Momentum in Futures Markets

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February 23, 2005

Abstract. Momentum has been examined extensively in equity markets, but little studied outside them. I document the existence of momentum and reversals in futures markets including commodity and financial futures contracts traded in the US and overseas. Futures momentum portfolios earn positive average returns even after adjusting for risk using canonical pricing models including the CAPM and Fama-French three factor models. If futures momentum portfolios are formed based on standardized performance, they earn positive average returns even after a momentum factor is included in the Fama-French model, although the momentum factor is statistically significant. Thus, futures momentum is related to, but not subsumed by, equity momentum. Non-parametric risk adjustment reduces momentum returns, but momentum portfolios formed based on standardized historical returns exhibit abnormal performance even allowing for time varying, non-parametric risk adjustment.

1 Introduction

Momentum is one of the most recalcitrant anomalies in the asset pricing literature. The phenomenon has been studied extensively since it was first documented by Jegadeesh and Titman (1993). For the most part, momentum portfolios earn positive returns even after adjusting for risk using canonical parametric asset pricing models such as the CAPM (conditional and unconditional) and the Fama-French three factor model. More recently, empirical evidence suggests that alternative methods for risk adjustment can eliminate momentum anomaly. Ahn *et al* ("ACD," 2003) find that a non-parametric stochastic discount factor model with time varying risk premia extinguishes most of the gains to momentum in US stock portfolios. Chordia and Shivakumar (2002) document that time varying expected returns driven by macroeconomic factors can explain momentum profits.

Virtually all research on momentum focuses on equities. Although some research examines international stocks (Bhojraj and Swaminathan, 2003) and bonds (Gebharrdt, Hvidkjaer, and Swaminathan, 2002; Naik, Trinh, and Rennison, 2002), most momentum studies focus on US stocks. Methodologies and sample periods differ, but the independence of contributions of various momentum studies based on a core of common data is limited. Moreover, behavioral theories of momentum (e.g., Barberis *et al,* 1998; Daniel *et al,* 1998) rely on allegedly pervasive psychological characteristics that should affect trader actions outside of US equity markets. To determine whether momentum is a fluke finding in a particular asset class or a ubiquitous phenomenon related to fundamental investor biases, it is therefore imperative to examine whether momentum is found in other, and heretofore unstudied, markets.

For a variety of reasons, futures markets are a particularly fruitful subject to explore for evidence of the pervasiveness of momentum.

First, since the mid-1970s futures markets have grown dramatically in size and scope. Whereas futures markets had once been restricted to agricultural products and some metals, by 20 years ago futures had been introduced on US goverment securities, short term interest rates, equity indices, foreign currencies, and energy products. In the late-1980s and early-1990s, futures markets grew dramatically overseas as well, especially in Europe. Moreover, in this period the volume of trading has exploded. Furthermore, due to the possibility of arbitrage trading, futures prices are tightly linked to the prices of their underlying instruments. Therefore, anomalies documented in futures prices almost certainly occur in the prices of the underlyings. Since futures markets represent directly or indirectly (via arbitrage) a much broader slice of investment and trading opportunities than do equity markets, they make it possible to determine whether momentum is a ubiquitous phenomenon, or is instead limited to stocks.

Second, there are significant institutional differences between equity markets and futures markets. Most important, whereas there are typically short selling restrictions in equity markets, there are no such restrictions in futures markets. Indeed, shorting futures is just the mirror image of buying. Moreover, trading costs in futures markets are typically far smaller than in equity markets. Thus, a detailed analysis of futures markets sheds light on whether institutional factors, such as the difficulty of short selling or transactions costs, contribute to momentum anomalies.

Momentum indeed exists in futures prices. During the 1982-2003 period, buying futures contracts with returns in the upper quntile over some period of months and selling futures contracts with returns in the lower quintile during this period generated a return of approximately 70 to 80 basis points per month, depending on the portfolio formation and holding periods. This return is statistically significant. Moreover, these momentum returns persist even after adjusting for risk using parametric models including the CAPM and Fama-French three factor models. Perhaps most important in light of recent evidence, momentum returns persist even after adjusting for risk using a stochastic discount factor estimated using a non-parametric approach *a la* ACD. Although the magnitude of the momentum premium declines after the non-parametric risk adjustment, this premium is statistically significant at a high level of confidence for several choices of portfolio formation and holding periods, if portfolios are formed on the basis of standardized performance.

Interestingly, futures momentum is related to stock momentum, but not subsumed by it. The correlation between the momentum portfolio return and the Fama-French momentum factor is between .26 and .30 (depending on the method of constructing the futures momentum portfolio), and the momentum factor is statistically significant in time series regressions of the momentum return on the three Fama-French factors and the momentum factor. Nonetheless, the constants in these regressions are positive and typically statistically significant at conventional levels, indicating a futures-specific momentum effect that is not completely explained by stock-based momentum returns.

In addition to short term momentum, there is evidence of long term reversals in futures prices. Specifically, returns to momentum portfolios are negative and statistically significant in the second year after portfolio formation. Indeed, the reversal typically more than offsets the momentum return earned in the first year after portfolio formation.

These results suggest that momentum and reversals are pervasive phenomena that cannot be explained by existing asset pricing methods, including the relatively unrestrictive non-parametric stochastic discount factor approach. The momentum puzzle cannot be put to rest just yet.

The remainder of this article is organized as follows. Section 2 outlines the empirical approach and the data employed. Section 3 presents the basic results on momentum and reversals, and shows that standard asset pricing models do not explain momentum returns in futures. Section 4 analyzes the ability of a non-parametric risk adjustment to explain momentum returns. Section 5 examines the characteristics of momentum portfolios. Section 6 summarizes the article.

2 Methodology and Data

2.1 Methodology

Momentum studies are based on returns. The method for constructing returns based on futures prices is motivated by the institutional features of these markets, particularly marking-to-market. Consider an agent who buys a futures contract on date t. The contract expires at date τ. The futures price is $F_{t,\tau}$. On day $t+1$ the futures price changes to $F_{t+1,\tau}$. From t to $t+1$

the agent realizes a gain of $F_{t+1,\tau} - F_{t,\tau}$. At the end of $t+1$, this amount is paid into the agent's margin account (if positive) or deducted therefrom if negative. The agent can then invest this margin inflow at the prevailing interest rate, or borrow to finance a margin outflow at this rate.

The lending (borrowing) of the t to $t+1$ gain (loss) can be repeated daily to the end of the month. The end of the month in which the trader purchased the contract is date T. The interest rate on date t', $t+1 \leq t' \leq T-1$ is $R_{t'}$. This is a daily rate (i.e., not annualized). At T, the agent will have

$$V_{t,T} = (F_{t+1,\tau} - F_{t,\tau})\Pi_{k=t+1}^{T-1}(1+R_k)$$

in his margin account.

