

NBIM DISCUSSION NOTE

Momentum in Futures Market

In this note, we survey the academic literature and provide empirical evidence related to time-series momentum strategies in the futures markets. We find that this phenomenon is remarkably consistent across 47 diverse futures contracts in our study, and has led some to consider time-series momentum an asset pricing anomaly.

Main findings

- We find strong time-series momentum patterns in monthly and weekly frequencies across 47 diverse futures contracts. In particular, we find significant return persistence in the first 12 months which partially reverses, consistent with behavioural theories of early under-reaction and delayed over-reaction.
- Similar to Baltas and Kosowski (2012), we find that time-series momentum strategies with different investment horizons appear to capture distinct return continuation phenomena. As a result, there exist potential diversification benefits from combining time-series momentum strategies of different frequencies.
- Further research is, however, required to assess the trade-off between the improvement in risk-return characteristics and the transaction costs and potential market impact associated with higher turnover.
- There exists asymmetry in the return contribution from the long and short legs, such that the long signals add more value to overall strategy performance.
- Consistent with the findings of Christoffersen and Diebold (2006) and Christoffersen, Diebold, Mariano, Tay, and Tse (2007), we find that the return profile of individual time-series momentum strategies generally deteriorates when underlying asset volatility is high.
- Assuming reasonable predictability of the volatility regime an asset is in, we argue that this relationship can help contribute to risk budgeting decisions in portfolio construction.
- We extend the findings of Moskowitz, Ooi and Pedersen (2012) who examine the positive relationship between time-series and cross-sectional momentum, and show that there is a statistically significant market timing element embedded in time-series momentum for some asset classes.
- The recent weakly positive performance of time-series momentum strategies based on volatility-parity weighting can be partially explained by lower trend persistence and higher asset correlations.

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1. Introduction

We start by asking why long-term investors should care about trend-following strategies. Kroencke, Schindler and Schrimpf (2013) quantify the diversification benefits (increase in Sharpe ratio) from adding foreign exchange investment styles (value, momentum and carry) to portfolios consisting of global equities and bonds. The authors show that this diversification effect holds for different portfolio weighing schemes. Moskowitz, Ooi and Pedersen (2012) show empirically that time-series momentum strategies in the futures market have payoffs similar to an option straddle on equity markets, delivering positive returns during extreme equity moves. Liquidity constraints aside, this implies overlaying a global portfolio of bonds and equities with trend following strategies may improve the risk-return profile of traditional long-term investors.

In this **note**, we survey the available academic literature and provide empirical evidence related to time-series momentum strategies in the futures markets. We find that this phenomenon is remarkably consistent across the 47 diverse futures contracts in our study, and has led some to document time-series momentum as an asset pricing anomaly.

We first construct a comprehensive dataset of daily futures returns by splicing contracts together in a consistent manner, and construct time-series momentum strategies at monthly and weekly frequencies. Similar to existing academic literature, we apply a volatility parity approach which allocates capital proportional to the inverse of asset volatility. We then test the time-series predictability of futures returns for each asset class and examine the risk-return and turnover characteristics related to momentum strategies over a range of look-back and holding periods. Motivated by Baltas and Kosowski (2012) who show that strategies of different trading frequencies capture distinct return continuation phenomenon, we examine the diversification benefits from combining strategies with different investment horizons by varying both the look-back and holding periods.

We then conduct a performance attribution analysis on the long-short time-series momentum portfolios which can exhibit variable market bias over time, and find that there exists asymmetry in the return contribution from the long and short legs. Christoffersen and Diebold (2006) and Christoffersen et al. (2007) find empirically that return signs are more (less) predictable in low (high) volatility regimes in some equity markets. We extend this analysis to see if this relationship is representative of other asset classes by conditioning the return of individual time-series momentum strategies for both long and short legs on asset volatility.

Moskowitz, Ooi and Pedersen (2012) show that time-series momentum is related to its cross-sectional counterpart through a regression approach. We extend this by directly linking both momentum types to the degree of weight overlap between both portfolios. In addition to cross-sectional momentum, we show that market timing may contribute incrementally to explaining the variability in time-series momentum for some asset classes. We observe that as markets exhibit less trend persistence and become more correlated over the past five years, time-series momentum has been weakly positive.

2. Data and preliminaries

2.1. Futures returns

Our data consists of daily closing futures prices for 20 commodities, 9 developed equity indices, 11 developed government bonds, and 7 cross-currency pairs. We focus on the most liquid instruments to avoid stale pricing and to ensure that a strategy of reasonable size can be practically implemented. The data source for all instruments is Bloomberg, and the sample goes up to June 2013, with variable starting dates depending on the instrument (see Table 1).

Since futures contracts are short-lived contracts, we construct a single futures price series for each instrument by splicing contracts together in an appropriate manner. Similar to Moskowitz et al. (2012) and Baltas and Kosowski (2012), we use the most liquid futures contract at each point in time¹. This means rolling over to the most liquid far contract when liquidity shifts from the near contract to one of the far contracts. In practice, the most liquid contract is the near contract up until a few days or

¹ Liquidity here is measured by volume data

weeks before delivery (depending on instrument), when the nearest far contract becomes the most liquid one. In the absence of volume data, we roll to the nearest far contract at the month end before the near contract expiry.

We note, however, that an instrument's futures return and risk properties may vary across contract choices and/or roll dates. Miffre et al. (2012) and Mouakhar and Roberge (2010) show empirically the added value of maximizing the roll yield of long-only investments to simply buying the most nearby contracts. Daal, Farhat and Wei (2006) show empirically that the volatility of futures returns tend to decrease with contract maturity. They further show that this effect is more pronounced in agricultural and energy commodities than in financial futures². Indeed, Samuelson (1965) hypothesized that the volatility of futures prices increases as their contracts approach maturity. One possible explanation is that most supply and demand shocks occur at the front-end of the curve. As a result, front contracts are most reactive to news, while contracts further along the curve are more inert as there is more time to overcome the shocks.

