EXPLOITING COMMODITY MOMENTUM ALONG THE FUTURES CURVES

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ABSTRACT

This study examines novel momentum strategies in commodities futures markets that incorporate term-structure information. We show that momentum strategies that invest in contracts on the futures curve with the largest expected roll-yield or the strongest momentum earn significantly higher risk-adjusted returns than a traditional momentum strategy, which only invests in the nearest contracts. Moreover, when incorporating conservative transaction costs we observe that our low-turnover momentum strategy more than doubles the net return compared to a traditional momentum strategy.

JEL Classification: G11, G13, G14

Keywords: commodity futures, momentum, term structure, futures curve, roll yield, backwardation, contango, transaction costs

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1. INTRODUCTION

Several studies document a cross-sectional momentum effect in commodity futures markets. Erb and Harvey (2006) report a return of more than 10% per annum on a portfolio that longs commodity futures with the highest prior 12-month returns and shorts the worst-performing commodity futures. Miffre and Rallis (2007) extend this strategy for different ranking and holding periods up to 12 months and find profitable results for almost all definitions. Shen, Szakmary and Sharma (2007) also report highly significant positive returns for holding periods up to nine months. In addition, Pirrong (2005) and Asness, Moskowitz and Pedersen (2013) investigate momentum in multiple asset classes including commodities. What these commodity studies have in common is that only the nearest futures contracts are used for both the construction and implementation of momentum signals. Often futures contracts of various maturities are available for a given commodity. By considering only the nearest futures contract, the majority of investable deferred futures is not considered. This collection of futures could potentially offer additional information and investment opportunities.[1] We propose alternative cross-sectional momentum strategies utilizing information further along the futures curve. We demonstrate that these strategies perform significantly better than a traditional momentum strategy.[2]

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[1] Various theories exist that try to explain the shape of the commodities futures curve. The oldest is the Normal Backwardation theory of Keynes (1930). Cootner (1960, 1967) generalizes the Normal Backwardation theory into the Generalized Hedging Pressure theory, while Kaldor (1939) and Working (1948, 1949) introduce an alternative explanation named the Theory of Storage.

[2] A related stream of literature investigates so-called time-series as opposed to cross-sectional momentum strategies, see e.g. Szakmary, Shen and Sharma (2010), Moskowitz, Ooi and Pedersen (2012) and Baltas and Kosowski (2013). The main difference is that these time-series strategies construct commodity portfolios with possibly more long than short positions or vice versa, which implies that part of the strategy consists of commodity market timing. In our research, we focus on the cross-sectional ‘pure’ momentum strategies without any market timing.

We identify four reasons why the futures curve potentially offers valuable information when exploiting a momentum strategy: contracts further along the curve could (i) exhibit more attractive roll yields, (ii) exhibit lower volatility, (iii) expand the opportunity set of our investable universe and (iv) lower the turnover of the portfolios. We will elaborate on these possible advantages in more detail. First, the excess returns of commodity futures can be decomposed in spot and roll returns, where roll return is defined as the yield that an investor captures when the futures price converges to the spot price as the futures contract comes closer to expiration, assuming that the spot price does not change.[3] The standard approach of investing in the nearest contracts might not be optimal in capturing roll returns. Commodity index providers have noticed the possible adverse effects of roll returns because long-only investments suffer from negative roll returns when the futures curve is upward sloping, i.e. is in contango. Miffre (2012) shows that long-only indices developed to minimize the exposure of negative roll returns have performed better than traditional long-only indices which are rolled based on the nearest contracts. Mouakhar and Roberge (2010) investigate the added value of maximizing the roll yield of long-only investments compared to simply buying the nearest contract in each of ten individual commodity futures. They find that buying the futures contract with the largest expected roll yield, as measured by the lowest price slope between two consecutive maturities, adds a return of on average 4.8% per year on top of buying the nearest futures contract. So far, this strand of literature has focussed

[3] This is under the assumption that the shape of the futures curve does not change. Note that it is difficult to ex-post decompose excess returns into spot and roll returns since both the “level” and the shape of the curve might have changed.

on enhancing traditional (long-only) indices and on stand-alone roll-yield strategies. However, it is not clear whether there is also added value to achieve on top of active momentum strategies.

Second, besides the possibility of finding more attractive roll yields, Samuelson (1965) argues that the volatility of futures returns decreases when the maturity of contracts increases. An economic argument is that most supply and demand shocks occur at the front-end of the curve. Hence the prices of these front contracts react most heavily to news, while prices further along the curve are influenced less as there is more time to overcome the shocks. Daal, Farhat, and Wei (2006) investigate this maturity effect empirically using an extensive futures dataset. They find that the effect tends to be stronger in agricultural and energy commodities than in financial futures. A possible implication of this maturity effect is that the volatility of a momentum strategy could be reduced by investing in futures with a longer maturity.

Third, even for the same commodity, contracts with different maturities exhibit large differences in returns and risks. For example in our data we find for lean hogs an average annualized return of -6.2% for the first contract, compared to 4.8% for the fifth contract. For WTI crude oil, we see an average annualized volatility of 33.2% for the front contract, compared to 22.2% for the tenth contract. These findings illustrate that non-front contracts behave differently from front contracts and essentially represent different investment opportunities. Therefore just like including more commodities into the universe, including non-front contracts further down the futures curves is expected to expand the opportunity set of our investable universe, which could potentially lead to more refined choices of contracts and better investment results.

And fourth, an interesting feature of buying contracts further along the curve is that these can potentially be kept longer in the portfolio. Contracts bought at the front-part of the curve soon need to be traded to avoid delivery, even though the commodity is still found to be attractive. On the other hand, as the trading volumes of contracts further on the curve are lower on average, the costs for trading a contract at the back-end of the curve could potentially be higher.

To exploit these four possible benefits, we propose three alternative momentum strategies in which we integrate term-structure information when generating and implementing momentum signals. All three strategies aim to reduce volatility by trading further on the curve and furthermore specifically aim to capture one or more of the above mentioned possible advantages. As a benchmark we take a cross-sectional generic momentum strategy that each month longs the commodities with the highest past 12-month returns (winner commodities) and shorts those with the lowest past 12-month returns (loser commodities).

The first alternative strategy that we propose aims to take advantage of the first benefit by maximizing the roll yield. More precisely, for the winner commodities we buy the most backwardated contract on the futures curve and for the loser commodities we sell the most contangoed contract, where we only include futures contracts that expire within 12 months. We show that implementing this roll-yield strategy on top of a traditional long-short momentum strategy generates significantly higher risk-adjusted returns, as the Sharpe ratio increases by more than 30% to 0.96 compared to 0.73 for the traditional front-contract momentum strategy. The improvement is both due to lower risk and higher returns.

The second strategy that we propose expands the traditional cross-sectional momentum strategy with curve momentum information. For each commodity, we first select the contract on the curve with the strongest and weakest momentum. We then cross-sectionally rank the commodities according to the selected contracts and long (short) the contracts with the highest (lowest) momentum. Besides enlarging our investment opportunity set, we implicitly take roll information into account as, even when a parallel shift in the term structure occurs, differences in roll return can cause differences in momentum returns along the curve.[4] We find that incorporating curve momentum leads to significantly higher returns (Sharpe ratios) compared to a traditional momentum strategy, namely 14.48% (0.97) versus 11.43% (0.73).

Our third strategy aims for higher roll returns and a much lower turnover compared to a traditional momentum strategy. We examine a strategy that remains invested in a particular contract even though it might not have the most optimal roll yield anymore. Only when the contract is about to expire or when the commodity switches from the long to the short portfolio (or vice versa) we again determine the most optimal contract. We observe that applying this strategy

[4] Momentum returns are based on excess futures returns, which are a combination of changes in the spot price and the roll yield.

leads to a reduction in turnover of more than 50% compared to a traditional momentum strategy.

To ensure that the excess returns are not absorbed by transaction costs, we examine the added value that is created when the momentum strategies are actually implemented. Although transaction costs in futures markets are considerably lower compared to stocks, the turnover of momentum strategies is relatively high, which means that the impact of costs could still be substantial. Therefore, we incorporate two different trading cost schemes based on estimates of Szakmary, Shen and Sharma (2010). Additionally, we contribute to the literature on commodity trading costs by proposing a third transaction cost scheme that links transaction costs to liquidity.[5] This ensures that transaction costs are higher for less liquid contracts, a component not covered by existing transaction cost schemes. We find that for all alternative momentum strategies and under all assumptions for transaction costs, alternative momentum strategies deliver higher returns and Sharpe ratios than for the generic momentum strategy. For example, using conservative trading cost estimates of approximately 22 basis points per trade, we observe that net returns increase from an insignificant 3.98% per annum for a traditional momentum strategy up to an economically and statistically significant 8.42% annual return for our alternative momentum strategies.

We next investigate if the stronger returns of the alternative momentum strategies can be attributed to implicitly loading on the commodity market factor or on the carry strategy. The carry strategy takes long positions in the most

[5] We thank an anonymous referee for this useful suggestion.

backwardated (or least contangoed) commodities and short positions in the most contangoed (or least backwardated) commodities, see e.g. Erb and Harvey (2006) and Gorton and Rouwenhorst (2006). To examine this we regress the returns of the alternative momentum strategies on possible explanatory factor returns. We find economically and statistically significant alphas and therefore it is unlikely that our results are driven by implicit loadings on the market of carry factor. Fuertes, Miffre and Rallis (2010) examine a double-sorted strategy of momentum and carry and find that buying the backwardated winners and shorting the contangoed losers outperforms a single momentum or carry strategy. Our results differ from this study as our alternative momentum strategies have added value beyond the momentum and carry factors. To further strengthen the finding that our approach adds value on top of well-known factors, we show that our proposed alternatives can also be profitably applied on top of such a double-sort strategy.

Finally, we analyse whether the additional profits of the momentum strategies that incorporate term-structure information are a compensation for lower liquidity. Besides imposing liquidity-dependent trading costs, we therefore perform a series of analyses to investigate this hypothesis in more detail. First, we examine whether the additional profits are due to investing in the back-end of the curve, where liquidity might be lowest. More specifically, we reduce the maximum maturity of futures contracts from 12 to 6 months and conclude that the additional profits are not driven by investing in futures contracts at the back-end of the curve. Second, we examine the impact of liquidity on our results more directly, by evaluating the momentum strategies when excluding the least liquid futures contracts from our universe. By using two types of liquidity measures, namely dollar trading volume and the Amihud (2002) illiquidity measure, we observe that the additional profits remain large and significant. Third, if we use a one-day implementation lag to ensure there is enough time to implement the trades, both gross and net performances remain similar. And fourth, we conclude that integrating term-structure information in momentum strategies also has substantial added value from 2000 onwards, when more investors participated in commodity markets and overall liquidity was the largest. Hence, we conclude that it is unlikely that the additional profits are a compensation for lower liquidity.