If the law of one price holds,

$$E_t(m_T V_{t,T}) = E_t[m_T(F_{t+1,\tau} - F_{t,\tau})\Pi_{k=t+1}^{T-1}(1+R_k)] = 0$$

where m_T is a stochastic discount factor. Therefore,

$$E_t[m_T r_{t+1}\Pi_{k=t+1}^{T-1}(1+R_k)] = 0$$

where $r_{t+1} = F_{t+1,\tau}/F_{t,\tau} - 1$. Summing across all $T_0 \leq t \leq T-1$, where T_0 is the first day of the month, and applying the law of iterated expectations implies:

$$E[m_T \sum_{t=T_0}^{T-1} r_{t+1}\Pi_{k=t+1}^{T-1}(1+R_k)] = 0 \tag{1}$$

where the expectations operator without a subscript represents the unconditional expectation.

Motivated by (1), I calculate the monthly return on a given futures contract by

$$r_T^m = \sum_{t=T_0}^{T-1}[r_{t+1}\Pi_{k=t+1}^{T-1}(1+R_k)] \tag{2}$$

This quantity represents a monthly return that adjusts for the effects of marking to market. This return calculation captures any convexity bias effects that arise from marking-to-market and correlations between the interest rate and futures returns. It is equivalent to the amount of money in an agent's margin account at the end of a month for each dollar of notional contract value traded at day t in that month.

Futures contracts with notional values and prices denominated in a currency other than dollars require a slightly different treatment. Denote f_t as the date t FX spot price (dollars per unit of foreign currency). An individual who buys a single unit of a futures contract at t can convert the mark-to-market gain or loss into dollars at $t+1$, and then invest the gain or finance the loss until T at the dollar interest rate. At T, the agent will have:

$$V_{t,T} = f_{t+1}(F_{t+1,\tau} - F_{t,\tau})\Pi_{k=t+1}^{T-1}(1 + R_k)$$

in his margin account. By the law of one price,

$$E_t(m_T V_{t,T}) = E_t[m_T f_{t+1}(F_{t+1,\tau} - F_{t,\tau})\Pi_{k=t+1}^{T-1}(1 + R_k)] = 0.$$

Moreover,

$$E_t(\frac{m_T V_{t,T}}{f_t}) = E_t[m_T \frac{f_{t+1}}{f_t}(F_{t+1,\tau} - F_{t,\tau})\Pi_{k=t+1}^{T-1}(1 + R_k)] = 0.$$

Therefore, by the law of iterated expectations

$$E[m_T \frac{f_{t+1}}{f_t} r_{t+1} \Pi_{k=t+1}^{T-1}(1 + R_k)] = 0.$$

As before, these terms can be summed for all t in a given month to calculate a mark-to-market adjusted return on the foreign futures contract.[1]

[1] The term $\frac{f_{t+1}}{f_t} r_{t+1}$ can also be interpreted as the dollar gain realized on a position in $1 of notional value of the foreign currency-denominated futures contract.

Returns are calculated using settlement prices for the next-to-expire contract. Note that futures contracts expire on a given date, which may (and typically does) occur in the middle of the month. For instance, grain and Treasury futures contracts expire 7 business prior to the last business day of the contract month. Therefore, when calculating the returns in a given month, I use the returns on the contract that is next to expire at the beginning of that month. If that contract expires during that month, I then "roll" to the new next-to-expire contract upon the last day of trading of the expiring contract. I use the one-month LIBOR rate (adjusted for the relevant holding period using the actual-over-360 day counting convention) to measure the interest rate R_k. For f_t I use the relevant spot exchange rate obtained from the Commodity Research Bureau data set.

Given a calculation of returns for each month for each available futures contract, at the beginning of each month I then sum returns over the previous J months, where $J = \{3, 6, 9, 12\}$. Denoting the return on futures contract i in the month ending at T by $r^m_{i,T}$, the cumulative return over the J month horizon ending in at T is $\bar{r}_{i,T,J} = \sum_{j=T-J}^{T} r^m_{i,j}$. The cumulative returns are then ordered from lowest ("losers") to highest ("winners"). Given the number of available futures contracts (discussed in more detail in the next section), it is not feasible to form decile portfolios of futures, as is conventional for stocks. Instead, I form quintile portfolios, with the 20 percent of the available contracts with lowest returns in the loser portfolio and the 20 percent of the available contracts with the highest returns in the winner portfolio.

As will be seen, although there is evidence of momentum in portfolios formed in this way, the disparity in volatility across futures contracts masks the momentum effect in some ways. In particular, very high variance futures are more likely to be in winner and loser portfolios, whereas low variance futures are seldom represented in either. As a consequence, the variances of the winner and loser portfolios are substantially higher than those of the intermediate portfolios. Moreover, even absent any momentum effect, more volatile futures are more likely to be included in momentum portfolios. Therefore, I implement another method for identifying winners and losers that attempts to mitigate this effect. Specifically, during the performance measurement period, I calculate the daily standard deviation of returns for each futures for each month. Call the daily standard deviation of return for futures i in month j $\sigma_{i,j}$. I then create standardized returns:

$$\hat{r}_{i,T,J} = \frac{\bar{r}_{i,T,J}}{\sqrt{\sum_{j=T-J}^{T} N_{i,j}\sigma_{i,j}^2}}$$

where $N_{i,j}$ is the number of daily returns on futures contract i in month j. These standardized returns are also ordered, and quintile portfolios based on standardized returns during the portfolio creation period are formed.

I then measure the performance of the quintile portfolios in the four quarters following formation, and in the second and third years following formation. Inasmuch as portfolios are formed each month, and their performance is measured over periods longer than a month, performance measurement periods overlap. Consequently, the statistical significance of returns is measured using Newey-West standard errors that adjust for the amount of overlap (2 months for quarterly returns and 11 months for annual returns).

The quarterly return analysis implies that the largest average monthly returns for momentum portfolios are for $J = 6$ with a 6 month holding period (i.e., $K = 6$) and $J = 9$ with a 3 ($K = 3$) month holding period. This is true for portfolios formed using standardized returns and non-standardized returns. Following Jegadeesh and Titman, I then determine the monthly return on portfolios with $J = 6$ and $K = 6$, and $J = 9$ and $K = 3$. The monthly return on the quintile portfolios in a given month is given by the equally weighted average of the portfolios formed over the last K months based on performance over the J months prior to portfolio formation. This permits the use of ordinary standard errors. Even when portfolios are formed based on standardized returns, post-formation portfolio performance is measured using the raw returns $r_{i,T}$.

The detailed analysis focuses on the performance of the momentum portfolio consisting of the return on a long position in the winner portfolio, and a short position in the loser portfolio. Note that there are no short sale constraints in futures markets that impede the shorting of the loser portfolio. Indeed, the nature and cost of buying and shorting are equivalent in futures markets.

Once the returns to the momentum portfolios are determined, I calculate the average return to these portfolios across the sample. In addition, to determine whether momentum returns represent a reward for risk bearing, I estimate time series regressions of the monthly returns on the momentum portfolios $\{J = 6, K = 6\}$ and $\{J = 9, K = 3\}$ against monthly risk factors. Risk factors include the market return, the three Fama-French factors (market return, market-to-book, and size), and the three Fama-French factors plus a momentum factor. Finally, I use a non-parametric stochastic discount factor approach as another way to ascertain whether risk adjustment eliminates momentum returns for these portfolios. The methodology for this analysis is discussed in Section 4.

