Momentum and Turnover:

Evidence from the German Stock Market

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Abstract

This paper analyzes the relation between momentum strategies (strategies that buy stocks with high returns over the previous three to 12 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. 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.

Keywords: Asset Pricing, Momentum, Turnover

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1 Introduction

Recently, the interaction between momentum and measures of trading volume such as turnover (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 12 months and sell stocks with low returns over the previous three to 12 months earn statistically significant profits in most of the world-wide equity markets.[1] Momentum 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.[2] There is a large literature on the relation between price changes and trading volume over short horizons from a few minutes to one month.[3]

In this study, we analyze the relation between momentum and turnover (number of shares traded divided by the number of shares outstanding) for the German stock market. We thus provide an out-of-sample test of the results of Lee and Swaminathan (2000), hereafter LS2000, for a large European stock market with a different institutional environment. LS2000 analyze the relation between momentum and turnover for the US stock market. In addition, we extend their analysis in various dimensions. We present size-, book-to-market-, and industry-adjusted returns, evidence on the seasonality of the returns, and

[1] Jegadeesh and Titman (1993, 2001) and Lee and Swaminathan (2000) show that momentum strategies are successful in the US stock market. Rouwenhorst (1998) demonstrates the profitability of momentum strategies in 11 out of 12 European stock markets. Schiereck, De Bondt, and Weber (1999) and Liu, Strong, and 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 6 countries. However, when momentum strategies are implemented across all 20 countries, the profits are significantly positive. Chui, Titman, and Wei (2000) and Hameed and Yuanto (2001) document the profitability of country-neutral momentum strategies in Asian stock markets when Japan is excluded.

[2] See Lo, Mamaysky, and Wang (2000) and Blume, Easley, and O'Hara (1994) for further references.

[3] See, for example, Karpoff (1987) and Gervais, Kaniel, and Mingelgrin (2001).

several robustness checks of the results.

Information on these issues is useful to discriminate between competing explanations for the momentum effect. While the existence of the momentum effect is not controversial, the interpretation of this result is even more so.

Theories that try to explain the momentum effect can broadly be categorized as risk-based or rational theories and non-risk-based or behavioral theories. Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) present behavioral models that explain the momentum effect by cognitive biases in the way investors process information which leads to time-series predictability of stock returns. In contrast, Conrad and Kaul (1998) argue that expected stock returns are constant over time. They show that momentum strategies 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.[4]

Those explanations have no explicit role for trading volume or turnover. Recently, empirical and theoretical papers have analyzed the relation between the momentum effect and measures of trading volume such as turnover. LS2000 show for the US stock market that momentum is stronger among high-turnover stocks. In addition, they find that turnover predicts the magnitude and persistence of momentum profits over long horizons. In contrast, Nagel (2000) argues that turnover has no special role in predicting long-horizon momentum returns. He finds that turnover is correlated with book-to-market. Chui, Titman, and Wei (2000) document 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 mo-

[4]There are other rational explanations for the momentum effect. Chordia and Shivakumar (2002) show that macroeconomic variables are able to predict momentum profits. Johnson (2002) proposes a rational model with time-varying expected dividend growth which produces a momentum effect. Berk, Green, and Naik (1999) show that momentum effects can arise in a dynamic model when firm's assets, systematic risk, and thus expected return change over the life-cycle of a firm's chosen investment projects.

mentum strategies are implemented. Hameed and Yuanto (2001) show that low-turnover stocks in six Asian countries do not exhibit momentum, whereas 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, and Tong (2000) analyze momentum strategies implemented on international stock market indices. 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 to early and ride losers to long.[5] 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.[6]

Our results are broadly consistent with this empirical and theoretical literature. Our main finding is that momentum is stronger among high-turnover stocks. In contrast to LS2000, we find that this relation is more pronounced for *winners*. We extend the study of LS2000 in the way that we analyze the seasonality of the relation between momentum and turnover. We show that large parts of the above-average performance of high-turnover momentum strategies comes from poor performance of high-turnover losers in the last three months of the year.