The remainder of this article is organized as follows. We start in Section 2 by describing the data and analysing the futures' risk and return characteristics. We describe the four momentum strategies and the methodology to estimate transaction costs in Section 3. In Section 4 we present our main results and the portfolio return regressions. In Section 5 we show the results of several liquidity analyses. Section 6 presents our conclusion.

2. DATA

Our investment universe consists of the constituents of the Standard & Poor's Goldman Sachs Commodity Index (S&P GSCI) over the period January 1990 to September 2011.[6] We start with 18 commodity series at the beginning of our sample; all 24 series are available from July 1997. The sample includes six energy commodities (Brent crude oil, West Texas Intermediate crude oil, gasoil,

[6] Before 1990 the number of futures contracts diminishes quite rapidly.

heating oil, natural gas and RBOB gasoline); seven metals (gold, silver, aluminium, copper, lead, nickel and zinc); four softs (cocoa, coffee, cotton, and sugar); four grains (corn, soybeans, Chicago wheat and Kansas City wheat); and three meat commodities (feeder cattle, lean hogs and live cattle). We follow the S&P GSCI methodology and use data from the futures' primary exchange, as the futures contracts of some of these commodities trade on multiple exchanges.[7] Furthermore, we only examine the individual futures contracts included in the S&P GSCI.[8] The number of distinct contracts a year varies per commodity; e.g. all the energy and industrial metal commodities have 12 distinct contracts a year, while cotton and sugar only have four distinct contracts. In addition to the above selection criteria we follow Mouakhar and Roberge (2010) and only include futures contracts in our analyses that expire within 12 months. For all individual contracts we collect futures prices from Bloomberg. Consistent with a large body of commodity research, such as Bessembinder (1992), Erb and Harvey (2006) and Miffre and Rallis (2007), we assume that the investment is made on a fully-collateralized basis.[9] In this case, the total monthly return of the investor is the

[7] The Brent crude oil, gasoil, cocoa, coffee, cotton, and sugar data are from the Intercontinental Exchange (ICE); the West Texas Intermediate crude oil, heating oil, natural gas, and RBOB gasoline data are from the New York Mercantile Exchange (NYMEX); the gold and silver data are from the Commodity Exchange, Inc. (COMEX); the aluminum, copper, lead, nickel, and zinc data are from the London Metals Exchange (LME); the corn, soybeans, and Chicago wheat data are from the Chicago Board of Trade (CBOT); the Kansas wheat data are from the Kansas Board of Trade (KBT); and the feeder cattle, lean hogs, and live cattle data are from the Chicago Mercantile Exchange (CME).

[8] See Table 1 in the 2013 S&P GSCI Methodology for the selected 2013 futures contracts (http://www.spindices.com/documents/methodologies/methodology-sp-gsci.pdf).

[9] The advantage of assuming a fully-cash-collateralized investment is threefold. First, the investment process is largely simplified as there will be no leveraged positions which require extra deposit in or withdrawal from the margin account from time to time. Second, the calculation of the real-world return is fairly straight-forward, and no longer depends on the assumption of the initial margin. Third, the investment results are then presented in the most conservative manner,

change in month-end settlement prices plus the risk-free interest rate (e.g. the U.S. T-bill rate) earned from the deposit account. In our study, we focus on the changes in settlement prices, which we refer to as excess returns similar to Gorton, Hayashi, and Rouwenhorst (2013).

Table 1 reports the annualized excess returns, volatilities, average dollar trading volumes and the Amihud illiquidity measure of all commodity futures over our sample period. When we consider Panel A, we observe a large dispersion in average returns across commodities. For example, for the nearest contracts we find the lowest average return of -16.2% per annum for natural gas and the highest return of 11.8% per annum for gasoline. This indicates the potential benefits of correctly predicting which commodities to invest in. Moreover, we also find large return differences along the futures curve, although these are somewhat smaller on average. For example, for lean hogs we observe an annualized return of -6.2% for the first contract and 4.8% for the fifth contract. These return differences support our idea of enhancing a traditional momentum strategy by selecting the optimal contract on the curve. From these numbers we can also conclude that contracts along the same futures curve are not perfectly correlated with each other. Therefore, the inclusion of non-front contracts into the investable universe is likely to expand the opportunity set of the strategies and lead to better results.

[INSERT TABLE 1 ABOUT HERE]

as strategy performances based on leverage are typically inflated compared to the base case which is fully-cash-collateralized.

Besides return differences we observe large differences in volatilities from Panel B of Table 1. For WTI crude oil, we see an annualized volatility of 33.2% for the front contract, compared to 22.2% for the tenth contract. In line with Samuelson (1965) we find that in almost all cases, volatility decreases when the time to maturity increases. Hence, strategies that trade in more distant contracts could potentially exhibit a lower volatility.

In Panel C we present average trading volume in million dollars, computed by multiplying the number of contracts traded by the contract size, and then multiplying this by the price in dollars.[10] We observe large differences in this liquidity measure among commodities. For example, the trading volume of crude oil is much higher than of lead. In addition we also observe large differences along the curve, as e.g. the first contract of Brent oil has an average trading volume of 1,506 million dollar, while that of the ninth contract is 65 million dollar. That more distant futures are less often traded than nearby contracts confirms that most investors use nearby contracts to take positions.

To give more insight in liquidity differences across different contracts, we also compute the Amihud (2002) illiquidity measure, which measures the price impact of a trade. It is computed as the monthly average of daily absolute return divided by dollar trading volume. We multiply the measure with one million, so that Panel D shows the return impact in basis points of a one million dollar trade. The results in Panel D are in line with the trading volume results. In general, the

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[10] The data for the number of contracts traded are from Bloomberg. For industrial metals these data are available from around 2005. We therefore approximate dollar volume by deflating the volume in January 2005 back in time by 9.8% per annum, which is the average annual change in dollar volume of the available commodity futures contracts from 1990 to 2004.

Amihud measure increases further along the curve, i.e. a one million dollar trade has a larger impact on more distant futures prices and hence those contracts are less liquid. Across commodities there are also large differences, e.g. a one million dollar trade in the first WTI crude oil contract impacts prices by 0.6 basis points on average, while a trade of the same size in the first cocoa contract influences prices by 56.7 basis points.

Overall, the variation of average returns and volatilities along each commodity futures' curve indicate the potential added value of integrating term-structure information into a generic momentum strategy. However, liquidity measures indicate that more distant contracts are less often traded, so there will be a trade off between the improvement in performance and the increase in trading costs.

3. METHODOLOGY

3.1. Constructing momentum strategies

To investigate commodity momentum strategies that integrate term-structure information, we construct four different types of momentum portfolios. The first portfolio is a "generic momentum" strategy that represents the traditional momentum strategy documented by Erb and Harvey (2006). Each month-end, we rank all commodities cross-sectionally according to the past 12-month returns of their nearest contracts. This portfolio takes long (short) positions in the 50% of commodities with the highest (lowest) returns, using equal weights.[11] We then compute the return of this portfolio in the following month.

Our first alternative strategy is an "optimal-roll momentum" portfolio, where we aim to maximize the roll yield. Compared to the generic momentum strategy, we select the same commodities for the long and short portfolios. However, this portfolio does not necessarily invest only in the front contracts as is the case for the generic strategy. Instead, for the 50% of commodities with the most attractive returns, we long the contract on the curve with the largest price slope (the most backwardated or least contangoed). The slope of contract i is defined as

$$(1) \qquad \frac{f_t^{i-1} - f_t^i}{f_t^i(\tau_i - \tau_{i-1})},$$

where f_t^i is the futures price of contract i at time t with time to maturity τ_i and f_t^{i-1} is the futures price of the adjacent contract with time to maturity τ_{i-1}.[12] For the 50% of commodities with the least attractive returns, we short the contract on the curve with the smallest slope (the most contangoed or least backwardated).

The second alternative strategy is an "all-contracts momentum" portfolio, where we expand a traditional cross-sectional momentum strategy with curve momentum information. For this portfolio, each month we compute the 12-month

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[11] There seems to be little consistency in the literature on the construction of commodities portfolios. Both Erb and Harvey (2006) and Gorton and Rouwenhorst (2006) construct top and bottom 50% portfolios. Miffre and Rallis (2007) investigate the top/bottom 20%, while Shen, Szakmary and Sharma (2007) the top/bottom 33%. Unreported results show that the returns of more concentrated portfolios go up. However, we simultaneously observe that the volatility of these portfolios increase even more, which results in portfolios with lower Sharpe ratios. The number of assets in commodity portfolios becomes very small once we move to the top and bottom 20%, as the commodity-specific risk of the portfolios increases.

[12] To compute the slope corresponding to an investable first contract we extrapolate the futures curve using a piecewise cubic interpolation method, see Fritsch and Carlson (1980). The advantage of this method is that it preserves the shape of the data and respects monotonicity. This method ensures we can also invest in the most nearby contract.

return of all contracts along the curve for all commodities.[13] We then select for each commodity the contract with the highest 12-month return and flag it as a candidate for the long portfolio. Likewise, we also select for each commodity the contract with the lowest 12-month return and label it as a short candidate. After repeating this selection process for all commodities, we next rank all contracts indicated as candidates for the long portfolio and long the 50% of commodities with the highest momentum. Similarly, we rank all short candidates and short the 50% of commodities with the lowest momentum. What is different from the generic and optimal-roll strategies is that this portfolio might take both long and short positions in different contracts of the same commodity, a situation which might occur when there is a large dispersion in the momentum values of the contracts for a particular commodity.

As portfolio turnover, and therefore trading costs, is relatively high for typical momentum strategies, we in addition examine a third alternative momentum strategy, using a "low-turnover roll momentum" portfolio. With this portfolio we still aim for a higher return due to better roll positions, but with a much lower turnover compared to the other momentum strategies. Contracts bought on the front-end of the curve regularly need to be traded, as these contracts are the closest to expiration. Even if according to the strategy a commodity remains in the portfolio, the position in its nearest contract still needs to be replaced (i.e. rolled forward) after a short period of time. An advantage of buying contracts further along the curve is that these could be kept in the

[13] In line with generic momentum, the 12-month return of the xth contract is based on the past returns of the xth nearby contract.

portfolio for much longer. Compared to the optimal-roll momentum strategy where each month we determine the contracts with the most optimal slope, we now remain invested in the same contract unless it is about to expire, or the commodity changes from the long to the short portfolio (or vice versa) based on its front-contract momentum. In that case, we take a new position in the contract with the most optimal slope. This way, we will not always have positions in the most optimal contracts and therefore expect a lower gross return of this strategy compared to the standard optimal-roll momentum strategy. However, due to a lower turnover, the expected trading costs are also lower. The impact on net return is therefore a trade-off between the expected reduction in gross return and the lower trading costs.[14]

3.2. Incorporating transaction costs

Although transaction costs involved with commodity futures are relatively low [see e.g. Locke and Venkatesh (1997)] and taking short positions is not more complex than taking long positions, momentum strategies typically exhibit high turnover. We therefore also evaluate the returns of the momentum strategies when incorporating realistic trading costs. We use three different transaction cost schemes: two are based on Szakmary, Shen and Sharma (2010) which are labelled as standard and conservative, while we propose a third novel scheme that incorporates trading cost variation along the futures curve based on liquidity differences. .