2.2 Data

I utilize data from futures contracts traded in North America, Europe, Asia, and Australia. The data was provided by the Commodity Research Bureau. For brevity, I present detailed results for two sets of futures contracts: dollar denominated contracts traded in the US and Europe, and all available contracts.

The analysis used futures returns beginning in January, 1982. I choose this year because a large number of futures contracts were introduced in that year, or slightly thereafter. For instance, in 1982 and 1983 futures contracts were introduced on stock indices, short term interest rates, and crude oil. Numerous other futures were launched in the mid-1980s. Prior to 1982, the available futures were limited primarily to grains and oilseeds, softs, precious metals, currencies, and two Treasury securities.

Panel A of Table 1 lists all of the dollar denominated contracts. Panel B lists the additional contracts included in the second set. Table I groups contracts into nine categories such as agricultural, stock index, and interest rates. The Table also indicates the number of observations included for each contract.

It should be noted that trading volume in these contracts is immense. In November, 2003 (the last month in the data set), daily dollar volume for dollar denominated futures contracts in the data set averaged $7.5 billion per contract. Across all 50 contracts available in this month, average daily turnover totaled \$376 billion. Inasmuch as this represents the volume for the front month contracts only, total trading volume for the futures covered was even larger. The largest contract, Eurodollars, had an average daily dollar volume of \$187 billion in the front month alone–average dollar volume for all months of this contract was approximately \$1 trillion. The median average daily turnover of futures included in the data set during this month was \$815 million. In November, 2003, there were 21 contracts (out of 50 in the data set) that averaged more than \$1 billion in volume per day, and 5 contracts with turnover in excess of \$20 billion per day. In contrast, total daily NYSE turnover was approximately \$40 billion in this period. The smallest volume contract in the data set in November, 2003 had an average daily dollar volume of \$6.84 million.

3 Results

3.1 Quarterly Performance of Momentum Portfolios

Table 2 reports mean quarterly and annual returns for momentum portfolios formed using dollar denominated futures with $J = \{3, 6, 9, 12\}$ based on non-standardized returns (in Panel A) and standardized returns (in Panel B) on dollar denominated futures contracts. Newey-West standard errors are used to calculate the t-statistics, which are reported in parentheses.

Several findings stand out. First, the unconditional mean returns on momentum portfolios are generally positive in the first two quarters after formation. For $J = 3$, returns are positive for each of the first four quarters after formation. For $J = 6$, returns are positive for the first 3 quarters. For

$J = 9$, returns are positive for the first two quarters whereas for $J = 12$, returns are positive for the first quarter only. These unconditional mean returns are significant at the one percent level for three quarters when $J = 3$, for two quarters when $J = 6$ and $J = 9$, and for one quarter when $J = 12$. These findings are similar to those documented for equity markets.

Second, there are strong reversals in the returns on the momentum portfolios. The reversals begin in the fourth quarter after portfolio formation when $J = 3$ and $J = 6$ (with stronger reversals for the latter in that quarter), in the third quarter after portfolio formation when $J = 9$, and in the second quarter when $J = 12$. Moreover, the reversals persist in the second year after portfolio formation. Indeed, the returns in the second year are negative, and larger in absolute value, than the returns in the first year for all except $J = 3$. The combination of momentum at short horizons and reversals at longer horizons is also consistent with evidence from equity markets. Returns in the third year after portfolio formation are indistinguishable from zero for all J.

Table 3 extends the analysis to include other, non-dollar denominated futures. The results are similar to those for dollar denominated futures.

Table 4 reports the results of cross-sectional regressions like those presented in Heston and Sadka (2002) and Bhojraj and Swaminathan (2003). Specifically, for each month i in the data, I regress all available returns in that month against the corresponding returns for month $i-k$, $k = 1, \ldots, 36$. The slope coefficients in these cross sectional regressions for a given lag are then averaged across all months in the data set, and reported in Table 4 along with their associated t-statistics. Table 4 reports the averaged results from the dollar denominated data set. As noted in Heston and Sadka, the slope coefficients are proportional to the returns of winner minus loser portfolios as formed by Lehmann (1990) and Lo and MacKinlay (1990). Thus, they represent another way of measuring the momentum effect.

Note that coefficient at the first lag is positive and significant. This contrasts to equity markets, where the coefficient on the first lag is often negative. This is typically attributed to a microstructure effect in equity markets, which is obviously absent in the futures markets studied, likely indicating their greater liquidity. Coefficients are mainly positive for the first 12 lags, and are significant and economically large at lags 1, 3, 5, 10, and 11. Coefficients are strongly negative, and statistically significant, at lags 13-15. Thereafter, with the exception of lag 25, the coefficients are economically small and statistically insignificant.

In brief, futures returns exhibit patterns similar to those documented for equity markets. Specifically, they exhibit short term momentum followed by long term reversals.

3.2 Monthly Returns and Risk Adjustment

In the interest of brevity, I calculate monthly returns for two J, K combinations rather than all 16 possible combinations. I choose $J = 6$, $K = 6$, and $J = 9$, $K = 3$ because these exhibit the most profitable unconditional momentum returns. For $J = 6$, $K = 6$ the unconditional monthly momentum return, calculated *a la* Jegadeesh-Titman, is 71 basis points per month ($t = 2.65$) for dollar denominated portfolios formed using non-standardized performance, and 79 basis points per month ($t = 3.70$) for dollar denominated portfolios formed based on standardized performance. For $J = 9$ and $K = 3$, the unconditional mean momentum return is 82 basis points ($t = 2.66$) for the non-standardized-based portfolios, and 86 basis points ($t = 3.32$) for the dollar denominated portfolios formed using standardized returns. Note that although the magnitude of momentum portfolio returns is similar regardless of whether portfolios are formed on the basis of standardized or non-standardized returns, the mean returns for the portfolios formed using standardized returns are estimated more precisely. This reflects that fact that when returns are not standardized, high variance futures are more likely to be in the variance portfolios. This elevates the variances of the loser and winner portfolios relative to the variances of returns for quintiles two through four.

For instance, when $J = 6$, when portfolios are formed without standardizing returns, the standard deviation of returns of the loser portfolio is .0372 and that for the winner portfolio is .0364. In contrast, the volatilities of portfolios based on performance quintiles two, three, and four are .0192, .0166, and .0194, respectively. In contrast, when standardized returns are used to form portfolios, the loser portfolio volatility is .0281 and that of the winner portfolio .0287. For the intermediate portfolios, the volatilities are .0238, .0234, and .0242.