To remove any artificial non-traded return from contract rollovers, we apply a price adjustment factor at each roll date; that is, we multiply the entire history of the instrument by the ratio of the first price of the new contract and the last price of the last contract. Having obtained a single price data series for each of our instruments, we then construct monthly and weekly returns for our empirical analysis.

Table 1 presents summary statistics for all assets in our dataset which includes the starting month for each contract as well as the first four moments of the monthly return distribution. Similar to the existing futures' literature (Moskowitz et al., 2012, Baltas and Kosowski, 2012), we see substantial cross-sectional variation in the return distributions across different instruments. In particular, we observe larger unconditional return dispersions, volatilities and maximum drawdowns³ for the riskier asset classes of commodities and equities relative to bonds and currencies. Return distributions for all assets also appear highly non-normal. While both commodities and equities exhibit greater excess kurtosis (higher probability of extreme outcomes) relative to normal distributions, equities tend to be negatively skewed relative to commodities, implying more downside risk in equities. On a risk-adjusted return basis, bonds appear most attractive. However, we note that the sample period studied coincided with an environment of declining interest rates which was favourable for bonds.

2 Futures contracts based on financial instruments, such as treasury bonds, currencies or equity indexes

3 From peak to trough

Table 1: Summary statistics on futures contracts

Underlying	Asset Type	Data Start Date	Annualized Returns	Annualized Volatility	Sharpe Ratio	Skewness	Excess kurtosis	Maximum Drawdown
Gold	Commodity	Feb-1975	1.9 %	19.6 %	0.10	0.46	3.39	-90.7 %
Copper	Commodity	Mar-1989	8.5 %	26.6 %	0.32	-0.02	2.48	-64.0 %
Silver	Commodity	Mar-1975	3.2 %	32.9 %	0.10	0.51	5.55	-98.1 %
Platinum	Commodity	Jan-1987	6.0 %	20.9 %	0.29	-0.48	3.19	-62.7 %
Nickel	Commodity	Jan-1998	14.4 %	37.4 %	0.38	0.19	0.10	-80.4 %
Aluminium	Commodity	Jan-1998	-1.3 %	20.2 %	-0.07	0.19	0.25	-60.0 %
LightCrude	Commodity	Dec-1983	14.5 %	35.5 %	0.41	0.38	2.86	-75.6 %
Cattle	Commodity	Apr-1965	4.9 %	17.2 %	0.29	-0.20	1.85	-63.3 %
Cocoa	Commodity	Mar-1960	3.3 %	31.3 %	0.11	0.68	1.35	-98.0 %
Coffee	Commodity	Mar-1973	4.3 %	38.0 %	0.11	1.05	3.11	-95.7 %
Corn	Commodity	Mar-1960	-0.2 %	23.9 %	-0.01	1.13	5.87	-94.0 %
Cotton	Commodity	July-1960	3.7 %	23.6 %	0.16	0.60	2.90	-91.4 %
HeatingOil	Commodity	Mar-1988	15.9 %	33.6 %	0.47	0.71	2.55	-69.1 %
Hogs	Commodity	Mar-1987	0.7 %	25.1 %	0.03	0.01	0.65	-87.7 %
NaturalGas	Commodity	May-1990	-5.0 %	54.7 %	-0.09	0.83	2.61	-99.7 %
Soybeans	Commodity	Jan-1960	6.4 %	25.2 %	0.26	1.17	7.43	-83.2 %
SoybeanMeal	Commodity	Jan-1960	10.9 %	30.2 %	0.36	1.98	13.66	-89.2 %
SoybeanOil	Commodity	Jan-1960	7.8 %	30.0 %	0.26	1.14	5.53	-87.7 %
Sugar	Commodity	Feb-1962	7.6 %	43.9 %	0.17	1.13	3.13	-99.3 %
Wheat	Commodity	Mar-1960	-1.1 %	25.2 %	-0.04	0.72	3.54	-96.8 %
SPX	Equity	Apr-1983	6.8 %	15.3 %	0.44	-0.70	2.04	-58.5 %
UKX	Equity	Apr-1988	5.1 %	15.0 %	0.34	-0.32	0.58	-53.0 %
AEX	Equity	Feb-1989	6.7 %	19.8 %	0.34	-0.72	1.66	-69.3 %
TOPIX	Equity	July-1990	-1.0 %	20.1 %	-0.05	-0.17	1.00	-71.2 %
CAC	Equity	Jan-1989	5.0 %	19.4 %	0.26	-0.36	0.26	-64.8 %
DAX	Equity	Jan-1991	7.7 %	21.5 %	0.36	-0.63	2.29	-74.4 %
HangSeng	Equity	May-1992	11.9 %	26.8 %	0.44	0.18	2.05	-57.7 %
ASS1	Equity	July-2000	3.7 %	13.4 %	0.28	-0.88	0.99	-53.2 %
SPTSX60	Equity	Jan-2000	3.7 %	15.4 %	0.24	-0.75	1.61	-51.5 %
Euro2Yr	Bond	July-1997	1.0 %	1.4 %	0.71	0.21	0.66	-4.2 %
Euro5Yr	Bond	Apr-1992	3.1 %	3.2 %	0.94	-0.04	-0.30	-7.8 %
Euro10Yr	Bond	Jan-1992	4.1 %	5.2 %	0.78	-0.06	-0.09	-10.3 %
Euro30Yr	Bond	Apr-1999	5.3 %	10.2 %	0.52	1.01	2.93	-17.5 %
Canada10Yr	Bond	Jan-1990	4.2 %	6.0 %	0.69	-0.10	0.19	-14.7 %
Japan10Yr	Bond	Jan-1986	3.4 %	5.3 %	0.64	-0.19	4.98	-18.0 %
UK10Yr	Bond	Apr-1983	2.9 %	7.5 %	0.39	0.15	1.47	-28.5 %
US2Yr	Bond	Oct-1990	1.7 %	1.7 %	0.98	0.23	0.33	-3.8 %
US5Yr	Bond	July-1988	3.2 %	4.2 %	0.76	0.06	0.75	-8.4 %
US10Yr	Bond	July-1982	5.4 %	7.1 %	0.77	0.20	0.96	-14.4 %
US30Yr	Bond	Jan-1978	4.3 %	11.4 %	0.38	0.25	1.67	-47.0 %
EURUSD	Currency	Apr-1999	1.5 %	10.7 %	0.14	-0.10	0.84	-24.9 %
CADUSD	Currency	Apr-1987	1.7 %	10.7 %	0.23	-0.32	3.90	-28.5 %
JPYUSD	Currency	Apr-1987	-0.6 %	11.5 %	-0.05	0.54	2.28	-58.3 %
NZDUSD	Currency	July-1997	4.6 %	13.5 %	0.34	-0.25	1.40	-40.2 %
CHFUSD	Currency	Apr-1987	0.8 %	11.7 %	0.07	0.00	0.62	-49.5 %
GBPUSD	Currency	Apr-1987	2.0 %	9.9 %	0.20	-0.46	1.77	-29.2 %
Dollar Index	Currency	Apr-1987	-1.3 %	8.9 %	-0.15	0.39	0.61	-44.3 %