[14] Due to the construction of the all-contracts momentum strategy there is no low-turnover parallel for this strategy, as the contracts with the most extreme momentum are selected before, instead of after, the cross-sectional comparison is made.

The standard transaction costs scheme consists of a fixed brokerage commission of USD 10 per contract and a bid-ask spread of one tick. Szakmary, Shen and Sharma estimate transaction costs (TC) as a percentage of the notional contract value in month t:

(2) $TC_t = [10 + (\text{Tick size} \times CM)] / (\text{Price}_t \times CM)$,

where the tick size is measured in dollars, CM is the contract multiplier (i.e. the number of units of the underlying commodity deliverable per contract) and Price_t is the price of the contract in dollars at the end of month t.[15] For conservative transaction costs, which might reflect the actual costs of large-scale trading activity, the brokerage commission is assumed to be USD 20 per contract and the bid-ask spread three ticks instead of one:

(3) $TC_t = [20 + (3 \times \text{Tick size} \times CM)] / (\text{Price}_t \times CM)$.

Compared to the standard cost estimates, the conservative estimates assume a market impact that is three times higher for trades in the same commodity futures contract, which is in line with the findings of Marshall, Nguyen and Visaltanachoti (2012). They conclude that a more aggressive trader who requires immediate liquidity exhibits costs on average three times higher compared to a more patient trader who splits the futures trades over one hour. The standard and conservative trading cost estimates could therefore also be interpreted as the costs associated with patient and more aggressive trading styles respectively.

Front contracts are in general more liquid, which could potentially lead to lower trading costs than contracts on the back end of the curve. Unfortunately

[15] The tick size defines the minimum price movement of a futures contract. It varies across different commodities and is specified in the contract specifications of each futures contract. We retrieved all tick size and contract multiplier data from the futures' exchange websites.

there is little information available on the relationship between trading costs and the time to maturity, as the academic literature in this area is scarce. To bridge this gap, we propose a third methodology, where we assume a linear relation between the Amihud illiquidity measure and transaction costs. Each month we assume for each commodity that the most liquid contract (i.e. with the lowest Amihud estimate) trades against the standard transaction costs while the least liquid contract with the highest Amihud estimate trades against the conservative costs. This implies that we assume that trading illiquid contracts is around three times more expensive. For the intermediate contracts we assume that the costs increase proportionally to the increase in the Amihud illiquidity measure. The implication of this trading costs scheme is that trading in contracts further on the curve involves higher trading costs.

We condition trading costs on the Amihud illiquidity measure because of two reasons. First, Marshall, Nguyen and Visaltanachoti (2012) find that the Amihud illiquidity measure has the largest correlation with high-frequency liquidity benchmarks. Second, besides a negative relation between trading volume and transaction costs, there is in general also a positive relation between volatility and transaction costs.[16] This implies that on the one hand estimated trading costs for more distant futures are higher due to their lower trading volumes, while on the other hand lower due to their lower volatility. Therefore, the Amihud

[16] In equities the positive relation between volatility and transaction costs is well established. For example. Chordia, Roll and Subrahmanyam (2001) note “it is well known that individual stock volatility is cross-sectionally associated with higher [bid-ask] spreads (Benston and Hagerman (1974)”. In commodities this relation between volatility and transaction costs is documented by Marshall, Nguyen and Visaltanachoti (2012). They only investigate front contracts and establish this relation based on time variation of volatility and transaction costs over time, and not along the futures curve.

illiquidity measure is highly appropriate as it incorporates both volatility, in the form of absolute returns, and trading volume.

4. MAIN RESULTS

4.1. Profitability of momentum strategies including term-structure information

In our first empirical analysis we evaluate the momentum profits of the generic momentum strategy and the strategies incorporating term-structure information. Panel A of Table 2 reports the average annualized gross returns and associated t-statistics, the volatilities and the Sharpe ratios of the generic momentum strategy and the three alternative momentum strategies. Furthermore, for all alternative strategies we show the Ledoit and Wolf (2008) test statistic, which evaluates whether the Sharpe ratios of the alternative strategies are significantly different from that of the generic momentum strategy. In this test we take into account the possibility that strategy returns can be non-normal and auto-correlated. As the distribution of this statistic is non-standard, the reported P-values are based on bootstrap resamples. In addition, the table also contains the maximum drawdown, the average maturity of the contracts deployed by each strategy and the average single-counted and one-sided annual turnover. This means that an annual turnover of 100% indicates that the long and short portfolio is completely changed once a year.

[INSERT TABLE 2 ABOUT HERE]

Consistent with Erb and Harvey (2006) and Miffre and Rallis (2007), we find large and significant profits for the generic momentum strategy. More specifically, the strategy earns a gross annual return of 11.43% and a gross Sharpe ratio of 0.73. Although the results are strong, we observe even higher risk-adjusted returns for our alternative momentum strategies. The Sharpe ratios of the alternative strategies range between 0.88 for low-turnover roll momentum and 0.97 for all-contracts momentum, due to higher returns and lower volatilities. These lower portfolio volatilities are in line with Samuelson (1965), as the average maturities of the contracts range between 3.85 months for the all-contracts strategy and 5.01 months for the optimal-roll strategy, all above the average maturity of 1.50 months for the generic strategy. Note that the average maturities are well below 12 months, which is the maximum maturity of the contracts we invest in. This indicates that the strategies on average invest more in contracts on the front part of the curve, where liquidity is likely to be highest. The Sharpe ratios of the alternative momentum strategies are significantly different from the generic strategy as the P-values are lower than 0.05. Moreover, the maximum drawdowns of the alternative strategies are all smaller than that of the generic strategy.

In addition, we observe that the low-turnover roll momentum strategy lives up to its name as it exhibits a turnover that is approximately 50% lower than the other strategies. The turnover of 855% per annum for the generic strategy implies that a portfolio manager needs to completely change the portfolio every 1.4 months on average. The implications on net returns can be observed in Panel B, C, and D of Table 2, assuming respectively the Szakmary, Shen and Sharma (2010) standard trading cost estimates, our Amihud-dependent estimates and the conservative cost estimates. The table also presents the average single-trip costs of the transactions in basis points. We observe that trading costs have a significant impact on the return of momentum strategies. As the average trading costs using the standard cost estimates are around 8 basis points per trade, we observe a deterioration in return of around 3% for the high-turnover momentum strategies. Note that this average cost is substantially higher than the often used 3.3 basis points as reported in Locke and Venkatesh (1997) and used by among others Fuertes, Miffre and Rallis (2010). The net Sharpe ratios of the optimal-roll and all-contracts momentum strategies of 0.75 and 0.76 respectively remain significantly higher than the net Sharpe ratio of 0.54 for the generic strategy. The impact of trading costs on the low-turnover roll strategy is much lower, resulting in only a 1.55% lower return. The net return and Sharpe ratio of this strategy are now higher than those of the optimal-roll momentum strategy.

Panel C reports the net results when assuming Amihud-dependent transaction costs. In line with our expectations we observe higher average costs for our alternative momentum strategies, which on average trade further on the curve. The costs for the generic momentum strategy are around 8 basis points, while those of the alternative strategies range between 10.67 and 12.26 basis points. Nevertheless, also using this trading costs scheme, we observe higher net returns and Sharpe ratios and less negative maximum drawdowns for all our alternative momentum strategies.

The contrast in net returns among the different strategies becomes even larger once the conservative cost estimates are taken into account, which might better reflect the actual costs in the case of large-scale trading activity or a more aggressive trading style. In Panel D we find that the average cost estimates are now about 22 basis points per trade. The return of the generic strategy drops by 65%, leading to an insignificant 3.98% annualized return. Obviously, the impact on return is also large for the two alternative high-turnover momentum strategies. However, we still observe economically and statistically significant returns of 5.94% and 6.52% respectively for the optimal-roll and all-contracts momentum strategies, with Sharpe ratios of 0.43. Interestingly, when assuming these relatively high trading costs we observe the highest net returns (8.42%) and Sharpe ratio (0.60) for the low-turnover roll momentum strategy.

We conclude that incorporating term-structure information in momentum strategies leads to significantly higher Sharpe ratios. When facing relatively high trading costs, it might be important to smartly reduce portfolio turnover to preserve the majority of returns.

Finally, we analyse the returns of the different momentum strategies over time. Figure 1A shows the cumulative returns when incorporating conservative transaction costs of the four momentum strategies over our sample period. We observe that the generic momentum strategy obtains the lowest returns, while the highest returns are generated by our low-turnover roll momentum strategy. We also observe a gradual increase of the difference in returns, so that the added value of the strategies is not generated in one particular sub-sample period. Figure 1B presents 5-year rolling Sharpe ratios of all momentum strategies. We observe that during most 5-year sub-periods, the alternative momentum strategies obtain higher Sharpe ratios than the generic momentum strategy. This confirms our previous finding that our results are not obtained during one particular sub-period in our sample.

[INSERT FIGURE 1A AND 1B ABOUT HERE]

4.2. Portfolio return regressions

We continue our empirical analysis by investigating to what extent the profits of the momentum strategies that integrate term-structure information can be attributed to exposures to well-known commodity factor premiums. In particular we focus on the commodity market factor and the carry strategy. The carry strategy is based on term-structure information and takes long positions in the most backwardated commodities and short positions in the most contangoed commodities, see e.g. Erb and Harvey (2006) and Gorton and Rouwenhorst (2006). We regress the gross and net returns of the momentum strategies on a market and carry factor:

(4) $R_{i,t} = \alpha + \beta_1 Market_t + \beta_2 Carry_t + \varepsilon_{i,t}$,

where $R_{i,t}$ is the return of momentum strategy i in month t. $Market_t$ is the excess return of the commodity market index as proxied by the S&P GSCI in month t. $Carry_t$ is the return of a carry strategy in month t defined as an equally-weighted portfolio that longs (shorts) the 50% of commodities with the highest (lowest) annualized ratio of the nearest futures price to the next-nearest futures price. The coefficients α, β_1 and β_2 are to be estimated, and $\varepsilon_{i,t}$ is the residual return of strategy i in month t. In addition, we perform regression analyses where we add the generic momentum factor to analyse the added value of the alternative momentum strategies on top of the traditional momentum strategy. All coefficient estimates, associated t-statistics and R–squared values are presented in Table 3.