To determine whether these mean returns merely reflect a reward for risk, I regress the monthly returns on the four portfolios against various risk factors. I first use the CAPM, with the return on the CRSP value weighted portfolio as the measure of the market return. I then use the three Fama-French factors, and the three Fama-French factors and a stock momentum factor as independent variables.[2]

Table 5 reports the results for dollar denominated futures. For each of the four momentum portfolios studied, the regression constants in each of the three regressions are positive and significantly different from zero (at p-values well below .01) except when the momentum factor is included in the regressions for the portfolios formed using non-standardized returns. Indeed, when a momentum factor is excluded, the constant is often larger than the unconditional mean return on the relevant momentum portfolio. Thus, as is the case with equity momentum portfolios, canonical asset pricing models cannot explain momentum returns.

Interestingly, the Fama-French momentum factor is positive and significant in each regression in which it is included. This reflects the fact that the correlation between this factor and the return on the futures momentum portfolio ranges between .26 and .28, depending on $\{J, K\}$ and whether portfolios are formed using standardized or non-standardized returns. Nonetheless, for the standardized return-based portfolios, the constant term in the regression including the momentum factor is significant with a p-value of 1.5 percent for $J = 9$, $K = 3$, and .4 percent for $J = K = 6$. This result suggests that futures momentum is related to, but not subsumed by, stock momentum. Moreover, the significance of the equity momentum variable in the futures momentum regressions bolsters the interpretation of momentum as a true risk factor.

Table 6 reports similar results for the entire set of contracts. Again, the

[2]In each regression, I also include a January dummy, the coefficients for which are not reported as they are typically insignificant.

constant terms remain positive and significant even after adjusting for risk as measured by the CAPM and the Fama-French factors. Indeed, the constant terms actually exceed the unconditional mean momentum returns when the CAPM and the three Fama-French factors are used to measure risk. When a momentum factor is included in the Fama-French time series regression using the standardized returns, the constant term is still significant although somewhat diminished in magnitude, and the coefficient on the momentum factor is positive and significant; the constants for the portfolios based on non-standardized returns are marginally significant. The correlation between the Fama-French momentum factor and the futures momentum returns based on the broad data set is .30.

Thus, as the case with stock momentum, futures momentum returns are not compensation for risks as measured by standard asset pricing models. There is a relationship between futures momentum returns and stock momentum returns, but including the latter as a "factor" does not eliminate futures momentum profits.

4 Risk Adjusted Momentum Returns Based on a SDF

ACD propose using a stochastic discount factor ("SDF") model to adjust for risk in place of parametric pricing models such as CAPM and Fama-French. ACD find that such an approach leads to sharp reductions in the estimates of momentum returns, particularly when the stochastic discount factor is time-varying.

I implement the ACD approach using the futures momentum portfolios

$J = K = 6$, and $J = 9$, $K = 3$, for both non-standardized and standardized return-based portfolio formation. I first estimate the SDF m_T assuming that it is not time varying. I then estimate a model that permits m_T to vary with variables that are plausibly related to time-varying expected returns.

Estimation of an SDF in this way requires a choice of basis assets. ACD use industry portfolios. I have done so as well, but find that industry portfolios augmented by futures portfolios perform better. Most important, when applied to momentum returns the Wald and likelihood ratio statistics used to test for spanning described in Kan-Zhou (2002) are larger using the 20 industry portfolios than is the case when one uses 5 industry portfolios, the riskless bond and 9 futures portfolios as the basis assets.[3] Thus, the probability that 20 industry portfokios do not span momentum returns is higher than the probability that the 5 industry and 9 futures portfolios do.

As discussed in section 2, the expected discounted returns on the futures portfolios and the futures momentum portfolio should equal zero. The expected discounted (gross) returns on the industry portfolios and the riskless bond should equal 1.

The SDF is posited to be a linear combination of the returns on the basis assets. As is conventional, I use GMM to estimate m_T. When the momentum portfolio is included in the estimation, the model is overidentified, with one overidentifying restriction. I use a J-test to determine whether the average pricing error on the momentum portfolio–denoted by α–is significantly

[3]The portfolios are grain and oilseeds, soft commodities, energy, industrials, interest rates, currencies, indices, livestock, and precious metals. The returns on the nine futures portfolios are given by the equally weighted monthly returns on futures contracts assigned to them. The portfolio assignments are set out in Table 1.

different from zero. If momentum returns represent compensation for risk, which is properly measured by the estimated SDF, the α equals zero.

Table 7 reports the mean pricing error α for the momentum portfolios and the p-values for testing the hypothesis $\alpha = 0$ when the SDF is not time varying. The estimates in Table 7 impose the constraint that $m_T \geq 0$. In this case, the SDF for month T is estimated as $m_T = \max\{\mathbf{x}'_\mathbf{T}\delta, 0\}$, where $\mathbf{x}_\mathbf{T}$ is the vector of gross returns on the basis assets (one plus the return on the equity industry portfolios, and the return on the futures portfolios), and δ is a vector of coefficients estimated using GMM. The fact that m_T is constrained to be non-negative imposes a no-arbitrage restriction.[4]

For the dollar denominated futures momentum portfolios, the momentum portfolio mean pricing errors are positive, and somewhat smaller than the associated unconditional mean momentum portfolio returns. Thus, the risk adjustment reduces the momentum return somewhat, but does not eliminate it. Moreover, one can reject the null of zero mean pricing error at the 1 percent level for portfolios formed using standardized returns. One can reject the null of zero mean pricing error for the non-standardized portfolios at the 5 percent level.

For the broader collection of futures that includes non-dollar denominated contracts, for portfolios based on standardized returns, one can reject the null of zero pricing error at a p-value of .0021 for the $J = K = 6$ portfolio, and

[4] In general, when the model is estimated only under the weaker law of one price assumption with a non-time varying m_T function, estimated momentum portfolio pricing errors are slightly smaller than the unconditional mean momentum returns. However, for the non-time varying SDF, one can still reject the null hypothesis of zero pricing error at the five percent level for most portfolios studied.

at $p = .0051$ for the $J = 9$, $K = 3$ portfolio. Here, these pricing errors are slightly larger than the unconditional mean momentum returns. Pricing errors for the portfolios formed using non-standardized returns are modestly smaller than the mean returns on the momentum portfolios. The α for both the $J = 6, K = 6$ and $J = 9, K = 3$ portfolios are significant.

Table 8 reports mean pricing errors for the momentum portfolios and the associated p-values, when the SDF is time varying. In this case, the SDF for month T is estimated as $m_T = \max\{(\mathbf{x_T} \otimes \mathbf{Z_T})'\delta, 0\}$ where $\mathbf{Z_T}$ is an vector of instruments.[5] I utilize instruments that have been documented to have predictive power for returns. Specifically, I utilize the term spread (i.e., the difference between the 10 year and 3 month Treasury yields), the default spread (the difference in yields between Baa and Aaa corporate bonds), the three month riskless interest rate, and the dividend yield on the CRSP value weighted index.[6]

For returns based on standardized performance-based portfolios, the pricing errors are approximately 40 percent smaller than the unconditional mean momentum portfolio return for dollar denominated futures. Thus, some of the mean momentum return is compensation for risk. However, for USD denominated contracts, the pricing errors are significantly different from zero at the 5 percent level for the portfolios formed using standardized returns.