Source: Bloomberg, NBIM calculations

2.2. Time-series momentum

The time-series momentum strategy on a single instrument is one that takes a long/short position in that instrument based on the sign of its historical return over a given look-back period. Throughout the note, we denote J as the look-back period over which the instrument's past performance is measured and K as the holding period.

Following Moskowitz et al. (2012), we aggregate the time series momentum strategy across all instruments as the inverse-volatility weighted average return of all individual momentum strategies. That is, we size each position to have constant ex-ante volatility so that we have equal risk (excluding correlations) contribution from each asset, and to ensure that the return profile is not dominated by volatile periods. The aggregate time series momentum strategy return at each point in time is given by:

$$R_f^K = \frac{1}{N} \sum_{i=1}^N \text{SIGN}(R_i(t-J, t)) \cdot \frac{\theta}{\sigma_i(t; D)} \cdot R_i(t, t+K) \quad (1)$$

where N is the number of instruments, $\text{SIGN}(R_i(t-J, t))$ denotes the sign of the J -period past return for instrument i , $R_i(t, t+K)$ is the K -month forward return, $\sigma_i(t; D)$ is the volatility of the i^{th} instrument based on the past D trading days and θ is the factor which scales the portfolio volatility accordingly for a given risk budget. This approach uses risk estimates to scale the exposure of the strategy in the same spirit as Barroso and Santa-Clara (2012), who use momentum risk to scale the exposure of the strategy in order to have constant portfolio risk over time⁴.

4 We note, however, that the net exposure to the market(s) and the corresponding leverage of the strategy is not held constant in such an approach and is a by-product of the volatility-conditioned portfolio construction. Other portfolio construction techniques exist such as equal risk contribution which incorporates correlations in the weighting process or relative strength where weights are assigned based on the magnitude of past returns, but is beyond the scope of this note.

2.3. Cross-sectional momentum

The cross-sectional momentum effect is based on the idea that assets with high returns in the recent past tend to have higher future returns than assets with low past returns. One commonly used definition of cross-sectional momentum can be represented by:

$$E \left[\frac{1}{N} \sum_{i=1}^N \left(R_{t-J,t}^i - \overline{R_{t-J,t}^i} \right) \left(R_{t,t+K}^i - \overline{R_{t,t+K}^i} \right) \right] > 0 \quad (2)$$

where $R_{t-J,t}^i$ is the realized return of asset i between time $t-J$ and t , and $\overline{R_{t-J,t}^i}$ is the realized cross-sectional median return across all assets between time $t-J$ and t . In other words, we apply a cross-sectional momentum strategy based on the relative ranking of each asset's past J -month returns and form portfolios that go long the past relative "winners" and short the past relative "losers". We note that time series momentum is a timing strategy using each asset's own past returns, which is separate but not unrelated to cross-sectional momentum. Similar to Asness, Moskowitz and Pedersen (2013), we equally weight⁵ the instruments within the long and short legs. We further note that while time-series momentum can have a net long or short bias, cross-sectional momentum is net zero dollar position at rebalance dates by construction.

2.4. Volatility parity

Volatility parity or inverse-volatility weighting allocates capital to assets such that their weighted volatilities are equal. When daily price moves become more volatile, clearing providers typically raise margins to account for the increased risk. Volatility parity portfolios which are based on inverse-volatility weighting are therefore less affected by margin calls, ignoring leverage levels for the moment. However, one of the main issues with volatility parity is that low-risk assets can dominate the portfolio in such an approach. In a multi-asset framework, this necessarily implies leveraging up on low-risk assets such as bonds to attain a certain volatility target. Jacobs and Levy (2012) propose that portfolio theory be augmented to incorporate investor aversion to leverage. They argue that the usual standard deviation of portfolio returns fail to take into account components of risk that are unique to leverage, such as risks and costs of margin calls, losses exceeding the capital invested and the possibility of bankruptcy. Alternative risk measures which capture higher moments and tail risk dependence are beyond the scope of this note and left for future research.

2.5. Explaining the time-series momentum effect

The time-series return predictability associated with momentum challenges the random walk (Fama, 1970) and efficient market hypothesis (Fama, 1991). The objective of this section is to briefly survey the main explanations for momentum put forward by existing academic literature. We start by focusing on the well-established risk-based and behavioural asset pricing theories which pertain to a single risky asset, and therefore having direct implications for time-series, rather than cross-sectional predictability. We then introduce alternative explanations of time-series momentum derived from empirical evidence.