[INSERT TABLE 3 ABOUT HERE]

Panel A reports the results for the gross returns. For the generic momentum strategy we observe a large and significant exposure to the carry factor and also a significant exposure to the market factor. This leads to an annualized alpha of 5.17% with a t-statistics of 1.80 for the generic strategy compared to the 11.43% "raw" return in Table 2. The high coefficient of the carry factor is consistent with Gorton, Hayashi and Rouwenhorst (2013) who argue that momentum portfolios take positions in similar commodities to the carry-sorted portfolios. We notice that the (untabulated) correlation between the returns of the carry and generic momentum strategy of 0.56 over our sample period is in line with these findings. When we consider the regressions in the left part of the panel, we observe similar exposures to the market and carry factors for the alternative momentum strategies. The alphas of all momentum strategies with integrated term-structure information remain significant and are all larger than the alpha of generic momentum, ranging from 6.40% for the low-turnover roll momentum strategy to 8.29% for the all-contracts momentum strategy.

We next consider the regressions including the generic momentum factor in the right part of Panel A. For the alternative momentum strategies, we observe small and insignificant coefficient estimates for the market factor. Not surprisingly, we find large positive coefficient estimates for the momentum factor, which also explains the high explanatory power of the regressions with R-squared values above 90%. Due to the positive correlation between the carry and generic momentum factors, we now find much smaller coefficient estimates for the carry factor. Interestingly, the alphas remain significantly different from zero, ranging from 2.04% for the low-turnover roll momentum strategy to 3.61% for the all-contracts momentum strategy.

We next consider the results when regressing net returns using standard, Amihud-dependent and conservative trading cost estimates in respectively Panel B, C and D of Table 3. We evaluate these returns also against the net returns of the carry and momentum factors. The alphas of the optimal-roll and all-contracts momentum strategies become lower, but remain in almost all cases significant and larger than the insignificant net alphas of the generic strategy. On the contrary, the low-turnover roll momentum strategy earns for two out of three applied trading cost schemes a higher alpha. This results in an alpha of 7.04% when incorporating conservative trading costs and regressed against the market and carry factors, which is much larger than the 2.85% alpha of the generic momentum strategy.

We conclude that the returns of the alternative momentum strategies are not driven by exposures to well-known commodity factors.[17] Finally, untabulated results further indicate that the optimal-roll and all-contracts momentum strategies are different types of strategies as their alphas have only a modestly positive correlation of 0.35.

4.3. Double-sort on momentum and carry

In this section we use an alternative method to examine the added value of our alternative strategies on top of momentum and carry strategies. Fuertes, Miffre and Rallis (2010) show that double-sort strategies on both momentum and carry lead to superior results compared to a generic momentum strategy. We therefore apply our alternative strategies of integrating term-structure information on top of these double-sorts.

Our starting point is a generic double-sort strategy where we first sort 50% of the commodities into a winner and 50% in a loser portfolio, based on their past 12-month momentum. Next, we sort 50% of the commodities within this winner portfolio in a high- and 50% in a low-carry portfolio, where carry is defined as the front-contract slope in Formula 1. Also for the loser portfolio we apply this sort on carry. We then take equally-weighted long positions in the winner/high-carry commodities and short positions in the loser/low-carry commodities. This set-up

[17] In addition, we also investigate to what extent the profits of the cross-sectional momentum strategies can be attributed to exposures to the time-series momentum factor of Moskowitz, Ooi and Pedersen (2012) and the Fung and Hsieh (2004) seven factor model. We conclude that the additional returns of the alternative momentum strategies cannot be explained by loading on the time-series momentum factor or on Fung and Hsieh's factors. All results are available on request.

is comparable to the double-sort investigated by Fuertes, Miffre and Rallis (2010).[18]

The alternative strategies we propose are constructed in a similar fashion as described in Section 3.1. The optimal-roll double-sort is based on the same commodities as the generic double-sort, however does not necessarily invest only in front contracts. The long positions in the winner/high-carry portfolio are taken in the most backwardated contracts along the curve, while the short positions in the loser/low-carry portfolio are invested in the most contangoed contracts along the curve. The all-contracts strategy sorts on optimal 12-month momentum candidates instead of front contract momentum values, where optimal momentum candidates are determined in the same way as before for our single-sort momentum portfolios. The 50% highest (lowest) momentum candidates end up in the winner (loser) portfolio and within this winner (loser) portfolio we select the 50% commodities with the highest (lowest) carry. The strategy then longs winner/high-carry commodities and shorts loser/low-carry commodities. Our low-turnover roll alternative is a reduced turnover version of the first alternative strategy, similar to the single-sort version. The results of the double-sort strategies are presented in Table 4. As the number of commodities in the double-sort portfolios is smaller, namely six in the top and six in the bottom instead of two times twelve, we also construct a generic single-sort momentum strategy based on quartiles portfolios as a comparison. We long the 25% most attractive commodities and short the 25% least attractive commodities. The

[18] The number of commodities in the long and short portfolio (six from 1998 onwards) is similar to Fuertes, Miffre and Rallis (2010), who construct two momentum and three carry portfolios, but have more commodities in their universe.

(untabulated) annualized returns of this strategy are 13.02% with a volatility of 24.88%. Compared to the generic portfolio in Table 2 we observe that a more concentrated portfolio generates a higher return, but also exhibits higher risk, which results in a lower Sharpe ratio (0.52 versus 0.73).

[INSERT TABLE 4 ABOUT HERE]

We confirm the findings of Fuertes, Miffre and Rallis (2010) as the generic double-sort achieves a higher return (16.09%) and a lower volatility (21.35%) than the generic momentum strategy with similar number of commodities. When we compare our three alternative strategies with the generic double-sort in Panel A of Table 4 we observe that all Sharpe ratios are higher, both due to higher returns and lower volatilities. And also when we observe the net results in Panel B to D, we observe that in all cases returns the Sharpe ratios for the alternative double-sort strategies are higher than the generic double-sort strategies. These results again confirm that our alternative strategies add value beyond momentum and carry factors.

5. LIQUIDITY ANALYSES

This section presents the results of a series of analyses to investigate whether the additional profits of the alternative momentum strategies are a compensation for lower liquidity. In Subsection 5.1 we examine the sensitivity of our results by limiting our universe to futures contracts with a maximum maturity of six months. In Subsection 5.2 we analyse the impact of excluding the most illiquid contracts. We investigate the implication of a one-day trading lag in Subsection 5.3. Finally, in Subsection 5.4 we present the results after 2000.

5.1. Implementation with futures contracts up to six months maturity

We continue our empirical analyses by evaluating the alternative momentum strategies if we reduce the maximum maturity of futures contracts to invest in from 12 months to 6 months. All the other settings are exactly the same as with the main approach. Note that Table 2 indicates that the average maturities of the alternative momentum strategies are well below 12 months, as they range between 3.85 and 5.01 months. However, there could still be regular investments in the back-end of the curve. We perform this analysis to ensure that the additional profits of the momentum strategies that incorporate term-structure information are not due to investing in the back-end of the curve, where liquidity might be the lowest. The results are presented in Table 5.

[INSERT TABLE 5 ABOUT HERE]

When we consider the gross returns in Panel A we observe that all three alternative momentum strategies remain able to deliver significantly higher risk-adjusted returns compared to a generic momentum strategy. When compared to the results in Table 2 with a 12-month maturity bound, we find slightly higher returns for the optimal-roll and low-turnover roll momentum strategies and somewhat lower returns for the all-contracts momentum strategy. As the average maturity of the contracts reduces by 1.5 to 2 months, the portfolios' volatilities increase somewhat. This leads to slightly lower Sharpe ratios compared to the 12-month maturity-bound results.

We observe significant net returns for most of the alternative strategies. And even though the turnover of the low-turnover roll strategy increases from 402% to 528%, the strategy remains statistically significant when including conservative trading costs. Thus, we conclude that the additional profits are not driven by investing in futures contracts at the back-end of the curve.

5.2. Implementation on most liquid futures contracts

To more directly examine the impact of liquidity on our results, we next evaluate the momentum strategies when excluding the least liquid futures contracts from our universe. For this purpose we use two different types of liquidity measures, namely dollar trading volume and the Amihud illiquidity measure.

Each month in our sample period we exclude the most illiquid futures contracts according to a certain measure. This way we acknowledge that liquidity varies substantially across commodities, and that for less liquid commodities, more contracts will be excluded than for more liquid commodities. Assuming a USD 100 million long/short portfolio, we set the dollar volume trading threshold in such a way that we currently do not trade more than 25% of the trading volume of a particular contract. As the universe currently consists of 24 commodities, we have 12 long and short positions. The value of one trade is therefore USD 8.33 (=100/12) million, implying a dollar volume threshold of USD 33.33 (=8.33/0.25) million at the end of our sample period. We deflate this threshold back in time by 4.05%, which is the average annual total return of the S&P GSCI index during our sample period. As a result, we exclude almost 50% of the futures contracts from our universe. For the Amihud illiquidity measure, we set the threshold at 4 basis points at the end of our sample period, so that we also exclude about 50% of the most illiquid futures contracts from the universe. This threshold implies we exclude commodity futures contracts for which the price impact resulting from trading USD 1 million is more than 4 basis points. Similarly, the Amihud illiquidity threshold is inflated back in time by 4.05% per annum. The results of the four momentum strategies applied to the most liquid futures contracts based on dollar trading volume and the Amihud illiquidity measure are presented in Table 6 and 7 respectively. [19]

[INSERT TABLE 6 AND 7 ABOUT HERE]

In Panel A of Table 6, we observe that the screening on dollar trading volume has a marginal impact on the gross performance of the four strategies. In all cases, we even observe a slightly higher gross return compared to the results in Table 2. Volatility increases as well, in line with the shorter average maturity of the invested contracts, which leads to similar gross Sharpe ratios. Results are similar when we apply the screening based on the Amihud illiquidity measure, as presented in Panel A of Table 7. As the screenings have hardly any impact on turnover, we also observe that the alternative strategies remain profitable after taking transaction costs into account (Panel B, C and D of Table 6 and 7). Only

[19] Unreported analyses show that conclusions remain similar when different liquidity threshold values are used for both dollar trading volume and the Amihud illiquidity measure.

the turnover of the low-turnover roll momentum strategy increases from 402% per annum to 555% and 560% when we apply a screening on dollar trading volume and the Amihud illiquidity measure respectively. However, as the gross returns are also 1% to 2% higher for this strategy after applying a liquidity screening, the net returns and Sharpe ratios have a similar magnitude as the results in Table 2. In addition, we observe that all alternative momentum strategies significantly outperform the generic momentum strategy. We therefore conclude that the added value of incorporating term-structure information in momentum strategies is not due to investing in contracts with a low liquidity.