In addition, our study has implications for investment management. Several studies show that 'pure' momentum strategies are no longer profitable when transaction costs are considered.[7] If it is possible to find subgroups of stocks that exhibit higher momentum than the average stock, momentum strategies could be exploitable after transaction costs. We find higher returns for high-turnover momentum strategies when compared to 'pure' mo-

[5]See Shefrin and Statman (1985), Odean (1998), and Weber and Camerer (1998) for empirical and experimental evidence on the disposition effect.

[6]Grinblatt and Han (2001) present a similar model.

[7]See, for example, Alexander (2000), Grundy and Martin (2001), Lesmond, Schill, and Zhou (2001), and Cochrane (2001) for a discussion.

mentum 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.

Last but not least, 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. Schiereck, De Bondt, and Weber (1999) document significant momentum profits in Germany using a sample of stocks from 1961 to 1991. This finding was confirmed by August, Schiereck, and 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).[8] The last point is important as other stock markets anomalies, such as the small-firm effect (first documented by Banz (1981)), have disappeared over time.[9]

The remainder of 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 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 closing prices and the number of shares traded on a particular day as well as 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

[8] 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.

[9] See Cochrane (2001) and Dimson and Marsh (2000).

we collect data, if available, from the beginning of June 1988 to the end of July 2001.[10]

Daily turnover is defined 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 employ the methodology used by Jegadeesh and Titman (1993).[11] At the beginning of each month, all stocks are ranked in ascending order based on past J month's cumulative raw returns and divided into 5 equal-weighted, monthly-rebalanced portfolios.[12] *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 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. The momentum portfolio ($R5 - R1$) is the zero-cost, winner minus loser portfolio.

To analyze the relation between momentum and turnover, all stocks are then independently sorted based on the average daily turnover in the J ranking months.[13] $TO1$ represents the portfolio with the lowest turnover, $TO3$ represents the portfolio with the highest

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

[11] In contrast to Jegadeesh and Titman (1993), we only build 5 portfolios based on past returns instead of 10 portfolios due to the smaller number of stocks in our sample.

[12] If a stock is delisted during the test period it is assumed that it was possible to sell the stock at the last trading day. After that a zero return is assumed until the end of the test period. Assuming the market return instead yields similar results.

[13] The same methodology (independent sort) is used by LS2000 except for the fact that they build 10 portfolios based on past returns. We also use another methodology (conditional sort) where we first sort stocks based on their past returns. Then we divide the stocks in 3 return-turnover portfolios *within* each return portfolio. Our results are robust to the choice of methodology.

turnover in the ranking period. The stocks at the intersection of the two independent sorts are grouped into portfolios.[14] Monthly returns are computed using the portfolio strategy described above.

3 Results for Turnover-Based Momentum Strategies

3.1 The Benchmark: Results for 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 simple t-statistics for monthly returns.

Our results are consistent with prior studies on price momentum. The last 4 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 the $J = 3/K = 3$, $J = 3/K = 6$ and $J = 6/K = 3$ strategies.[15] For example, the $J = 9/K = 6$ zero-cost strategy earns 0.96 % per month or about 12 %

[14]Note that the number of 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.

[15]Jegadeesh and Titman (1993) find similar results for their $J = 3/K = 3$ strategy. 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 (See Lehmann (1990)).

per year (t-value 3.40).[16]

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 went up about 5% *per month* and losers went down by 4.23 % *per month*.[17]

Turnover is positively correlated with absolute returns. The highest turnover values are found 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.[18]

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 all stocks are sorted independently based on the returns in the past J months and grouped into

[16]All monthly returns are slightly lower than the returns in LS2000. This can possibly 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 LS2000, 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 LS2000 are presumably biased upwards due to the positive size effect which was found in the US in the sample period studied by these authors. In addition, we only build 5 portfolios based on past returns due to the smaller number of stocks when compared to the US which leads to lower momentum returns (see Cochrane (2001). The turnover values are approximately twice as high as in LS2000. This might be explained by different trading volume definitions. We use, in contrast to LS2000, a measure of trading volume (Umsatzstatistik), that includes both orderbook 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 buy and sell side of transactions, henceforth double counting any trade. LS2000 exclude Nasdaq stocks from their study because of the double counting of dealer trades as this would lead to an inconsistent treatment across stocks. Note, that our study is *not* biased by an inconsistent treatment across stocks.