A satisfactory risk-based explanation of momentum requires a plausible pricing kernel⁶, and shows how and why the risk exposures of relative winners on the pricing kernel differ from those of relative losers. We will introduce a few related papers which pertain to a single risky asset. Berk, Green and Naik (1999) argue that a firm's optimal investment choices can change its systematic risk exposure and expected return, and consequently bring about time-series return predictability. Chordia and Shivakumar (2002) extend this idea and link time-series momentum to time variation in expected returns as a function of macroeconomic variables driven by the business cycle. Using a single-firm partial equilibrium model, Johnson (2002) argues that past performance is correlated to the expected growth rate of the dividend process, which in turn is monotonically related to risk. Sagi and Seasholes (2007) show that firm-specific attributes such as revenues, costs, growth options and shutdown options can contribute to return autocorrelation. Motivated by Johnson (2002), and Sagi and Seasholes (2007)

5 We acknowledge that there are other ways to weight the names such as the inverse-volatility weighting approach used in time-series momentum. However, a strict inverse-volatility weighting applied to long-short portfolios may not result in dollar neutrality. For example, if the long leg consists of lower risk assets, then we will have a net positive dollar position as the approach looks to equalize risk across both the long and short legs.

6 The pricing kernel is of fundamental importance in asset pricing theory and reflects the fact that the price of an asset is its expected discounted future cash flow. The stochastic discount factor applied to the cash flow is referred to as the pricing kernel.

who argue that momentum profits are linked to temporary increases in growth-related risk, Liu and Zhang (2008) show that the growth rate of industrial production is an important driver of momentum.

Behavioural models rely on different (irrational) behaviour patterns and provide competing explanations for the momentum anomaly. We present two prominent behavioural models. Daniel et al. (1998) incorporate the overconfidence effect and the biased self-attribution effect of investment outcomes and eventually link momentum to over-reaction to private information. In contrast, Hong and Stein (1999) argue that momentum profitability is linked to investor under-reaction caused by gradual information diffusion. These models predict that pricing errors are high when private information is dispersed and that, as the information spreads, the market gradually corrects this mispricing and manifest momentum. Hong and Stein (2007) further extend this framework such that information diffusion, limited attention and heterogeneous priors can be combined to understand a broad range of stylised facts such as return continuation up to 12 months and return reversals thereafter.

Vayanos and Wooley (2013) link momentum and reversals to flows between investment funds. The authors argue that flows are triggered by changes in fund managers' efficiency, which investors either observe directly or infer from past performance. Momentum arises if flow exhibits inertia, which results in rational prices underreacting to expected future flows. On the other hand, reversal arises because flow pushes prices away from fundamental values.

Moskowitz et al. (2012) show empirically that time-series momentum in the futures markets is driven by the trading activity of "speculators" and "hedgers" around historical return patterns. Using the positions of speculators and hedgers as defined by the Commodity Futures Trading Commission (CFTC), the authors find that speculators profit from momentum investing at the expense of hedgers, who compensate speculators for liquidity provision in order to maintain their hedge. Decomposing futures return into components arising from spot price and roll yield⁷, they argue that information diffusion affects mainly spot prices, whereas hedger's price and liquidity pressure impacts the roll yield. Using return predictability regressions, they show that both the spot return change and roll yield provide predictive power for futures returns.

Finally, Gorton, Hayashi and Rouwenhorst (2013) show that commodity futures basis⁸, prior futures returns and prior spot price changes are correlated with inventory levels. The authors go on to show that the returns earned on momentum strategies can be interpreted as compensation earned for bearing risk during times when inventories are low.

3. Empirical evidence

In this section, we start by examining the time series predictability of futures returns across different time horizons. We then investigate the profitability of both time-series and cross-sectional momentum strategies by varying the look-back and holding periods in months and weeks. Polbennikov et al. (2010) show that horizon diversification, a technique which combines strategies with various investment horizons or trading frequencies, can help reduce portfolio risk even when asset returns are correlated. Baltas and Kosowski (2012) show empirically there exist potential diversification benefits from combining monthly and weekly momentum strategies.

We next examine if momentum strategy efficacy is dependent on volatility regimes. Christoffersen and Diebold (2006) and Christoffersen et al. (2007) show that there exists a direct link between asset return volatility predictability and asset return sign predictability. The authors find empirically that return signs are more (less) predictable in low (high) volatility regimes in the US, UK and Hong Kong equity markets. We note that return sign predictability is sufficient to generate time-series momentum trading signals. We extend their analysis and examine the return contribution from both long and short legs, conditioned on asset volatility.

7 The roll yield, which may be either positive or negative, results from replacing an expiring near contract with a further out contract in order to avoid physical delivery and yet maintain positions in the futures market.

8 The difference between the current spot commodity price and the current (nearest to maturity) futures price, expressed as a percentage of the spot price.

Finally, we examine the positive relationship between time-series and cross-sectional momentum as documented by Moskowitz et al (2012) and show empirically that there is a market timing element embedded in the former.