5.3. Results with a one-day implementation lag

We next examine the profitability of the momentum strategies assuming a one-day implementation lag. Although we use various trading costs estimates when evaluating the net returns of the strategies, it is still possible that their profitability is largely concentrated in the period just after rebalancing, and that the gross returns would decline significantly when there is a delay in trading. Marshall, Nguyen and Visaltanachoti (2012) claim that the commodity futures markets are resilient and that liquidity returns to pre-trade levels after 30-60 minutes. Therefore, we evaluate the profitability of the momentum strategies by assuming that investors have one full trading day to rebalance their portfolio and that by gradually implementing the new positions, the trade impact can largely be mitigated. More specifically, we construct the portfolios in a similar fashion as before, the difference being that we determine the long and short positions based on data up to the day before every month-end. The results are reported in Table 8.

[INSERT TABLE 8 ABOUT HERE]

When we consider the gross returns in Panel A, we observe only a slight reduction for most of the strategies compared to the returns without an implementation lag in Table 2. We therefore conclude that a one-day implementation has hardly any impact on our results.

5.4. Results since 2000

Due to the increased popularity of commodity investing since 2000, we conclude our empirical analyses by examining the momentum strategies from January 2000 to September 2011 when overall liquidity was highest. The results are presented in Table 9. When we consider Panel A we observe higher gross returns for all strategies in the most recent 11 years of our sample compared to the returns of the whole sample period in Table 2. Next to that, we observe higher volatilities in the most recent sample period, in line with increased market volatility. All in all, we observe a similar Sharpe ratio for the generic momentum strategy and higher Sharpe ratios for the alternative momentum strategies. For example, the Sharpe ratio of the low-turnover roll momentum strategy is 0.99 during the last 11 years of our sample, while the ratio is 0.88 over the whole sample period.

[INSERT TABLE 9 ABOUT HERE]

We observe in Panel B, C and D of Table 9 that due to lower average costs since 2000, the differences in net returns are even larger. For instance, when assuming conservative transaction costs, the optimal-roll momentum strategy is able to deliver a higher net return of around 3%. Also in the recent period, the alternative strategies obtain higher returns at lower risk compared to the generic momentum strategy. We therefore conclude that integrating term-structure information in momentum strategies also has added value since 2000, when more investors participated in commodity markets and overall liquidity was highest.

6. CONCLUDING REMARKS

This study examines novel momentum strategies in commodities futures markets that incorporate term-structure information. Previous studies only use the nearest futures contracts both for the construction and implementation of momentum signals. These strategies might therefore potentially miss out on valuable information regarding the futures curve, such as the possibility that contracts further along the curve could exhibit more attractive roll yields and lower volatility.

We show that alternative momentum strategies which integrate term-structure information by selecting contracts on the curve with the largest expected roll-yield or with the strongest momentum earn significantly higher risk-adjusted returns than a traditional momentum strategy, even when incorporating three different transaction costs schemes.

To lower transaction costs even further, we examine another alternative momentum strategy aiming for higher roll returns with a much lower turnover compared to the other momentum strategies. An advantage of buying contracts further along the curve is that these can potentially be kept in the portfolio much longer. We observe that applying such a strategy leads to a reduction of more than 50% in turnover and more than doubles the net return to 8.42% per annum compared to a traditional momentum strategy.

Our results are not due to exposure to the commodity market factor or the carry strategy. Also, liquidity seems unlikely to explain the results as even when accounting for liquidity differences through trading costs, reducing the maximum maturity of futures contracts from 12 to 6 months, investing in the most liquid futures contracts, allowing for a one-day implementation lag to reduce trade impact or focusing on the period since 2000, the results remain qualitatively the same.

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TABLE 1. Summary statistics.

This table presents the annualized excess returns (Panel A), volatilities (Panel B), average monthly dollar trading volumes (Panel C) and Amihud (2002) illiquidity measures (Panel D) of the 24 commodity futures from the nearest contract (i.e. first contract) up to the furthest contract with a maximum maturity of 12 months. The sample period is from January 1990 to September 2011. The trading volumes are computed as number of contracts traded multiplied by contract size multiplied by contract price and are expressed in million dollars. The Amihud illiquidity measure is computed as the monthly average of absolute daily return divided by the daily dollar trading volume.

		Xth nearest contract									
		1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Panel A: Return											
Energy	Brent oil	10.0%	11.4%	11.2%	10.6%	11.5%	11.4%	11.4%	14.6%	14.4%	-
	Crude oil	5.9%	8.6%	9.7%	10.0%	10.2%	10.4%	10.2%	10.0%	9.8%	9.5%
	Gasoil	8.1%	8.0%	7.7%	8.6%	9.2%	8.3%	8.6%	10.5%	9.8%	9.3%
	Heating oil	5.5%	6.7%	8.3%	9.1%	9.2%	9.3%	9.5%	9.5%	9.7%	9.8%
	Natural gas	-16.2%	-8.0%	-2.9%	-1.3%	-1.3%	-0.3%	0.1%	1.4%	3.8%	4.9%
	Gasoline	11.8%	11.7%	11.8%	12.1%	11.7%	11.7%	11.1%	9.3%	9.5%	9.6%
Metals	Gold	2.9%	2.9%	2.9%	2.8%	-	-	-	-	-	-
	Silver	4.2%	4.6%	4.8%	4.9%	-	-	-	-	-	-
	Aluminum	-2.5%	-0.2%	-0.4%	0.1%	0.6%	0.7%	0.9%	1.2%	1.5%	1.6%
	Copper	8.1%	10.4%	10.0%	10.5%	10.8%	11.0%	11.2%	11.3%	11.4%	11.5%
	Lead	8.2%	10.3%	9.7%	9.8%	9.8%	9.8%	9.6%	10.2%	10.4%	12.3%
	Nickel	7.9%	10.4%	10.2%	10.9%	11.3%	11.4%	11.5%	11.7%	11.7%	11.7%
	Zinc	-3.5%	-0.1%	0.0%	0.5%	1.0%	1.4%	1.9%	2.2%	2.6%	-0.4%
Softs	Cocoa	-4.2%	-2.6%	-2.0%	-1.6%	-	-	-	-	-	-
	Coffee	-3.8%	-2.7%	-2.7%	-2.2%	-	-	-	-	-	-
	Cotton	-3.6%	-1.1%	-0.4%	-	-	-	-	-	-	-
	Sugar	4.6%	5.6%	5.5%	-	-	-	-	-	-	-
Grains	Corn	-6.7%	-3.8%	-2.6%	-1.4%	-	-	-	-	-	-
	Soybeans	1.9%	3.2%	2.1%	2.8%	-	-	-	-	-	-
	Wheat	-8.3%	-4.3%	-2.0%	-1.5%	-	-	-	-	-	-
	Wheat (Kansas)	-2.1%	-0.7%	1.3%	1.6%	-	-	-	-	-	-
Meats	Feeder cattle	2.0%	3.8%	4.4%	4.4%	4.2%	3.6%	-	-	-	-
	Lean hogs	-6.2%	4.5%	4.3%	4.3%	4.8%	-	-	-	-	-
	Live cattle	0.4%	3.4%	2.1%	2.3%	2.4%	-	-	-	-	-

TABLE 1 (Continued). Summary statistics.

		Xth nearest contract									
		1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Panel B: Volatility											
Energy	Brent oil	31.3%	29.4%	28.5%	27.3%	24.2%	23.5%	22.8%	23.1%	22.6%	-
	Crude oil	33.2%	30.9%	29.2%	27.8%	26.5%	25.4%	24.4%	23.5%	22.8%	22.2%
	Gasoil	31.9%	30.2%	28.8%	27.5%	26.6%	25.1%	24.4%	24.0%	22.5%	22.1%
	Heating oil	32.1%	30.3%	28.9%	27.6%	26.5%	25.4%	24.5%	23.8%	23.2%	22.7%
	Natural gas	51.0%	43.6%	37.4%	33.7%	31.4%	29.2%	27.3%	25.6%	24.7%	24.0%
	Gasoline	34.4%	31.1%	28.8%	27.3%	26.0%	25.0%	24.4%	24.4%	24.4%	23.4%
Metals	Gold	15.5%	15.5%	15.5%	15.4%	-	-	-	-	-	-
	Silver	28.3%	28.2%	28.0%	27.9%	-	-	-	-	-	-
	Aluminum	20.0%	19.7%	19.4%	19.1%	18.8%	18.6%	18.3%	18.1%	17.9%	17.6%
	Copper	28.2%	27.9%	27.8%	27.7%	27.4%	27.2%	27.0%	26.7%	26.5%	26.3%
	Lead	31.5%	30.8%	30.5%	30.2%	29.8%	29.5%	29.4%	29.2%	29.1%	29.7%
	Nickel	37.9%	37.7%	37.4%	37.0%	36.4%	35.8%	35.3%	34.8%	34.4%	34.0%
	Zinc	28.5%	28.2%	27.9%	27.6%	27.3%	27.1%	26.9%	26.7%	26.5%	24.7%
Softs	Cocoa	30.1%	29.1%	28.1%	27.3%	-	-	-	-	-	-
	Coffee	38.5%	35.8%	34.0%	32.7%	-	-	-	-	-	-
	Cotton	26.9%	25.0%	22.7%	-	-	-	-	-	-	-
	Sugar	31.6%	28.4%	25.6%	-	-	-	-	-	-	-
Grains	Corn	25.4%	24.5%	23.1%	21.6%	-	-	-	-	-	-
	Soybeans	23.5%	22.8%	21.9%	20.9%	-	-	-	-	-	-
	Wheat	27.6%	26.3%	24.5%	22.3%	-	-	-	-	-	-
	Wheat (Kansas)	26.9%	25.8%	24.6%	22.7%	-	-	-	-	-	-
Meats	Feeder cattle	13.0%	12.1%	11.0%	10.5%	10.0%	9.7%	-	-	-	-
	Lean hogs	23.7%	20.2%	16.9%	14.7%	13.7%	-	-	-	-	-
	Live cattle	12.9%	10.5%	8.9%	8.1%	8.0%	-	-	-	-	-

TABLE 1 (Continued). Summary statistics.