[5]Without the no arbitrage restriction, one can reject the hypothesis of zero mean pricing error at the 5 percent level for dollar denominated futures. Risk adjustment reduces pricing errors by between 6 and 11 basis points.

[6]When only three instruments are used (regardless of the combination) the mean pricing errors are significant at the 2 percent level regardless of whether standardized or non-standardized returns are used.

The probability that the $J = K = 6$ mean pricing error is zero for portfolios constructed using standardized returns is .0007. For $J = 9$ and $K = 3$, the probability is somewhat larger, .0215. However, for the portfolios constructed using non-standardized performance, the p-value is .3454 for $J = K = 6$ and .2687 for $J = 9$, $K = 3$. Thus, one cannot reject the null of zero mean pricing error for a time varying SDF when one forms winner and loser portfolios based on non-standardized performance. This is similar to what is documented for equities by ACD, although (a) the differences between unconditional mean momentum returns and risk adjusted momentum returns and (b) the p-values found here are both substantially smaller than those they report.

For the broader momentum portfolios, time varying risk adjustment also results in pricing errors that are about 40 percent smaller than the unconditional mean momentum return when momentum portfolios are formed using standardized performance. For $J = K = 6$ one can reject the null of zero pricing error with a $p = .0117$. With $J = 9$, $K = 3$ one rejects the null with $p = .0167$. For portfolios based on non-standardized returns, the mean pricing error is not significant at the 10 percent level for for all portfolios studied.

These results provide an interesting contrast to those of ACD, who find that risk adjustment using an SDF, especially including conditioning information, eliminates virtually all of the superior performance of US equity momentum portfolios. In contrast, when momentum portfolios are formed using standardized performance, SDF-based risk adjustment reduces but does not eliminate the momentum portfolio pricing errors, regardless of whether the

SDF is time varying or not. In this case, momentum returns are reliably different from zero even after a time varying risk adjustment. Results are weaker for portfolios formed using non-standardized relative performance. Therefore, even non-parametric risk adjustment does not necessarily eliminate momentum returns in futures portfolios, especially if one constructs momentum portfolios so as to reduce the likelihood that high variance futures are included in the extreme performance portfolios. Absent standardization, more volatile futures are more likely to be included in the momentum portfolios. This adds noise to the momentum portfolios. Given the sensitivity of results to the method of determining winners and losers, results documented in equity markets may change if momentum portfolios are formed on the basis of standardized relative performance rather than absolute relative performance.

5 Characteristics of Momentum Portfolios

Momentum strategies are trading-intensive. Therefore, the ability of market participants to realize momentum returns depends crucially on the transactions costs of buying and selling momentum portfolios. These costs, in turn, may depend on the characteristics of the instruments in the momentum portfolios. For instance, transactions costs are likely to be high if low volume contracts are disproportionately represented in momentum portfolios.

Each month, I examine three characteristics of the contracts included in momentum portfolios: average daily volume, average open interest, and variance. Volume is measured as the number of contracts traded (in the front month) multiplied by the notional value of each contract (in dollars).

Notional value for a given day is the size of the contract (e.g., 5000 bushels for corn) multiplied by the settlement price on that day. Open interest is similarly defined as the dollar notional value of open positions at the end of each day. Dollar values are used to reflect the large variation in the value of different futures contracts; whereas the value of the commodity that is deliverable against a single grain contract might be worth \$10000, the securities underlying a single T-bond contract are worth ten times as much. Variance in a month is the variance of the daily returns on the front month futures contract.

Volume and open interest grew dramatically over the sample period, particularly for financial futures contracts. Moreover, the composition of the contracts included in the data set changed somewhat, with more financial futures represented in the later period. Finally, there is considerable skewness in the volume and open interest figures. In particular, the dollar volumes and open interest for the Eurodollar contract are far larger than for any other contract included in the data set. The notional value of an individual Eurodollar futures contract is approximately \$1 million, and towards the end of the sample, volume in this contract totaled several hundred thousand contracts. Thus, notional turnover on the Eurodollars was routinely in the hundreds of billions of dollars. In contrast, notional turnover on a large commodity contract such as corn or crude oil is typically on the order of \$1 billion.

The changes in the composition of the futures contract included in the data set, and the skewness in volumes and open interest make sample average values of volume and open interest for the quintile portfolios difficult to interpret. Table 9 therefore reports the mean percentile volume and open interest of the futures contracts in the quintile portfolios, along with the mean variances of these futures. Results reported pertain to the $J = 6$, $K = 6$ momentum portfolios, but similar findings obtain for other portfolios.

To calculate the mean volume percentile, for each month in which portfolios were formed, I calculate the average dollar trading volume for each futures contract in the prior 6 months, which I use to determine the volume percentile of each of these contracts. Finally, in each month, I calculate the average of the volume percentiles of the contracts in the first quintile portfolio, the second quartile portfolio, and so on. Table 9 reports the average of the average percentiles for each portfolio across all 257 months in the sample. The open interest average percentiles are calculated similarly.

Panel A of Table 9 reports the results for portfolios formed on the basis of standardized returns, and Panel B depicts the results for portfolios formed using non-standardized returns. Note that for the standardized portfolios, the volume rank of loser portfolios is very slightly below the median, whereas that of the winner portfolios is very slightly above the median. However, the disparity in volume ranks is small. Similar results hold for the hold for the open interest ranks. Thus, implementation of the momentum strategy based on standardized returns does not require an investor to trade in relatively low volume or open interest contracts. Nor are the variances of the futures in the winner and loser portfolios substantially different from the variances of the futures in the intermediate performance quintiles.

Results are somewhat different for the portfolios formed using raw monthly returns. Winner and loser portfolios consist of relatively low volume contracts; the average future in each of these portfolios is falls approximately the 45th percentile for volume and open interest. Moreover, note that the average variances of the futures included in the winner and loser portfolios are almost 60 percent greater those of the variances of the futures in the intermediate performance portfolios. These results reflect almost exclusively the impact of Eurodollar futures. Eurodollar futures prices exhibit very low variance as compared to other contracts included in the data set. When portfolios are formed using non-standardized returns, Eurodollar futures are almost never included; they only appear in three loser portfolios and one winner portfolio, out of a possible 257 portfolios. However, as noted earlier, Eurodollars almost always have the largest volume and open interest. In contrast, when portfolios are formed on the basis of standardized returns, Eurodollars are in the winner or loser portfolio in about 25 percent of the portfolio formation months; this is actually larger than the 20 percent that would be expected if all contracts were equally likely to be represented in these portfolios.

In sum, implementation of a momentum trading strategy in futures does not require an investor to trade disproportionately in low volume, low open interest, or high variance contracts, especially if he forms portfolios based on standardized past performance. This undercuts any contention that the momentum results are attributable to differences in transactions costs across quintile portfolios.