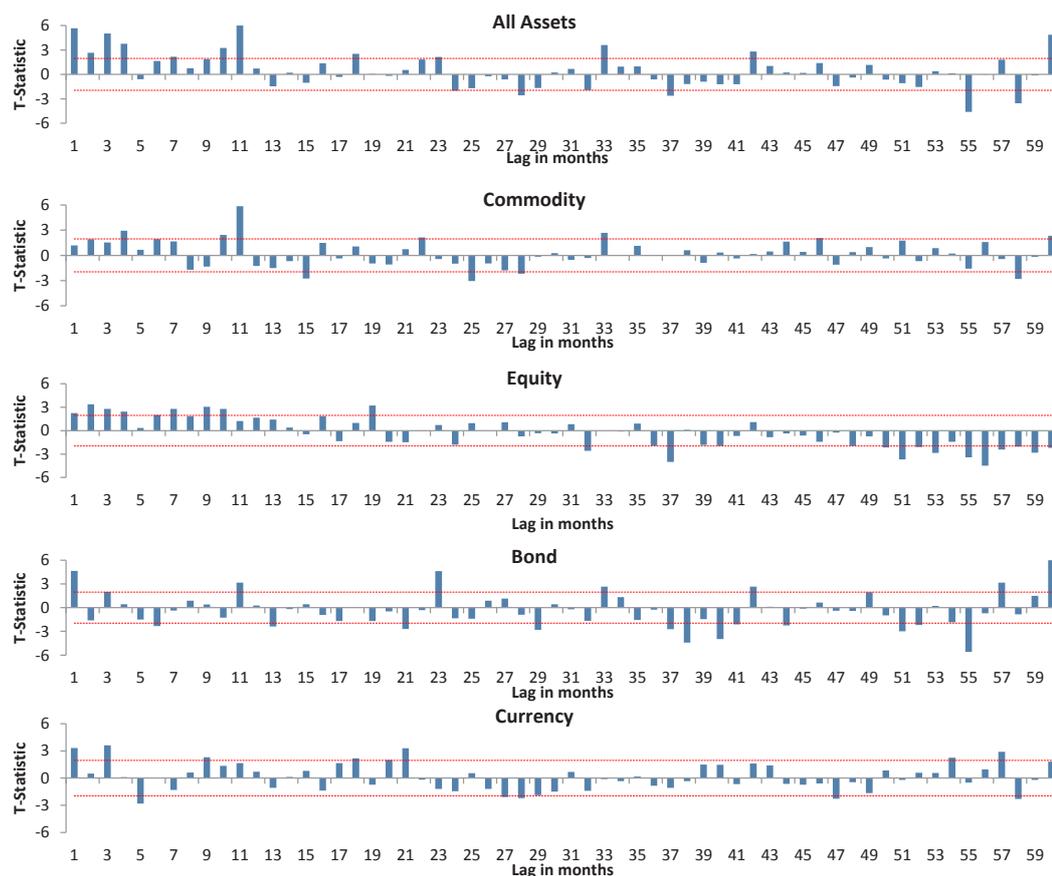
3.1. Return autocorrelation

Following the notation by Moskowitz et al. (2012), we regress the excess return⁹ r_t^s for instrument s in month t on the sign of its return lagged h months. We further scale r_t^s by its ex-ante volatility¹⁰ σ_{t-1}^s to make meaningful comparisons across assets, where the ex-ante volatility is estimated by the realized volatility over the last 252 trading days. In a regression setting, this predictability test is specified as:

$$\frac{r_t^s}{\sigma_{t-1}^s} = \alpha + \beta_h \text{sign}(r_{t-h}^s) + \varepsilon_t^s \quad (3)$$

The regression above is estimated for each lag and regressor by pooling all the futures contracts together. The t-statistics of the β coefficients are computed using standard errors that are clustered by time and asset to account for potential correlation between contemporaneous asset returns and serial correlation in the return series of each asset. T-statistics above two reject the null hypothesis of no time-series predictability.

Chart 1: Time series predictability across all assets based on monthly returns (Sample period is January 1990 to May 2013)



Source: NBIM calculations

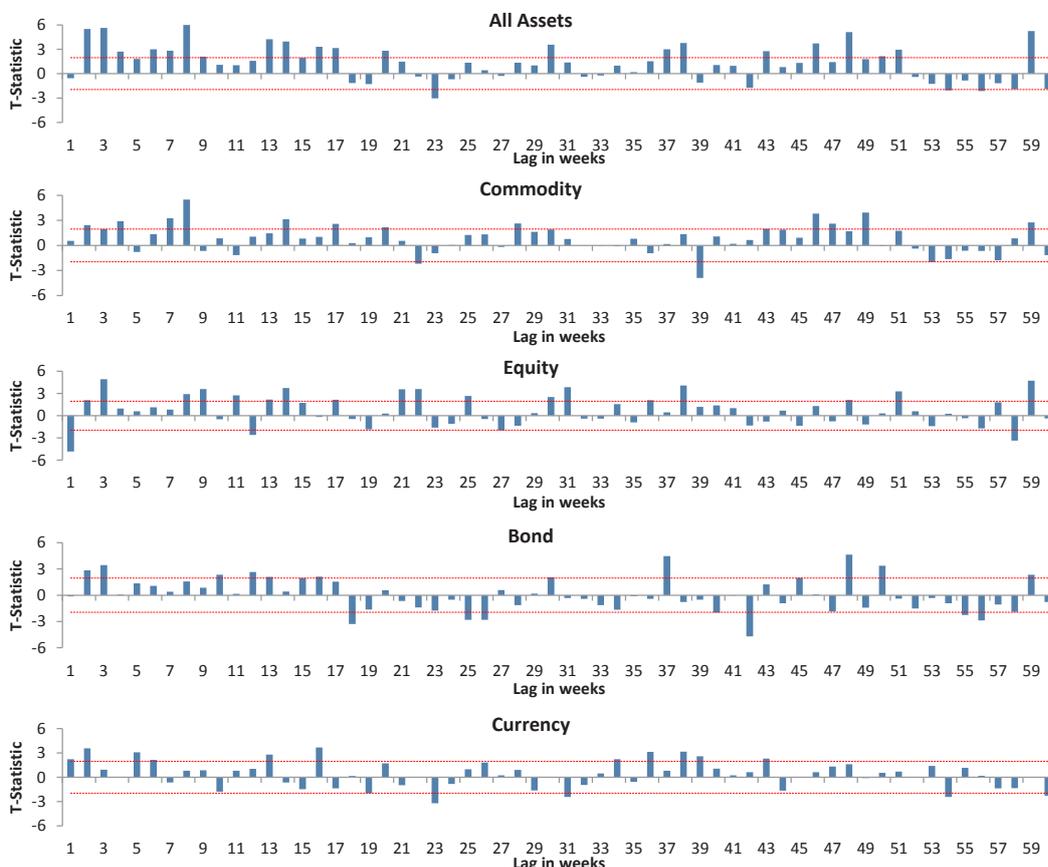
Chart 1 plots the t-statistics from the pooled regressions by month lag h by asset class and for all assets combined, as well as the corresponding significance at the 95% confidence level (red dashed

9 The returns on the futures contracts do not include any returns on collateral from transacting in futures contracts, hence these are comparable to returns in excess of the risk-free rate.