		Xth nearest contract									
		1st	2nd	3rd	4th	5th	6th	7th	8th	9th	10th
Panel C: Trading volume (expressed in million dollars)											
Energy	Brent oil	1,505.7	641.7	324.7	211.9	151.4	113.2	97.9	86.1	65.2	-
	Crude oil	5,091.5	1,734.0	780.3	435.2	295.9	218.0	164.9	139.8	112.0	89.6
	Gasoil	854.4	344.2	172.7	107.4	79.0	59.5	43.4	41.3	34.0	24.7
	Heating oil	943.5	331.4	171.1	104.8	73.2	55.8	40.6	31.8	20.8	14.5
	Natural gas	1,038.3	436.5	250.4	163.7	124.6	99.0	79.9	68.8	54.0	43.5
	Gasoline	952.4	352.6	170.2	91.3	53.5	32.7	19.4	13.1	9.2	6.3
Metals	Gold	2,830.1	113.9	38.4	22.4	-	-	-	-	-	-
	Silver	868.7	49.3	17.2	7.2	-	-	-	-	-	-
	Aluminum	553.2	521.9	174.6	86.6	71.5	57.0	46.6	40.8	29.5	30.6
	Copper	676.8	626.2	190.1	112.5	86.4	67.3	49.9	54.3	43.2	37.7
	Lead	77.0	52.5	18.9	11.4	8.8	6.6	7.5	7.5	5.7	4.8
	Nickel	143.9	133.8	40.0	16.6	13.0	8.2	7.1	5.6	5.0	4.4
	Zinc	195.9	176.8	52.5	23.2	24.6	18.4	11.2	11.4	6.8	6.7
Softs	Cocoa	96.8	24.1	22.1	4.1	-	-	-	-	-	-
	Coffee	317.7	70.9	22.1	9.4	-	-	-	-	-	-
	Cotton	246.7	75.7	28.9	-	-	-	-	-	-	-
	Sugar	325.2	115.6	48.9	-	-	-	-	-	-	-
Grains	Corn	932.8	380.9	170.3	85.8	-	-	-	-	-	-
	Soybeans	1,667.5	361.6	158.6	80.3	-	-	-	-	-	-
	Wheat	509.7	158.3	61.5	29.7	-	-	-	-	-	-
	Wheat (Kansas)	149.4	49.5	19.5	9.3	-	-	-	-	-	-
Meats	Feeder cattle	82.3	17.9	8.6	3.7	1.3	0.6	-	-	-	-
	Lean hogs	161.9	59.2	26.3	12.0	5.6	-	-	-	-	-
	Live cattle	315.5	130.9	55.3	23.7	7.3	-	-	-	-	-

TABLE 1 (Continued). Summary statistics.

		Xth nearest contract									
		1st	**2nd**	**3rd**	**4th**	**5th**	**6th**	**7th**	**8th**	**9th**	**10th**
Panel D: Amihud illiquidity measure (expressed in basis points per 1 million dollar trade)											
Energy	Brent oil	0.9	5.5	18.7	37.1	71.0	149.3	120.2	155.3	229.3	-
	Crude oil	0.6	1.5	1.5	3.6	3.2	12.3	13.0	23.4	38.5	87.8
	Gasoil	1.3	4.1	18.3	45.2	95.6	137.0	192.4	159.3	305.2	243.0
	Heating oil	4.4	4.2	6.6	8.1	13.8	37.3	82.3	122.1	172.9	295.5
	Natural gas	5.8	7.2	8.8	16.3	21.5	25.8	36.2	48.4	60.6	85.5
	Gasoline	2.6	3.8	6.0	19.6	70.3	159.9	341.6	409.9	555.6	777.8
Metals	Gold	6.5	43.0	105.5	159.4	-	-	-	-	-	-
	Silver	6.9	105.7	378.0	629.4	-	-	-	-	-	-
	Aluminum	3.1	5.0	8.5	9.8	9.7	17.1	18.6	21.5	40.6	35.1
	Copper	1.8	2.9	5.0	10.9	9.2	11.2	21.9	20.4	24.0	31.0
	Lead	25.8	32.4	70.4	124.4	124.7	214.3	238.5	231.4	246.2	245.5
	Nickel	13.8	10.5	20.1	63.2	74.1	121.9	172.3	199.5	253.3	237.5
	Zinc	13.8	19.4	18.7	39.3	48.3	86.9	154.8	143.4	224.5	159.0
Softs	Cocoa	56.7	55.1	99.2	433.7	-	-	-	-	-	-
	Coffee	22.7	46.9	72.5	140.6	-	-	-	-	-	-
	Cotton	21.2	17.8	36.5	-	-	-	-	-	-	-
	Sugar	26.3	19.4	25.6	-	-	-	-	-	-	-
Grains	Corn	0.3	1.1	2.6	9.0	-	-	-	-	-	-
	Soybeans	0.5	8.3	14.9	68.5	-	-	-	-	-	-
	Wheat	0.8	6.7	24.6	157.8	-	-	-	-	-	-
	Wheat (Kansas)	1.5	6.5	65.8	364.5	-	-	-	-	-	-
Meats	Feeder cattle	1.8	6.3	15.1	39.4	113.1	238.0	-	-	-	-
	Lean hogs	1.1	3.2	8.9	28.7	95.1	-	-	-	-	-
	Live cattle	0.3	0.6	1.3	4.4	19.4	-	-	-	-	-

TABLE 2. Strategies' performance - 12 months maturity bound.

This table shows the performance of four cross-sectional commodity momentum strategies over the sample period January 1990 to September 2011. Panel A reports the gross annualized performance while Panel B, C and D report the net annualized performance based on respectively standard, Amihud-based and conservative trading costs. "Generic momentum" ranks commodities according to the past 12-month returns of the nearest contracts and longs (shorts) the 50% of commodities with the highest (lowest) returns. "Optimal-roll momentum" also ranks commodities based on front-contract momentum, but longs (shorts) the contract with the most backwardated (most contangoed) slope. "All-contracts momentum" first selects the contract on each commodity curve with the highest (lowest) 12-month and then longs (shorts) the 50% of commodities with the highest (lowest) momentum. "Low-turnover roll momentum" compared to optimal-roll momentum, which monthly determines the contracts with the most optimal slope, remains invested in the same contract unless it is about to expire or the commodity changes position. All portfolios are equally weighted. The Ledoit and Wolf (2008) test evaluates whether the Sharpe ratios of the alternative strategies are significantly different from that of the generic momentum strategy. The average maturity of the contracts in portfolio is presented in months. The turnover figures presented in this table are single-counted and one-sided. In addition the average single-trip costs of the transactions in basis points (bps) are shown.

	Generic	Optimal roll	All contracts	Low-turnover roll
Panel A: Gross returns				
Return	11.43%	13.05%	14.48%	12.31%
T-statistic	3.33	4.36	4.44	4.03
Volatility	15.65%	13.62%	14.86%	13.91%
Sharpe ratio	0.73	0.96	0.97	0.88
Ledoit and Wolf Statistic	-	2.67	3.29	2.67
P-value	-	0.01	0.00	0.01
Max. drawdown	-23.70%	-21.21%	-21.57%	-21.09%
Maturity (months)	1.50	5.01	3.85	4.22
Turnover	855%	756%	880%	402%
Panel B: Net returns assuming standard transaction costs				
Return	8.43%	10.19%	11.27%	10.76%
T-statistic	2.45	3.40	3.44	3.51
Volatility	15.69%	13.65%	14.91%	13.95%
Sharpe ratio	0.54	0.75	0.76	0.77
Ledoit and Wolf Statistic	-	2.55	3.06	4.14
P-value	-	0.01	0.00	0.00
Max. drawdown	-25.30%	-22.74%	-22.00%	-21.96%
Average costs (bps)	8.10	8.56	8.20	8.71
Panel C: Net returns assuming Amihud-based transaction costs				
Return	8.36%	9.01%	10.34%	10.32%
T-statistic	2.43	3.00	3.15	3.37
Volatility	15.70%	13.65%	14.94%	13.96%
Sharpe ratio	0.53	0.66	0.69	0.74
Ledoit and Wolf Statistic	-	1.56	2.25	3.63
P-value	-	0.12	0.02	0.00
Max. drawdown	-25.30%	-23.33%	-22.21%	-22.29%
Average costs (bps)	8.30	12.26	10.67	11.22
Panel D: Net returns assuming conservative transaction costs				
Return	3.98%	5.94%	6.52%	8.42%
T-statistic	1.15	1.98	1.98	2.74
Volatility	15.79%	13.71%	15.00%	14.01%
Sharpe ratio	0.25	0.43	0.43	0.60
Ledoit and Wolf Statistic	-	2.33	2.67	6.24
P-value	-	0.02	0.01	0.00
Max. drawdown	-30.59%	-25.75%	-23.55%	-23.24%
Average costs (bps)	20.95	22.17	21.24	22.29

TABLE 3. Portfolio return regressions.

This table presents the coefficient estimates, t-statistics (between brackets) and R-squared values obtained from regressions of the monthly gross (Panel A) and net returns using standard (Panel B), Amihud-based (Panel C) and conservative (Panel D) transaction costs of the four cross-sectional momentum strategies on the carry, market and momentum factors. Carry is the return of a strategy defined as an equally-weighted portfolio that longs (shorts) the 50% of commodities with the highest (lowest) annualized ratio of nearby futures price to the nearest futures price. Market is the excess return of the S&P GSCI market index. Momentum is the return of the generic momentum strategy. The intercepts of the regressions are annualized and reported as alpha.