6 Summary and Conclusions

There have been numerous studies of momentum in equity markets. This raises the question of whether momentum is a broader phenomenon, as behavioral models predicated on the assumption of widespread investor biases would predict. This article examines futures prices for evidence of momentum. Several results stand out. First, like equities, futures returns exhibit momentum at short horizons and reversals at long horizons. Second, standard parametric asset pricing models cannot explain the returns on momentum portfolios. Thus, if these models capture the relevant priced risks, momentum in futures markets presents another pricing anomaly. Third, futures momentum returns are correlated with stock momentum returns, but futures momentum portfolios earn positive risk-adjusted returns even if stock momentum returns are included as a risk factor. Fourth, although using a non-parametric stochastic discount factor to control for risk reduces momentum returns, it does not eliminate them, especially if momentum portfolios are formed based on standardized performance rather than raw performance. Finally, the futures contracts included in momentum portfolios do not have unusually low or high volumes or open interests.

In brief, the momentum phenomenon is not restricted to stocks. Indeed, inasmuch as the futures contracts included in this analysis represent directly or indirectly a far broader slice of available investment opportunities than do equities alone, the results of this article suggest that momentum is pervasive. These results therefore present a further challenge to asset pricing models.

This article also suggests that futures prices represent fertile ground for the testing of asset pricing models more generally.[7] Futures markets represent a much broader and more diverse cross section of investment opportunities than do equities alone. Moreover, futures prices are closely related to the prices of a variety of other instruments (e.g., government bonds, swaps) that are economically important, but which are not typically included in empirical asset pricing work. Futures prices are readily available, and since most major futures contracts were introduced no later than the mid-1980s, it is now possible to assemble a respectable time series of monthly futures returns. Thus, including futures price data would benefit empirical asset pricing research.

[7]Dusak (1973), Breeden (1980), Reynauld and Tessier (1984), Cutler *et al* (1981) and Chan and Bessembinder (1992) represent early examples of empirical testing of asset pricing models on futures price data.

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Table 1
Futures Contracts Used in Analysis

Panel A–Dollar Denominated Futures

Commodity	Exchange	NOBS
Grains & Oilseeds		
Corn	CBT	263
Wheat	CBT	263
Wheat	KCBT	263
Oats	CBT	263
Soybeans	CBT	263
Soybean Oil	CBT	263
Soybean Meal	CBT	263
Meats & Livestock		
Feeder Cattle	CME	263
Lean Hogs	CME	263
Live Cattle	CME	263
Pork Bellies	CME	263
Softs		
Coffee	CSCE (NYBOT)	263
Cocoa	CSCE (NYBOT)	263
World Sugar	CSCE (NYBOT)	263
US Sugar	CSCE (NYBOT)	179
Cotton	NYCE (NYBOT)	263
Orange Juice	NYCE (NYBOT)	263
Industrials		
Aluminum	LME	198
Copper	LME	263
Copper	COMEX	263
Lead	LME	215
Nickel	LME	215
Plywood	CME	263
Zinc	LME	183
Precious Metals		
Gold	COMEX	263
Silver	COMEX	263
Platinum	NYMEX	263
Palladium	NYMEX	263

Table 1 Continued		
Panel A–Dollar Denominated Futures		
Commodity	Exchange	NOBS
Energy		
Crude Oil	NYMEX	248
Gasoline	NYMEX	228
Heating Oil	NYMEX	263
Natural Gas	NYMEX	164
Foreign Currency		
Australian Dollar	CME	203
British Pound	CME	263
Canadian Dollar	CME	263
Deutsche Mark/Euro	CME	263
Dollar Index	NYFE	217
Japanese Yen	CME	263
Swiss Franc	CME	263
Interest Rate		
Eurodollars	CME	261
Five Year T-Notes	CBT	187
Municipal Bonds	CBT	222
Ten Year T-Note	CBT	259
Thirty Year T-Bond	CBT	263
Treasury Bill	CBT	263
Indices		
Dow Jones 30	CBT	71
GSCI	CME	137
NASDAQ 100	CME	71
NYSE Composite	NYFE	244
Nikkei 225	CME	159
Russell 5000	CME	130
S&P 500	CME	260

Table 1		
Panel B–Foreign Futures		
Commodity	Exchange	NOBS
Grains & Oilseeds		
Barley	LCE	99
Rapeseed	WCE	263
Wheat	WCE	263
Potatoes	LCE	99
Feed Wheat	LCE	147
Softs		
Cocoa	LCE	209
Coffee	LCE	152
Sugar #5	LCE	163
Interest Rates		
Australian 10 Year Bond	SFE	186
Australian 3 Year Bond	SFE	227
Japanese 10 Year Government	TSE	217
Eurosterling	LIFFE	252
Euroswiss	LIFFE	153
Euroyen	TIFFE	165
Long Gilt	LIFFE	227
Canadian 10 Year Bond	ME	163
Canadian Bankers' Acceptances	ME	188
Bund	EUREX	155
Notionel	MATIF	203
Indices		
FTSE 100	LIFFE	227
TOPIX	TSE	137
Iberian Index	MEFF	132
CAC 40	MATIF	179
Hang Seng	HKFE	145
Nikkei 225	SGX	206

The foregoing table lists the futures contracts used in the empirical analysis, the exchanges on which they are traded, and the number of observations for each. Exchange abbreviations are: CBT-Chicago Board of Trade; CME-

Chicago Mercantile Exchange; KCBT-Kansas City Board of Trade; CSCE-Coffee, Sugar, Cocoa Exchange; NYBOT-New York Board of Trade; NYCE-New York Cotton Exchange; LME-London Metals Exchange; NYMEX-New York Mercantile Exchange; COMEX-Commodity Exchange of New York; NYFE-New York Futures Exchange; LCE-London Commodity Exchange; WCE-Winnipeg Commodity Exchange; SFE-Sydney Futures Exchange; TSE-Tokyo Stock Exchange; TIFFE-Tokyo International Financial Futures and Options Exchange; LIFFE-London International Financial Futures and Options Exchange; HKFE-Hong Kong Futures Exchange; SGX-Singapore Futures Exchange; ME-Montreal Exchange; MEFF-Mercade De Opciones Y Futuros Financieros; MATIF-Marche a Termes d'Instruments Financiers. NOBS is the number of months of available returns for each future.

Table 2
Panel A
Returns on Momentum Portfolios
USD Momentum Portfolios Formed Using Non-Standardized Performance

	J			
Time After Portfolio Formation	3	6	9	12
1st Quarter	.0211 (2.59)	.0146 (2.40)	.0273 (3.96)	.0189 (2.66)
2nd Quarter	.0144 (2.49)	.0241 (3.46)	.0154 (2.30)	-.0004 (-.05)
3rd Quarter	.0196 (3.01)	.0101 (1.45)	-.0104 (-1.65)	-.0089 (-1.45)
4th Quarter	-.0005 (-.08)	-.0248 (-4.34)	-.0273 (-4.24)	-.0197 (-3.03)
1st Year	.0538 (3.68)	.0243 (1.46)	.0064 (.38)	-.0078 (-.43)
2nd Year	-.0459 (-2.76)	-.0594 (-3.12)	-.0653 (-3.70)	-.0660 (-3.90)
3rd Year	.0115 (.90)	.0034 (.23)	-.0038 (-.25)	.0040 (.021)