[17]LS2000 find similar results. Table 1 nicely shows the extreme performance differences in the ranking period that lead to small but significant return differences in the test period. See Cochrane (2001) for a discussion of this issue.

[18]See LS2000 and Lakonishok and Smidt (1986).

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 turnover, $TO3$ 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. Monthly returns are computed 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 LS2000. 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 whereas high turnover winners have a monthly return of 1.27 %. The difference (0.78 % per month)[19] is significantly positive (t-statistic = 2.37). 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 LS2000 for the US stock market who 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 whereas the results among winners are mixed. However, the results are consistent with Hameed and Yuanto (2001) who find that in Malaysia, Singapor, Thailand, Taiwan,

[19]The differences are calculated with exact values rather than rounded values which explains the difference of 0.01 % per month.

and South Korea high-turnover winners outperform low-turnover winners.

3.3 Portfolio Characteristics

Table 3 presents various portfolio characteristics of the return-turnover portfolios presented in Table 2. J represents the number of months in the ranking period. $R5$ represents the *winner* portfolio, $R1$ the *loser* portfolio. $TO1$ represents the portfolio with the lowest turnover, $TO3$ 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 very similar to the results of LS2000, table IV, panel A. Winners are larger than losers. High-turnover (TO3-) stocks are larger than low-turnover (TO1-) stocks. Surprisingly, the time-series average of the median size-decile of TO2-stocks is even lower than *SizeDecile* of TO1-stocks. The difference of the geometric average monthly return of winners and losers in the ranking period is larger for TO3-stocks than for TO1 stocks. The portfolio with the lowest average number of stocks is the R5TO1-portfolio with values of N from 13.75 to 15.05. LS2000 and Hvidkjaer (2000) find the same result that winners with low turnover are quite rare.[20]

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 (5 return portfolios,

[20] The average number of low-turnover winners (R10V1) in LS2000 is 35, which is the lowest value of N in table IV, panel A.

3 turnover portfolios, i.e. 5×3) and to the methodology of independent sort alter our results. We focus on a 6 months formation period and a 6 months holding period to conserve space ($J = 6, K = 6$).[21] Panel A in Table 4 once again states our benchmark results (5×3).

Panel B, Panel C, and Panel 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. The highest momentum returns can be found for $TO4$-stocks.

In addition, the methodology of independent sort does not bias the results. When conditional sort, as described above, is used, the results are very similar.

3.5 Momentum, Turnover, and Firm Size

Table 5 shows how our results are related to firm size or market capitalization. Panel A states our benchmark results once again. 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 Panel C to Panel E we once again rank all stocks on 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. Panel C to Panel E show that our results are almost completely driven by the middle tercile.[22] These results show that once one moves apart from the stocks with the lowest market capitalization momentum declines sharply with size. This 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), whereas 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

[21] The results for three, nine, and 12 months formation and holding period are similar.

[22] Hong, Lim, and Stein (2000) also find that momentum is mainly driven by mid-cap stocks.

0.065 (t-value 0.81).[23] As Cochrane (2001) points out, momentum exploits the small, but significant predictability of monthly returns. If there is no predictability, 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, 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.[24] Each firm's monthly adjusted return is calculated 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.[25]

The intuition of 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.[26] Whatever interpretation is true, 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 and Grinblatt (1999) who find that momentum profits are related to returns of portfolios formed by industry.

[23] The results are very similar to the US stock market. Campbell, Lo, and 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, whereas 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 the time period from 1962 to 1994 the numbers are even more close (0.17 and 0.043, respectively).

[24] Prior *raw* returns are used to build portfolios, so the stocks in the respective portfolios are the same as in Panel A.