	Generic	Optimal roll	All contracts	Low-turnover roll	Optimal roll	All contracts	Low-turnover roll
Panel A: Gross returns							
Alpha	5.17%	6.97%	8.29%	6.40%	2.84%	3.61%	2.04%
	(1.80)	(2.85)	(3.00)	(2.52)	(3.29)	(3.82)	(2.64)
Market	0.11	0.09	0.10	0.10	0.00	0.00	0.00
	(2.93)	(2.71)	(2.80)	(2.88)	(-0.08)	(0.13)	(0.30)
Carry	0.66	0.60	0.61	0.60	0.07	0.01	0.04
	(10.82)	(11.57)	(10.43)	(11.03)	(3.35)	(0.61)	(1.94)
Momentum	-	-	-	-	0.80	0.90	0.84
	-	-	-	-	(42.09)	(43.29)	(49.27)
R^2	34%	37%	32%	35%	92%	92%	94%
Panel B: Net returns assuming standard transaction costs							
Alpha	4.25%	6.08%	7.11%	6.66%	2.68%	3.26%	3.08%
	(1.50)	(2.51)	(2.60)	(2.65)	(3.14)	(3.49)	(4.03)
Market	0.11	0.09	0.10	0.10	0.00	0.00	0.00
	(2.94)	(2.72)	(2.81)	(2.88)	(-0.09)	(0.14)	(0.27)
Carry	0.66	0.60	0.62	0.60	0.07	0.02	0.04
	(10.90)	(11.59)	(10.52)	(11.05)	(3.22)	(0.65)	(1.80)
Momentum	-	-	-	-	0.80	0.90	0.84
	-	-	-	-	(42.00)	(43.28)	(49.43)
R^2	34%	37%	33%	35%	92%	92%	94%
Panel C: Net returns assuming Amihud-based transaction costs							
Alpha	4.22%	5.02%	6.29%	6.29%	1.64%	2.46%	2.73%
	(1.49)	(2.07)	(2.30)	(2.50)	(1.92)	(2.63)	(3.57)
Market	0.11	0.09	0.10	0.10	0.00	0.00	0.00
	(2.94)	(2.73)	(2.82)	(2.89)	(-0.08)	(0.15)	(0.28)
Carry	0.66	0.60	0.62	0.60	0.07	0.02	0.04
	(10.91)	(11.58)	(10.53)	(11.06)	(3.18)	(0.66)	(1.80)
Momentum	-	-	-	-	0.80	0.91	0.84
	-	-	-	-	(41.89)	(43.24)	(49.50)
R^2	34%	37%	33%	35%	92%	92%	94%
Panel D: Net returns assuming conservative transaction costs							
Alpha	2.85%	4.67%	5.31%	7.04%	2.39%	2.74%	4.63%
	(1.01)	(1.94)	(1.96)	(2.82)	(2.82)	(2.96)	(6.12)
Market	0.11	0.09	0.10	0.10	0.00	0.00	0.00
	(2.96)	(2.73)	(2.83)	(2.88)	(-0.10)	(0.14)	(0.22)
Carry	0.67	0.60	0.62	0.59	0.07	0.02	0.03
	(11.04)	(11.63)	(10.68)	(11.10)	(3.00)	(0.70)	(1.56)
Momentum	-	-	-	-	0.80	0.90	0.84
	-	-	-	-	(41.69)	(43.24)	(49.36)
R^2	35%	37%	33%	35%	92%	92%	94%

TABLE 4. Double-sort strategies' performance.

This table shows the performance of double-sort cross-sectional strategies on momentum and carry over the sample period January 1990 to September 2011. We sort first on momentum and then on carry. The alternative strategies are constructed in a similar fashion as in Table 2. Panel A reports the gross annualized performance while Panel B, C and D report the net annualized performance based on respectively standard, Amihud-based and conservative trading costs.

	Generic	Optimal roll	All contracts	Low-turnover roll
Panel A: Gross returns				
Return	16.09%	17.27%	19.85%	16.52%
T-statistic	3.43	3.99	4.33	3.78
Volatility	21.35%	19.71%	20.87%	19.90%
Sharpe ratio	0.75	0.88	0.95	0.83
Ledoit and Wolf Statistic	-	1.61	5.08	1.30
P-value	-	0.11	0.00	0.20
Max. drawdown	-26.19%	-27.28%	-26.15%	-27.62%
Maturity (months)	1.49	3.88	3.01	3.62
Turnover	926%	857%	933%	620%
Panel B: Net returns assuming standard transaction costs				
Return	12.60%	13.82%	16.19%	13.93%
T-statistic	2.68	3.19	3.52	3.18
Volatility	21.40%	19.76%	20.93%	19.95%
Sharpe ratio	0.59	0.70	0.77	0.70
Ledoit and Wolf Statistic	-	1.49	4.94	1.96
P-value	-	0.14	0.00	0.05
Max. drawdown	-32.56%	-28.75%	-27.67%	-28.81%
Average costs (bps)	8.38	8.85	8.46	9.15
Panel C: Net returns assuming Amihud-based transaction costs				
Return	12.50%	12.95%	15.59%	13.43%
T-statistic	2.66	2.98	3.39	3.07
Volatility	21.41%	19.78%	20.94%	19.96%
Sharpe ratio	0.58	0.65	0.74	0.67
Ledoit and Wolf Statistic	-	0.94	4.37	1.57
P-value	-	0.35	0.00	0.12
Max. drawdown	-32.57%	-29.06%	-27.91%	-29.07%
Average costs (bps)	8.61	11.15	9.88	10.95
Panel D: Net returns assuming conservative transaction costs				
Return	7.45%	8.72%	10.79%	10.08%
T-statistic	1.58	2.00	2.34	2.29
Volatility	21.50%	19.84%	21.04%	20.04%
Sharpe ratio	0.35	0.44	0.51	0.50
Ledoit and Wolf Statistic	-	1.29	4.69	2.97
P-value	-	0.20	0.00	0.00
Max. drawdown	-42.66%	-37.37%	-37.67%	-34.03%
Average costs (bps)	21.71	22.94	21.93	23.57

TABLE 5. Strategies' performance - six months maturity bound.
This table shows the risk and return characteristics of four cross-sectional commodity momentum strategies over the sample period January 1990 to September 2011. The strategies are constructed in the same way as in Table 2 with the difference that the strategies invest in contracts with a maturity up to six months. Panel A reports the gross annualized performance while Panel B, C and D report the net annualized performance based on respectively standard, Amihud-based and conservative trading costs.

	Generic	**Optimal roll**	**All contracts**	**Low-turnover roll**
Panel A: Gross returns				
Return	11.43%	13.38%	13.47%	12.96%
T-statistic	3.33	4.23	4.01	3.96
Volatility	15.65%	14.40%	15.28%	14.89%
Sharpe ratio	0.73	0.93	0.88	0.87
Ledoit and Wolf Statistic	-	3.72	3.10	3.84
P-value	-	0.00	0.00	0.00
Max. drawdown	-23.70%	-21.66%	-21.09%	-22.19%
Maturity (months)	1.50	2.94	2.18	2.40
Turnover	855%	812%	853%	528%
Panel B: Net returns assuming standard transaction costs				
Return	8.43%	10.36%	10.43%	10.91%
T-statistic	2.45	3.27	3.10	3.33
Volatility	15.69%	14.41%	15.33%	14.93%
Sharpe ratio	0.54	0.72	0.68	0.73
Ledoit and Wolf Statistic	-	3.47	3.03	5.35
P-value	-	0.00	0.00	0.00
Max. drawdown	-25.30%	-22.85%	-21.47%	-22.98%
Average costs (bps)	8.10	8.44	8.07	8.76
Panel C: Net returns assuming Amihud-based transaction costs				
Return	7.89%	8.28%	9.30%	9.93%
T-statistic	2.29	2.62	2.76	3.02
Volatility	15.72%	14.42%	15.36%	14.96%
Sharpe ratio	0.50	0.57	0.61	0.66
Ledoit and Wolf Statistic	-	1.38	2.19	4.65
P-value	-	0.17	0.03	0.00
Max. drawdown	-25.45%	-24.04%	-22.26%	-23.34%
Average costs (bps)	9.60	14.50	11.18	13.02
Panel D: Net returns assuming conservative transaction costs				
Return	3.98%	5.87%	5.93%	7.82%
T-statistic	1.15	1.85	1.75	2.37
Volatility	15.79%	14.45%	15.42%	15.00%
Sharpe ratio	0.25	0.41	0.38	0.52
Ledoit and Wolf Statistic	-	3.00	2.90	7.37
P-value	-	0.00	0.00	0.00
Max. drawdown	-30.59%	-25.68%	-24.83%	-24.41%
Average costs (bps)	20.95	21.85	20.86	22.56

TABLE 6. Strategies' performance - dollar trading volume screening.

This table shows the risk and return characteristics of four cross-sectional commodity momentum strategies over the sample period January 1990 to September 2011. The strategies are constructed in the same way as in Table 2 with the difference that here we first exclude futures contracts which do not meet the minimum requirement of the monthly average of daily dollar trading volume. This threshold is set at USD 33.33 million at the end of our sample period and is deflated back in time by 4.05% per annum. Panel A reports the gross annualized performance while Panel B, C and D report the net annualized performance based on respectively standard, Amihud-based and conservative trading costs.

	Generic	Optimal roll	All contracts	Low-turnover roll
Panel A: Gross returns				
Return	11.90%	13.59%	15.55%	13.54%
T-statistic	3.42	4.26	4.54	4.14
Volatility	15.87%	14.54%	15.60%	14.89%
Sharpe ratio	0.75	0.93	1.00	0.91
Ledoit and Wolf Statistic	-	2.49	3.64	3.51
P-value	-	0.01	0.00	0.00
Max. drawdown	-24.84%	-22.46%	-22.13%	-22.40%
Maturity (months)	1.51	3.42	2.97	2.83
Turnover	860%	777%	838%	555%
Panel B: Net returns assuming standard transaction costs				
Return	8.90%	10.67%	12.51%	11.34%
T-statistic	2.55	3.33	3.65	3.46
Volatility	15.91%	14.58%	15.63%	14.92%
Sharpe ratio	0.56	0.73	0.80	0.76
Ledoit and Wolf Statistic	-	2.47	3.68	4.58
P-value	-	0.01	0.00	0.00
Max. drawdown	-26.79%	-24.43%	-22.52%	-23.92%
Average costs (bps)	8.02	8.48	8.06	8.89
Panel C: Net returns assuming Amihud-based transaction costs				
Return	8.81%	10.36%	12.24%	11.22%
T-statistic	2.52	3.23	3.57	3.42
Volatility	15.91%	14.59%	15.63%	14.93%
Sharpe ratio	0.55	0.71	0.78	0.75
Ledoit and Wolf Statistic	-	2.29	3.53	4.78
P-value	-	0.02	0.00	0.00
Max. drawdown	-26.81%	-24.65%	-22.61%	-24.04%
Average costs (bps)	8.26	9.41	8.80	9.42
Panel D: Net returns assuming conservative transaction costs				
Return	4.44%	6.33%	8.00%	8.04%
T-statistic	1.26	1.97	2.32	2.44
Volatility	15.99%	14.65%	15.69%	15.00%
Sharpe ratio	0.28	0.43	0.51	0.54
Ledoit and Wolf Statistic	-	2.40	3.72	6.22
P-value	-	0.02	0.00	0.00
Max. drawdown	-30.25%	-27.36%	-25.38%	-26.21%
Average costs (bps)	20.77	21.97	20.85	22.95

TABLE 7 Strategies' performance - Amihud illiquidity measure screening.
This table shows the risk and return characteristics of four cross-sectional commodity momentum strategies over the sample period January 1990 to September 2011. The strategies are constructed in the same way as in Table 2 with the difference that here we first exclude futures contracts which do not meet the maximum threshold of the Amihud illiquidity measure. This measure is calculated as the monthly average of the absolute daily return divided by the daily dollar trading volume. The maximum requirement is set at 4 basis points for a one million dollar trade at the end of our sample period and is inflated back in time by 4.05% per annum. Panel A reports the gross annualized performance while Panel B, C and D report the net annualized performance based on respectively standard, Amihud-based and conservative trading costs.