10 We use volatility estimates at time $t-1$ to scale our returns to ensure no look-ahead bias.

lines). The positive t-statistics for almost all of the first 12 lagged months indicate significant trend persistence, while there exist relatively weaker signs of return reversals between lags of 12 and 60 months.

Chart 2: Time series predictability across all assets based on weekly returns (Sample period is January 1990 to May 2013)



Source: NBIM calculations

Moving to the weekly frequency in Chart 2, we focus on the return predictability for all assets around three distinct past periods. First, return autocorrelation is generally much weaker at one week lags for all asset classes. In particular, we find significant short-term price reversal in equity futures (t-statistic of almost -5 at one week lag). Second, the periods between 2 and 16 weeks, and between 36 and 52 weeks, appear to exhibit significant return continuation. This matches to some degree the stronger trend persistence in the most recent 4-month period and the period between 9 and 12 months captured by the monthly frequency results¹¹.

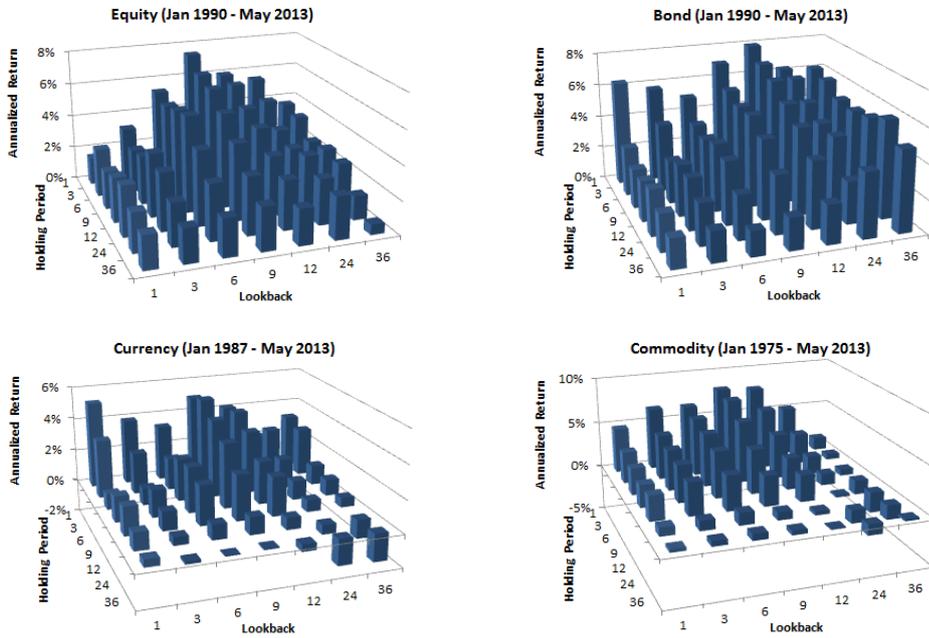
3.2. Time series momentum profitability

We next investigate the profitability of time-series momentum trading strategies by varying both the look-back period (J) and holding period (K). We follow the portfolio construction methodology as detailed in section 2.2. We first size each asset's position by its realised volatility over the last 252 trading days, and scale each position proportionally such that the portfolio's ex-ante annualized volatility is 10%. For holding periods of more than one period ($K > 1$), we follow the overlapping methodology of Jegadeesh and Titman (1993) and rebalance $\frac{1}{K}$ of the portfolio every period. The portfolio return at time t is then the average return over all portfolios at that time, namely the return on the portfolio that was constructed last month, the month before that, and so on for all currently "active" portfolios.

¹¹ We note that the lagged weekly return is not always aligned with the "equivalent" monthly return as the former is based on Wednesday-to-Wednesday weekly returns, whereas the latter is based on end of month calendar dates.

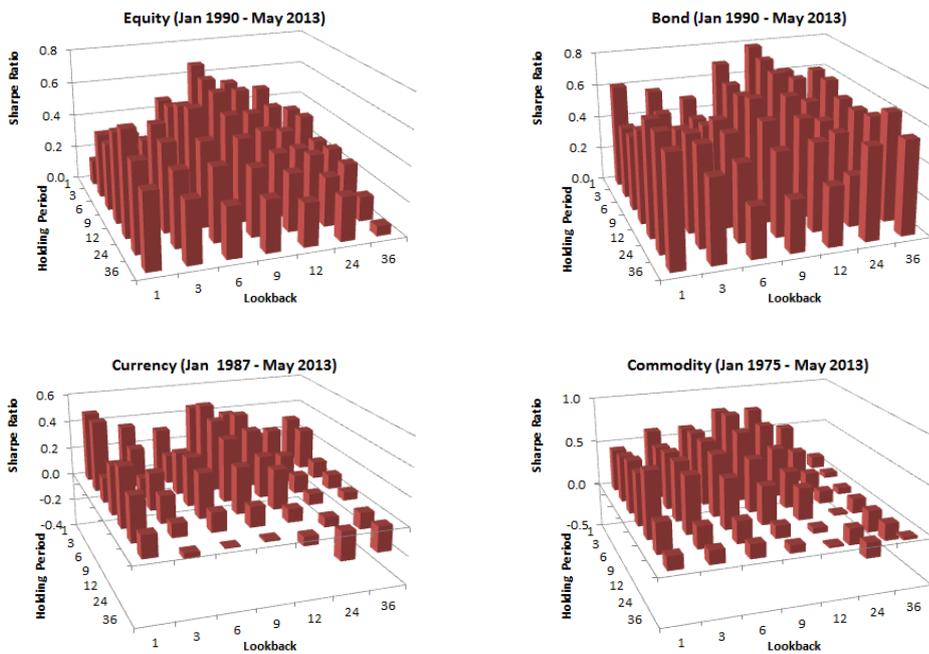
To ensure that the strategy can be implemented practically, we calculate daily returns such that the portfolio rebalances at the “close” of the next trading day after generating our momentum signals.

