles) using NYSE, AMEX, and Nasdaq stocks from 1976 to 1996. They find an inverted U-shape relation. Momentum is unprofitable in the deciles of stocks with the lowest (decile 1) and the highest (decile 10) market capitalization. After the third size decile (decile 3), the profitability of momentum strategies declines monotonically with firm size[24]. We find similar results. Momentum is mainly driven by mid-cap stocks. Momentum strategies are unprofitable when implemented among stocks with high market capitalization, which are presumably the most liquid stocks. Transaction costs seem to make it difficult, at least in part, to arbitrage away momentum profits.

Momentum profits exhibit a striking seasonality. Momentum strategies are unprofitable in January. Therefore, we are able to confirm U.S. evidence on the seasonality of momentum profits. *Jegadeesh/Titman* (1993) find that momentum strategies are profitable in all months except January. This finding is confirmed by *Jegadeesh/Titman* (2001b) in a later study.

The results of *Hvidkjaer* (2002), who analyzes buying and selling pressure of winner and loser portfolios, suggest that a tax-loss selling explanation of momentum profits seems to be warranted. He finds strong selling pressure on losers in the last three months of the year, especially among small trades. This fact might explain

22 See the recent momentum survey of *Jegadeesh/Titman* (2001a) and the list of stylized momentum facts therein.

23 *Jegadeesh/Titman* (1993), p. 78.

24 *Hong/Lim/Stein* (2000), *Figure 1*.

the strong momentum effect among mid-cap stocks, which are known for a higher proportion of individual investor ownership than are large stocks. However, why momentum is unprofitable in the subgroup of stocks with the lowest market capitalization is a result that remains a puzzle. One explanation for this finding might be the problem with return calculations due to infrequent trading and low liquidity. However, this argument is speculation.

Long-term event-time returns show that in any post-ranking period, winners do not consistently overperform and losers do not consistently underperform. These patterns are difficult to reconcile with a risk-based explanation, which assumes that risk and expected return are constant over time. Whether we observe reversals after 12 months or not seems to depend on the time period and the stock market or country studied.

Our CAPM beta estimates are also very similar to the original beta estimates in *Jegadeesh/Titman* (1993). Losers have higher beta estimates than do winners. Hence, the beta of the zero-cost winner minus loser portfolios is negative. But losers have lower returns than winners despite higher beta estimates. Thus, cross-sectional dispersion in expected returns is unlikely to be a plausible explanation for the momentum effect.

5 Conclusion

Our results generally support prior empirical research on price momentum and turnover. Momentum is stronger among high-turnover stocks. We show that momentum profits are, to some extent, due to size-, B/M-, and industry-factors. Our results contribute to a better understanding of the momentum effect. In addition, our study evaluates competing explanations for the momentum effect.

We find clear support for behavioral explanations of the momentum effect, but we show that this finding is only one part of the story. Within the group of stocks with the largest market capitalization, turnover has almost no predictive power. This finding casts doubt on the possibility of realizing profits after transaction costs.

Our results also show a striking seasonality. We find that large parts of high returns of high-turnover momentum strategies are due to the extreme low returns of high-turnover losers in the last three months of the year. Indeed, *Cochrane* (2001) argues that the momentum effect "sounds a lot more like a small microstructure glitch rather than a central parable for risk and return in asset markets"[25]. On the other hand, it is remarkable that investors do not appear to anticipate the low returns of high-turnover losers at the end of the year. Therefore, momentum, especially among high-turnover stocks, remains an anomaly.

25 See *Cochrane* (2001), p. 447.

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