	Generic	Optimal roll	All contracts	Low-turnover roll
Panel A: Gross returns				
Return	12.02%	14.47%	15.39%	14.04%
T-statistic	3.51	4.51	4.52	4.32
Volatility	15.59%	14.61%	15.51%	14.81%
Sharpe ratio	0.77	0.99	0.99	0.95
Ledoit and Wolf Statistic	-	2.45	3.17	3.83
P-value	-	0.01	0.00	0.00
Max. drawdown	-23.72%	-22.10%	-22.06%	-22.05%
Maturity (months)	1.51	3.41	2.94	2.87
Turnover	868%	782%	844%	560%
Panel B: Net returns assuming standard transaction costs				
Return	8.98%	11.51%	12.29%	11.84%
T-statistic	2.62	3.58	3.61	3.64
Volatility	15.62%	14.63%	15.53%	14.83%
Sharpe ratio	0.57	0.79	0.79	0.80
Ledoit and Wolf Statistic	-	2.38	3.16	4.89
P-value	-	0.02	0.00	0.00
Max. drawdown	-24.88%	-23.31%	-22.46%	-23.25%
Average costs (bps)	8.05	8.48	8.17	8.79
Panel C: Net returns assuming Amihud-based transaction costs				
Return	8.85%	11.19%	12.02%	11.70%
T-statistic	2.58	3.48	3.53	3.59
Volatility	15.62%	14.63%	15.53%	14.83%
Sharpe ratio	0.57	0.76	0.77	0.79
Ledoit and Wolf Statistic	-	2.25	3.05	4.80
P-value	-	0.03	0.00	0.00
Max. drawdown	-24.92%	-23.50%	-22.72%	-23.37%
Average costs (bps)	8.40	9.43	8.90	9.34
Panel D: Net returns assuming conservative transaction costs				
Return	4.46%	7.11%	7.70%	8.53%
T-statistic	1.29	2.21	2.25	2.61
Volatility	15.69%	14.67%	15.57%	14.87%
Sharpe ratio	0.28	0.49	0.49	0.57
Ledoit and Wolf Statistic	-	2.41	3.13	6.18
P-value	-	0.02	0.00	0.00
Max. drawdown	-27.41%	-25.66%	-26.04%	-25.18%
Average costs (bps)	20.86	21.93	21.15	22.65

TABLE 8. Strategies' performance - one-day implementation lag.

This table shows the risk and return characteristics of four cross-sectional commodity momentum strategies over the sample period January 1990 to September 2011. The strategies are constructed in similar fashion as in Table 2 with the difference that the long and short positions are based on data up to the day before month-end. Panel A reports the gross annualized performance while Panel B, C and D report the net annualized performance based on respectively standard, Amihud-based and conservative trading costs.

	Generic	Optimal roll	All contracts	Low-turnover roll
Panel A: Gross returns				
Return	11.37%	12.79%	14.57%	12.23%
T-statistic	3.21	4.13	4.38	3.90
Volatility	16.12%	14.10%	15.16%	14.29%
Sharpe ratio	0.71	0.91	0.96	0.86
Ledoit and Wolf Statistic	-	2.84	3.44	2.57
P-value	-	0.00	0.00	0.01
Max. drawdown	-23.88%	-21.36%	-22.80%	-20.85%
Maturity (months)	1.49	5.01	3.85	4.21
Turnover	855%	768%	883%	400%
Panel B: Net returns assuming standard transaction costs				
Return	8.38%	9.91%	11.34%	10.72%
T-statistic	2.36	3.19	3.40	3.41
Volatility	16.16%	14.14%	15.21%	14.32%
Sharpe ratio	0.52	0.70	0.75	0.75
Ledoit and Wolf Statistic	-	2.60	3.14	4.03
P-value	-	0.01	0.00	0.00
Max. drawdown	-25.27%	-23.01%	-25.00%	-21.74%
Average costs (bps)	8.08	8.53	8.21	8.57
Panel C: Net returns assuming Amihud-based transaction costs				
Return	8.31%	8.68%	10.42%	10.27%
T-statistic	2.34	2.79	3.11	3.27
Volatility	16.17%	14.16%	15.24%	14.33%
Sharpe ratio	0.51	0.61	0.68	0.72
Ledoit and Wolf Statistic	-	1.36	2.37	3.54
P-value	-	0.18	0.02	0.00
Max. drawdown	-25.27%	-23.64%	-26.14%	-21.97%
Average costs (bps)	8.28	12.30	10.63	11.10
Panel D: Net returns assuming conservative transaction costs				
Return	3.94%	5.63%	6.57%	8.43%
T-statistic	1.11	1.80	1.96	2.67
Volatility	16.25%	14.22%	15.30%	14.38%
Sharpe ratio	0.24	0.40	0.43	0.59
Ledoit and Wolf Statistic	-	2.21	2.66	6.10
P-value	-	0.03	0.01	0.00
Max. drawdown	-29.05%	-25.46%	-28.89%	-23.05%
Average costs (bps)	20.91	22.08	21.25	21.93

TABLE 9. Strategies' performance after 2000.

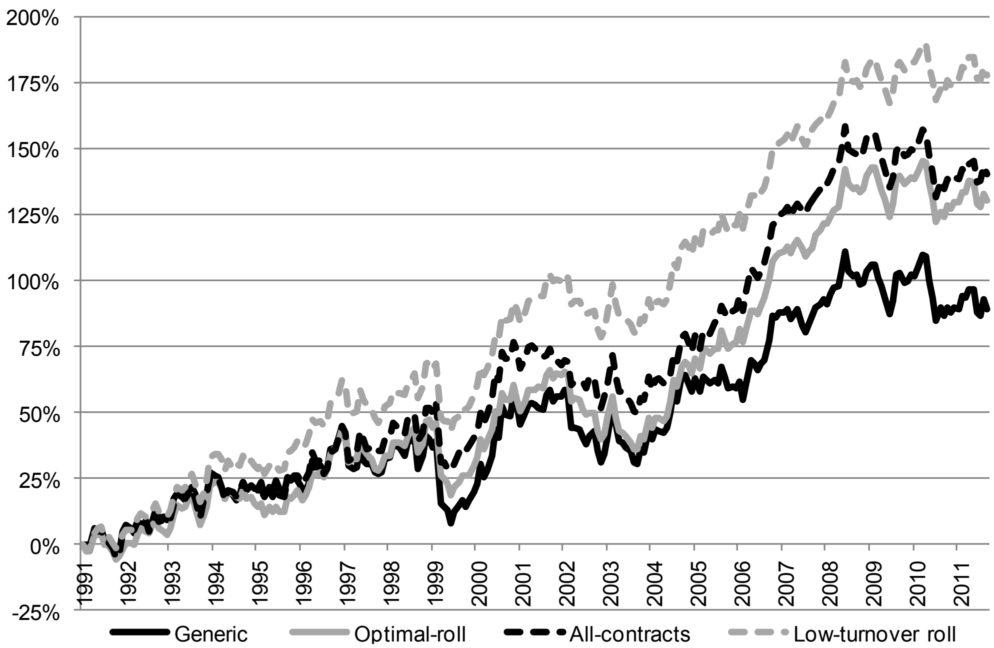
This table shows the risk and return characteristics of four cross-sectional commodity momentum strategies over the sample period January 2000 to September 2011. The strategies are constructed in the same way as in Table 2. Panel A reports the gross annualized performance while Panel B, C and D report the net annualized performance based on respectively standard, Amihud-based and conservative trading costs.

	Generic	Optimal roll	All contracts	Low-turnover roll
Panel A: Gross returns				
Return	11.97%	14.71%	15.23%	14.04%
T-statistic	2.54	3.62	3.42	3.39
Volatility	16.12%	13.92%	15.27%	14.21%
Sharpe ratio	0.74	1.06	1.00	0.99
Ledoit and Wolf Statistic	-	2.03	2.17	4.36
P-value	-	0.05	0.03	0.00
Max. drawdown	-21.39%	-19.62%	-21.57%	-19.03%
Maturity (months)	1.46	5.03	3.93	4.14
Turnover	881%	773%	893%	404%
Panel B: Net returns assuming standard transaction costs				
Return	9.58%	12.37%	12.68%	12.77%
T-statistic	2.03	3.04	2.84	3.07
Volatility	16.15%	13.94%	15.31%	14.24%
Sharpe ratio	0.59	0.89	0.83	0.90
Ledoit and Wolf Statistic	-	1.98	2.03	5.48
P-value	-	0.05	0.04	0.00
Max. drawdown	-21.78%	-20.01%	-22.00%	-19.19%
Average costs (bps)	6.17	6.75	6.33	6.98
Panel C: Net returns assuming Amihud-based transaction costs				
Return	9.54%	11.38%	11.92%	12.43%
T-statistic	2.03	2.80	2.66	2.99
Volatility	16.14%	13.95%	15.34%	14.25%
Sharpe ratio	0.59	0.82	0.78	0.87
Ledoit and Wolf Statistic	-	1.54	1.63	5.06
P-value	-	0.13	0.11	0.00
Max. drawdown	-21.78%	-21.28%	-22.21%	-19.35%
Average costs (bps)	6.28	9.68	8.28	8.83
Panel D: Net returns assuming conservative transaction costs				
Return	6.06%	8.89%	8.92%	10.85%
T-statistic	1.28	2.18	1.99	2.60
Volatility	16.19%	13.98%	15.38%	14.29%
Sharpe ratio	0.37	0.64	0.58	0.76
Ledoit and Wolf Statistic	-	1.89	1.83	7.10
P-value	-	0.06	0.07	0.00
Max. drawdown	-24.63%	-25.75%	-23.55%	-20.98%
Average costs (bps)	15.80	17.30	16.22	17.76

FIGURE 1. Strategies' performance over time.

These figures show the performance over time of our cross-sectional commodity momentum strategies over the sample period January 1991 to September 2011. The performance is based on net returns assuming conservative transaction costs. Subfigure A shows cumulative log returns and Subfigure B shows 5-year rolling Sharpe ratios. Note that subfigure B starts in 1996 due to the 5-year rolling window.

SUBFIGURE A. Cumulative performance



SUBFIGURE B. Rolling Sharpe Ratio