Chart 3: Annualized excess return of time-series momentum strategies across different look-back and holding periods



Source: NBIM calculations

Chart 4: Risk-adjusted annualized return of time-series momentum strategies across different look-back and holding periods



Source: NBIM calculations

Charts 3 and 4 present the out-of-sample annualized excess returns and Sharpe ratios for the *J-K* time-series momentum strategies for the different asset classes. With the exception of bonds, we observe that the average return and Sharpe ratios tend to increase as we extend the look-back period from 1 month to 12 months, after which the performance deteriorates, in line with our return autocorrelation analysis in the previous section. As mentioned in section 2.1, the relatively stable positive bond performance over our back-testing period between Jan 1990 and May 2013 is driven by the fact that there were few turning points during this time period. Hence, using longer look-back periods did not materially hurt strategy performance. We also find that for a given look-back period, the performance generally decreases monotonically as we increase the holding period, reflecting the decay in information coefficient as the investment horizon increases. Lastly, we note that portfolio volatility for the (1,36) time-series momentum strategy will be the lowest by construction due to the netting of positions when we average across all the 1-month look-back portfolios constructed over the last 36 months.

Table 2: Two-way monthly turnover of monthly rebalancing time series momentum strategies with different look-back and holding periods

		Holding Period (months)						
		1	3	6	9	12	24	36
All assets (Jan 1975 - May 2013)								
Look-back Period (months)	1	362 %	124 %	65 %	44 %	34 %	18 %	12 %
	3	207 %	117 %	61 %	40 %	33 %	17 %	12 %
	6	148 %	81 %	55 %	38 %	31 %	17 %	12 %
	9	115 %	61 %	43 %	36 %	29 %	16 %	11 %
	12	94 %	55 %	39 %	32 %	28 %	16 %	11 %
	24	70 %	41 %	30 %	25 %	22 %	15 %	11 %
	36	58 %	33 %	25 %	21 %	18 %	13 %	10 %
Equity (Jan 1990 - May 2013)								
Look-back Period (months)	1	137 %	46 %	23 %	15 %	12 %	6 %	4 %
	3	82 %	42 %	21 %	14 %	11 %	6 %	4 %
	6	47 %	25 %	16 %	12 %	9 %	5 %	4 %
	9	36 %	20 %	14 %	11 %	9 %	5 %	4 %
	12	34 %	17 %	12 %	10 %	9 %	5 %	4 %
	24	32 %	17 %	12 %	10 %	8 %	6 %	4 %
	36	26 %	15 %	11 %	9 %	8 %	6 %	5 %
Bond (Jan 1990 - May 2013)								
Look-back Period (months)	1	619 %	211 %	110 %	74 %	56 %	31 %	20 %
	3	356 %	189 %	97 %	64 %	52 %	27 %	19 %
	6	282 %	140 %	91 %	61 %	50 %	27 %	19 %
	9	215 %	110 %	72 %	55 %	45 %	26 %	19 %
	12	145 %	89 %	61 %	50 %	44 %	26 %	18 %
	24	127 %	71 %	51 %	43 %	37 %	24 %	18 %
	36	109 %	66 %	48 %	39 %	34 %	22 %	16 %
Currency (Jan 1987 - May 2013)								
Look-back Period (months)	1	258 %	85 %	44 %	29 %	23 %	12 %	8 %
	3	152 %	80 %	41 %	26 %	21 %	11 %	8 %
	6	117 %	58 %	38 %	26 %	20 %	11 %	8 %
	9	94 %	46 %	31 %	25 %	20 %	12 %	8 %
	12	85 %	46 %	31 %	25 %	20 %	12 %	8 %
	24	68 %	37 %	26 %	20 %	17 %	12 %	9 %
	36	51 %	29 %	22 %	18 %	15 %	10 %	8 %
Commodity (Jan 1975 - May 2013)								
Look-back Period (months)	1	151 %	51 %	26 %	18 %	14 %	7 %	5 %
	3	92 %	50 %	26 %	17 %	14 %	7 %	5 %
	6	67 %	36 %	24 %	17 %	13 %	7 %	5 %
	9	54 %	28 %	19 %	16 %	13 %	7 %	5 %
	12	49 %	26 %	18 %	14 %	13 %	7 %	5 %
	24	34 %	19 %	14 %	12 %	10 %	7 %	5 %
	36	29 %	17 %	13 %	11 %	10 %	6 %	5 %

Source: NBIM calculations

Table 2 shows the average two-way monthly turnover¹² of monthly rebalancing time-series strategies for different look-back and holding periods. Not surprisingly, we find that portfolio turnover decreases as we increase both the look-back and holding periods for all asset classes. Note that increasing the look-back period implies more stable momentum signals resulting in lower turnover, while holding periods greater than one means only a portion of the portfolio gets rebalanced each period. We also note that portfolio turnover for bonds is the highest amongst all asset classes due its relatively lower risk and the inverse-volatility weighting scheme used in our portfolio construction. On the flip side, we see equities and commodities exhibiting lower turnover due to the lower leverage required to attain the same volatility target. We also note that portfolio turnover will fall naturally as the portfolio volatility target is lowered due to the smaller leverage required.

12 We calculate two-way portfolio turnover at time t as the sum of the absolute differences between the portfolio weights at time t and $t-1$, which is the total buys and sells required to transition the portfolio.