Table 2 Panel B Returns on Momentum Portfolios USD Momentum Portfolios Formed Using Standardized Performance				
	J			
Time After Portfolio Formation	3	6	9	12
1st Quarter	.0175 (3.14)	.0194 (3.37)	.0252 (3.87)	.0194 (2.86)
2nd Quarter	.0146 (2.73)	.0253 (4.03)	.0158 (2.30)	.0019 (.28)
3rd Quarter	.0174 (2.87)	.0120 (1.79)	-.0060 (-.89)	-.0075 (-1.16)
4th Quarter	.0018 (.31)	-.0203 (-3.57)	-.0199 (-3.23)	-.0137 (-1.92)
1st Year	.0500 (3.20)	.0366 (1.89)	.017 (.79)	-.0137 (.10)
2nd Year	-.0463 (-2.38)	-.0566 (-2.40)	-.0567 (-2.31)	-.0588 (-2.43)
3rd Year	-.0040 -.26	-.0051 (-.27)	.0010 (.05)	.0007 (.027)

This table reports mean momentum returns for dollar denominated futures over quarterly and annual periods following portfolio formation. J indicates the number of months used to measure performance for the purpose of forming momentum portfolios. The line labelled 1st Quarter reports performance in the first quarter after formation, that labelled 2nd Quarter reports performance in the second quarter after formation, and so on. t-statistics are in parentheses, and are calculated using Newey-West standard errors that adjust for overlapping observations.

Table 3
Panel A
Returns on Momentum Portfolios
All Momentum Portfolios Formed Using Non-Standardized Performance

	J			
Time After Portfolio Formation	3	6	9	12
1st Quarter	.0205 (3.77)	.0164 (3.10)	.0273 (4.50)	.0209 (3.35)
2nd Quarter	.015 (2.69)	.0237 (3.63)	.0204 (3.38)	.0039 (.61)
3rd Quarter	.0169 (2.66)	.0132 (2.07)	-.0035 (-.63)	-.0052 (-.90)
4th Quarter	.0021 (.37)	-.0188 (-3.74)	-.0182 (-3.33)	-.0166 (-2.78)
1st Year	.0539 (3.70)	.0346 (2.28)	.0282 (2.20)	.0051 (.32)
2nd Year	-.0460 (-2.98)	-.0484 (-3.17)	-.0580 (-3.92)	-.0775 (-4.45)
3rd Year	-.0068 (-.54)	-.0120 (-.81)	-.0200 (-1.19)	-.0116 (-.67)

Table 3 Panel B Returns on Momentum Portfolios All Momentum Portfolios Formed Using Standardized Performance				
	J			
Time After Portfolio Formation	3	6	9	12
1st Quarter	.0161 (3.35)	.0175 (3.43)	.0211 (3.61)	.0191 (3.10)
2nd Quarter	.0118 (2.44)	.0196 (3.34)	.0152 (2.37)	.0039 (.65)
3rd Quarter	.0175 (3.13)	.0130 (2.10)	-.0050 (-.08)	-.0027 (-.45)
4th Quarter	.0012 (.23)	-.0161 (-3.21)	-.0153 (-2.36)	-.0119 (-2.04)
1st Year	.0453 (3.18)	.0351 (1.73)	.0239 (1.40)	.0126 (.59)
2nd Year	-.0373 (-2.27)	-.0459 (-2.31)	-.0514 (-2.36)	-.0594 (-2.74)
3rd Year	-.0135 (-.92)	-.0137 (-.84)	-.0130 (-.70)	-.0136 (-.66)

This table reports mean momentum returns for the entire set of futures contracts over quarterly and annual periods following portfolio formation. J indicates the number of months used to measure performance for the purpose of forming momentum portfolios. The line labelled 1st Quarter reports performance in the first quarter after formation, that labelled 2nd Quarter reports performance in the second quarter after formation, and so on. t-statistics are in parentheses, and are calculated using Newey-West standard errors that adjust for overlapping observations.

Table 4		
Cross Section Regressions on Lagged Returns		
Lag	Slope Coefficient	t-statistic
1	0.0813	3.54
2	0.0258	1.26
3	0.0366	1.88
4	-0.0068	-0.37
5	0.0338	1.89
6	0.0300	1.64
7	0.0244	1.34
8	-0.0027	-0.14
9	0.0092	0.48
10	0.0605	2.97
11	0.0491	2.71
12	0.0007	0.03
13	-0.0533	-3.02
14	-0.0303	-1.68
15	-0.0737	-4.09
16	0.0137	0.78
17	-0.0201	-1.19
18	-0.0089	-0.55
19	0.0006	0.04
20	0.0071	0.40
21	0.0215	1.20
22	-0.0067	-0.39
23	0.0068	0.45
24	-0.0095	-0.55
25	-0.0577	-3.20
26	-0.0233	-1.46
27	-0.0032	-0.20
28	-0.0115	-0.75
29	-0.0073	-0.46
30	0.0136	0.84
31	0.0009	0.05
32	-0.0077	-0.47
33	0.0082	0.47
34	0.0168	1.04
35	0.0110	0.71
36	0.0187	1.16

This table reports the average slope coefficients and their associated t-statistics in monthly cross sectional regressions of futures returns against lagged futures returns.

Table 5 Panel A Risk Adjusted Performance USD Standardized Return-based Momentum Portfolios J=6,K=6				
Variable	Monthly Mean Return	Fama French 4 Factor	Fama French 3 Factor	CAPM
Intercept	.0079 (3.70)	.0064 (2.76)	.0088 (3.96)	.0080 (3.56)
Market		.03 (.60)	-.02 (-.39)	.04 (.91)
MTB		.04 (.62)	-.00 (-.02)	
SIZE		-.07 (-.90)	-.21 (-3.33)	
MOMENTUM		.17 (2.90)		
R^2		.0818	.051	.035

Table 5 Panel B Risk Adjusted Performance USD Non-Standardized Return-based Momentum Portfolios J=6,K=6				
Variable	Monthly Mean Return	Fama French 4 Factor	Fama French 3 Factor	CAPM
Intercept	.0071 (2.65)	.0052 (1.88)	.0085 (3.12)	.0080 (3.37)
Market		.03 (.50)	-.04 (-.62)	.04 (.85)
MTB		.03 (.36)	-.03 (-.36)	
SIZE		-.07 (-.90)	-.26 (-3.32)	
MOMENTUM		.24 (3.28)		
R^2		.0884	.0572	.0323

Table 5 Panel C Risk Adjusted Performance USD Standardized Return-based Momentum Portfolios J=9,K=3				
Variable	Monthly Mean Return	Fama French 4 Factor	Fama French 3 Factor	CAPM
Intercept	.0086 (3.32)	.0061 (2.19)	.0095 (3.56)	.0087 (3.18)
Market		.06 (.92)	-.02 (-.26)	.05 (.93)
MTB		.01 (.16)	-.05 (-.62)	
SIZE		-.05 (-.55)	-.26 (-3.34)	
MOMENTUM		.25 (3.50)		
R^2		.0921	.0457	.0352

Table 5 Panel D Risk Adjusted Performance USD Non-Standardized Return-based Momentum Portfolios J=9,K=3				
Variable	Monthly Mean Return	Fama French 4 Factor	Fama French 3 Factor	CAPM
Intercept	.0082 (2.66)	.0057 (1.75)	.0098 (3.12)	.0086 (3.38)
Market		.03 (.35)	-.06 (-.87)	.04 (.81)
MTB		-.02 (-.15)	-.01 (-.94)	
SIZE		-.11 (-.99)	-.36 (-3.92)	
MOMENTUM		.30 (3.56)		
R^2		.106	.0607	.0370

This table reports coefficients from regressions of monthly dollar denominated futures momentum returns against risk factors. Market is the return on the value-weighted CRSP index. MTB is the return on the Fama-French Market-to-Book portfolio. SIZE is the return on the Fama-French Size portfolio. MOMENTUM is the return on the Fama-French momentum portfolio. t-statistics in parentheses.