[25] 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.

[26] See Fama and French (1992) and Lakonishok, Shleifer, and Vishny (1994).

Panel B shows size-adjusted returns using 10 size-deciles. The momentum returns are substantially lower than in Panel A. Panel C reports B/M-adjusted returns based on 10 B/M-portfolios. To create Panel C we proceed as described above except for the fact 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 a independent two-dimensional sort.

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

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.

3.7 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:[27]

$$r_t^i - r_t^f = \alpha_i + \beta_i(r_t^m - r_t^f) + \epsilon_t^i, \qquad t = 1, \ldots, 151 \tag{1}$$

As risk free rate we use the three-month-fibor. Focusing on the first four columns, the results indicate that losers have a higher β than winners which contradicts a CAPM-based

[27] 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).

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 low-turnover stocks.

3.8 Seasonality

Table 9 reports results on the seasonality of our results. We confirm prior results on seasonality and momentum. Momentum returns are negative in Januaries.[28] Table 9 shows that all results on turnover and momentum apply for all turnover portfolios, but the results are always stronger for high-turnover stocks.

Motivated by Hvidkjaer (2000) who finds strongest selling pressure for losers in the last three months of the year 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 taken in the last three months of the year.

3.9 Long-Horizon Results

In this section we study the long-horizon returns of the benchmark momentum strategy as well as the high-turnover and low-turnover momentum strategy 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. Event date is the respective portfolio formation date. Monthly returns are averaged in event time. This methodology provides information about the persistence of

[28] Note that *all* returns (except for the returns of the zero-cost portfolios) are above average in January. This is evidence for 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. See Hawawini and Keim (1995) for international evidence on this issue.

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 due to 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, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999)) explain momentum by delayed overreaction that drives prices above fundamental value that corrects in the long-run. Another explanation argues that the momentum effect is due to cross-sectional dispersion in mean returns that are constant over time (Conrad and Kaul (1998)). The prediction of this hypothesis is momentum continuation 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. The 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 US in the most recent period (Jegadeesh and Titman (2001), p. 713, Figure 3). The long-run performance of the benchmark strategy is consistent with the underreaction hypothesis, whereas the long-run performance of the high-turnover momentum strategy (HTOW-HTOL) shows delayed overreaction and correction. As in LS2000, the magnitude and persistence of momentum over long horizons seems to be a function of past turnover. The behavioral models of Barberis, Shleifer, and Vishny (1998), Daniel, Hirshleifer, and Subrahmanyam (1998), and Hong and Stein (1999) predict, as Hirshleifer (2001) stresses, that, in case of market segmentation, stocks with a strong price momentum will exhibit the largest return reversals as the mistaken beliefs that are responsible for the momentum effect are also responsible for the long-run reversal.[29] If one interprets

[29]Hirshleifer (2001), p. 1575.

our sort on turnover as market segmentation, Figure 1 is a clear evidence in favor of these behavioral models.

4 Discussion

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

Hong and 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 whereas momentum traders condition their forecasts on past price movements. The main finding of Hong and Stein (1999) 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 our results contradict this theory of the momentum effect because we do not find stronger momentum among low-turnover stocks.

Daniel, Hirshleifer, and 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 trading activity of overconfident investors mispricing and thus momentum should be stronger among high-turnover stocks. This prediction is supported by our data.

One problem of these models is that they have no explicit role for trading volume and therefore do not make precise predictions about the relation between momentum and turnover. So, 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, anything else being equal, higher demand for losers than for winners. With no reinvestment opportunities profit taking after paper gains and buying after paper losses implies, in equilibrium, strong momentum among high volume stocks which is consistent with our data.

This discussion shows that our results are consistent with behavioral models. The long-horizon results presented in Section 3.9 do not support the Conrad and Kaul (1998) conjecture. But 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 October-December returns are excluded. 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 (2000)). Above that, high-turnover stocks have a higher β-risk than low-turnover stocks.

The turnover effect almost completely disappears when the largest and presumably most liquid stocks are considered. 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 addition, it would be interesting to analyze other measures of trading volume such as raw trading volume or the number of trades.[30] If turnover is a measure of a stock's visibility (see Gervais, Kaniel, and Mingelgrin (2001)), measures such as changes in turnover (see LS2000), abnormal turnover (see Ajinkya and Jain (1989)), or volatility of turnover (see Chordia, Subrahmanyam, and Anshuman (2001)) could be more appropriate than turnover to optimize momentum strategies. Another suggestion for future research is to study to what extent our results are related to the skewness and liquidity literature.[31]

[30] See Karpoff (1987) and Lo and Wang (2000) for surveys on trading volume and price changes and definitions of measures of trading volume.

[31] See Chen, Hong, and Stein (2001), Ang, Chen, and Xing (2001) and Harvey and Siddique (2000) for the relation between

Above that, momentum seems to be related to the ownership structure of firms.[32] Our turnover measure could be a proxy for ownership structure as we have not considered the fact that some firms have only a small percentage of free floating stocks. These firms have a low turnover measure even if the turnover of the free floating stocks is high.

5 Conclusion

Our results are broadly consistent with 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. Above that, our study evaluates competing explanations for the momentum effect.

We find clear support for behavioral explanations of the momentum effect but show that this is only one part of the story. Within the group of stocks with the largest market capitalization turnover has almost no predictive power which casts doubt on the possibility of realizing profits after transaction costs. In addition, our results show a striking seasonality. We document 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. Cochrane (2001) thus 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" (p. 447). 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. So, momentum,

skewness and stock returns. Chen, Hong, and 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, and Xing (2001) find that parts of the profitability of momentum strategies is compensation for bearing downside risk. Harvey and Siddique (2000) show that a momentum investor has to accept substantial negative skewness of returns. Franke and Weber (2001) propose a model that is consistent with these empirical findings. Baker and Stein (2001) find that an increase in liquidity such as high turnover leads to low subsequent stock returns.

[32] Chui, Titman, and Wei (2000) show that momentum is stronger for independent firms than for group-affiliated firms. Chen, Hong, and Stein (2001) find that changes in breadth of ownership forecast stock returns.

especially among high-turnover stocks, remains an anomaly.

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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 month's 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 simple t-statistics for monthly returns.

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)

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. $R5$ 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 turnover, $TO3$ 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 simple t-statistics for monthly returns.

		$K = 3$				$K = 6$				$K = 9$				$K = 12$			
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)

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. $R5$ represents the *winner* portfolio, $R1$ the *loser* portfolio. $TO1$ represents the portfolio with the lowest turnover, $TO3$ 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.

		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

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. The numbers in parentheses are simple t-statistics for monthly returns.

		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 on 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 simple t-statistics for monthly returns.

		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**

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 a 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 simple t-statistics for monthly returns.

		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)

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

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:

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

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
					(2.8)	(-4.27)	
				TO3	0.012	-0.036	0.062
					(3.08)	(-3.31)	

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 simple t-statistics for monthly returns.

		Portfolio	TO1	TO2	TO3	TO3-TO1
Panel A:	5×3	R1	0.37	0.13	0.10	-0.27
	(Benchmark)		(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	R1	1.39	3.40	5.15	3.76
	January-		(1.34)	(1.74)	(2.69)	(2.76)
	Returns	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	R1	0.28	-0.16	-0.36	-0.64
	February-		(0.78)	(-0.35)	(-0.64)	(-1.45)
	December-	R2	0.44	0.33	0.20	-0.24
	Returns		(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	R1	0.65	0.58	0.59	-0.07
	January-		(1.58)	(1.04)	(0.86)	(-0.13)
	September-	R2	0.65	0.69	0.62	-0.03
	Returns		(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	R1	-0.53	-1.24	-1.41	-0.88
	October-		(-1.10)	(-1.80)	(-1.65)	(-1.31)
	December-	R2	0.00	-0.23	-0.28	-0.28
	Returns		(-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)

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.