Table 6
Panel A
Risk Adjusted Performance
All Standardized Return-based Momentum Portfolios
J=6,K=6

Variable	Monthly Mean Return	Fama French 4 Factor	Fama French 3 Factor	CAPM
Intercept	.0066 (3.31)	.0048 (2.36)	.0074 (3.63)	.0067 (3.21)
Market		.05 (1.09)	-.01 (-.11)	.05 (1.16)
MTB		.04 (.53)	-.05 (-.77)	
SIZE		-.06 (-.75)	-.22 (-3.63)	
MOMENTUM		.20 (3.57)		
R^2		.1033	.0576	.0371

Table 6
Panel B
Risk Adjusted Performance
All Non-Standardized Return-based Momentum Portfolios
J=6,K=6

Variable	Monthly Mean Return	Fama French 4 Factor	Fama French 3 Factor	CAPM
Intercept	.0078 (3.68)	.0051 (1.95)	.0082 (3.27)	.0073 (2.88)
Market		.05 (.87)	-.02 (-.20)	.05 (.94)
MTB		.01 (.14)	-.05 (-.61)	
SIZE		-.06 (-.67)	-.25 (-3.54)	
MOMENTUM		.23 (3.37)		
R^2		.0906	.0442	.0422

Table 6
Panel C
Risk Adjusted Performance
All Standardized Return-based Momentum Portfolios
J=9,K=3

Variable	Monthly Mean Return	Fama French 4 Factor	Fama French 3 Factor	CAPM
Intercept	.0074 (3.06)	.0042 (1.69)	.0080 (3.30)	.0072 (2.88)
Market		.05 (.95)	-.03 (-.51)	.04 (.72)
MTB		-.01 (-.15)	-.09 (-1.11)	
SIZE		-.04 (-.47)	-.25 (-3.77)	
MOMENTUM		.28 (4.35)		
R^2		.1225	.0562	.0452

Table 6
Panel D
Risk Adjusted Performance
All Non-Standardized Return-based Momentum Portfolios
J=9,K=3

Variable	Monthly Mean Return	Fama French 4 Factor	Fama French 3 Factor	CAPM
Intercept	.0090 (2.86)	.0057 (1.95)	.0099 (3.52)	.0089 (3.07)
Market		.05 (.77)	-.04 (-.6)	.04 (.65)
MTB		-.02 (-.17)	-.01 (-1.07)	
SIZE		-.06 (-.61)	-.31 (-3.84)	
MOMENTUM		.31 (4.14)		
R^2		.1179	.0576	.0381

This table reports coefficients from regressions of monthly all futures momentum returns against risk factors. Market is the return on the value-weighted CRSP index. MTB is the return on the Fama-French Market-to-Book portfolio. SIZE is the return on the Fama-French Size portfolio. MOMENTUM is the return on the Fama-French momentum portfolio. t-statistics in parentheses.

Table 7

Panel A

Unconditional No-Arbitrage Momentum Performance

Momentum Portfolios Based on Non-Standardized Returns

Futures	J	K	Unconditional	α	p-value
USD	6	6	.0071	.0059	.0453
USD	9	3	.0082	.0069	.0481
All	6	6	.0072	.0065	.0112
All	9	3	.0090	.0083	.0039

Panel B

Unconditional No-Arbitrage Momentum Performance

Momentum Portfolios Based on Standardized Returns

Futures	J	K	Unconditional	α	p-value
USD	6	6	.0079	.0073	.0003
USD	9	3	.0086	.0078	.0106
All	6	6	.0066	.0068	.0021
All	9	3	.0072	.0073	.0051

This table reports mean pricing errors–α–for momentum portfolios. The stochastic discount factor is non-time varying, and equals $\max\{\mathbf{x_t}\delta, 0\}$, where $\mathbf{x_t}$ is a vector of gross returns on basis assets, and δ is a vector of coefficients. δ is estimated using GMM. p-values are based on a Hansen J-test.

Table 8					
Panel A					
Conditional No-Arbitrage Momentum Performance					
Momentum Portfolios Based on Non-Standardized Returns					
Futures	J	K	Unconditional	α	p-value
USD	6	6	.0071	.0032	.3454
USD	9	3	.0082	.0040	.2687
All	6	6	.0072	.0037	.1367
All	9	3	.0090	.0046	.1212
Panel B					
Conditional No-Arbitrage Momentum Performance					
Momentum Portfolios Based on Standardized Returns					
Futures	J	K	Unconditional	α	p-value
USD	6	6	.0079	.0049	.0007
USD	9	3	.0086	.0050	.0215
All	6	6	.0066	.0038	.0117
All	9	3	.0072	.0040	.0167

This table reports mean pricing errors–α–for momentum portfolios. The stochastic discount factor is time varying, and equals $\max\{(\mathbf{x_t} \otimes \mathbf{Z_t})'\delta, 0\}$, where $\mathbf{x_t}$ is a vector of gross returns on basis assets, $\mathbf{Z_t}$ is a vector of instruments and δ is a vector of coefficients. The instruments are the default spread, the time spread, and the dividend yield. δ is estimated using GMM. p-values are based on a Hansen J-test.

Table 9
Momentum Portfolio Characteristics
Panel A–Portfolios Based on Standardized Performance

Characteristic	Q1	Q2	Q3	Q4	Q5
Volume	.4920	.5099	.5081	.5096	.5350
Open Interest	.4919	.5022	.5025	.5070	.5187
Variance	.5089	.5191	.5181	.5132	.4995
Panel B–Portfolios Based on Non-Standardized Performance					
Volume	.4537	.5382	.5510	.5351	.4763
Open Interest	.4456	.5318	.5536	.5300	.4604
Variance	.6543	.4269	.3852	.4381	.6543

This table reports average percentiles for the volume, open interest, and variance of the futures contracts in each of the quintile portfolios. Q1, Q2, Q3, Q4, and Q5 represent the 5 quintile portfolios. A value of .4920 for portfolio Q1 volume indicates that on average, the volume of futures contracts included in the loser portfolio fell in the 49.2 volume percentile during the portfolio formation period. All figures based on $J = 6$ portfolio formation period.