Combining the results from above, we observe the trade-off between performance degradation and lower turnover as the look-back (beyond 12 months) and holding periods are increased. We believe further research is required to assess the trade-off between the improvement in risk-return characteristics and the transaction and potential market impact costs associated with higher turnover. Transaction costs will vary with contract specifications (minimum tick size) and method of gaining access to the market. For example, the smallest move on the FTSE 100 futures contract on NYSE Liffe London is a tick equivalent to £5 per contract of £65,390 based on the closing price of 25 July 2013. Market impact costs, on the other hand, are less deterministic, and are a function of assets under management and trading style. Market impact models calibrated using historical tick data will be required to estimate the trade-off between market impact and opportunity costs where the latter component is a function of trade urgency.

Stock market cross-sectional momentum studies are often criticized on the grounds that the profits generated may be illusory. Korajczyk and Sadka (2004), and Lesmond et al. (2004) both document that cross-sectional momentum returns are not robust to trading costs prior to the decimalization of US stock price quotes. However, Shen et al. (2007), Miffre and Rallis (2007), and Szakmary, Shen and Sharma (2010) all show that momentum strategies in commodity futures earn significant returns that are too large to be subsumed by the relatively low transaction costs prevailing in these markets. A detailed analysis on the impact of transaction costs on the profitability of time-series momentum strategies is beyond the scope of this note, and is left for further research.

3.3. Abnormal performance of time-series momentum

Similar to Moskowitz et al. (2012), we also calculate the “alphas” from the following contemporaneous regression to evaluate the abnormal performance of time-series momentum strategies:

$$r_t^{j,k} = \alpha + \beta_1 \text{MKT}_t + \beta_2 \text{BOND}_t + \beta_3 \text{GSCI}_t + \beta_4 \text{SMB}_t + \beta_5 \text{HML}_t + \beta_6 \text{UMD}_t + \varepsilon_t \quad (4)$$

where we control for the passive exposures to the broad equity market proxied by the MSCI World Index (MKT_t), bond market proxied by the US Barclays Aggregate Bond Index (BOND_t), and the commodity market proxied by the S&P GSCI Index (GSCI_t). We also control for the equity-based Fama-French factors commonly associated with the size (SMB_t), value (HML_t) and momentum (UMD_t) risk premiums found in the equity markets.

Table 3 shows the estimated “alphas” (t-statistics in parenthesis) from the above regression for each asset class and for all asset classes. In line with our earlier observations, we see that the abnormal performance is highly significant at look-back and holding periods of 12 months or less, with the “optimal” in-sample look-back period between 9 and 12 months. We further note that the alpha profile for all asset classes show relatively greater resemblance to that of commodities because of the greater number of commodity contracts in our sample of instruments used in the analysis.

Table 3: Monthly alphas (t-statistics¹³) of monthly rebalancing time series momentum strategies with different look-back and holding periods

		Holding Period (months)													
		1	3	6	9	12	24	36	1	3	6	9	12	24	36
All assets (Jan 1975 - May 2013)															
Look-back Period (months)	1	0.85%	(5.99)	0.45%	(4.80)	0.27%	(3.94)	0.25%	(4.19)	0.28%	(5.01)	0.10%	(1.93)	0.06%	(1.32)
	3	0.68%	(3.72)	0.42%	(2.66)	0.27%	(2.57)	0.33%	(3.64)	0.30%	(3.61)	0.06%	(0.76)	0.01%	(0.16)
	6	0.67%	(4.30)	0.47%	(3.33)	0.46%	(3.85)	0.46%	(4.04)	0.33%	(3.02)	0.09%	(0.89)	0.01%	(0.09)
	9	0.83%	(5.52)	0.74%	(5.16)	0.61%	(4.54)	0.46%	(3.52)	0.30%	(2.28)	0.09%	(0.71)	0.01%	(0.11)
	12	0.79%	(5.50)	0.61%	(4.37)	0.44%	(3.22)	0.31%	(2.35)	0.25%	(1.86)	0.04%	(0.30)	-0.02%	(-0.13)
	24	0.48%	(3.00)	0.35%	(2.13)	0.24%	(1.47)	0.21%	(1.30)	0.14%	(0.88)	-0.05%	(-0.26)	-0.08%	(-0.49)
	36	0.39%	(2.23)	0.29%	(1.59)	0.14%	(0.75)	0.07%	(0.41)	0.01%	(0.08)	-0.05%	(-0.25)	0.03%	(0.14)
Equity (Jan 1990 - May 2013)															
Look-back Period (months)	1	0.21%	(1.04)	0.21%	(1.48)	0.10%	(1.00)	0.12%	(1.39)	0.16%	(1.77)	0.09%	(1.06)	0.06%	(0.72)
	3	0.16%	(0.74)	0.11%	(0.57)	0.10%	(0.78)	0.17%	(1.37)	0.16%	(1.26)	0.08%	(0.77)	0.05%	(0.49)
	6	0.23%	(1.00)	0.22%	(1.15)	0.25%	(1.27)	0.29%	(1.52)	0.19%	(1.03)	0.10%	(0.74)	0.01%	(0.09)
	9	0.42%	(2.17)	0.33%	(1.72)	0.31%	(1.54)	0.26%	(1.27)	0.19%	(0.95)	0.09%	(0.60)	0.03%	(0.21)
	12	0.29%	(1.29)	0.29%	(1.35)	0.22%	(1.01)	0.20%	(0.95)	0.14%	(0.71)	0.06%	(0.36)	-0.01%	(-0.06)
	24	0.38%	(1.83)	0.30%	(1.43)	0.22%	(1.09)	0.18%	(0.89)	0.19%	(0.96)	0.12%	(0.65)	0.07%	(0.38)
	36	0.33%	(1.65)	0.31%	(1.54)	0.19%	(0.90)	0.18%	(0.89)	0.15%	(0.72)	0.04%	(0.16)	-0.06%	(-0.28)
Bond (Jan 1990 - May 2013)															
Look-back Period (months)	1	0.62%	(5.15)	0.31%	(2.83)	0.21%	(2.15)	0.19%	(1.95)	0.22%	(2.15)	0.19%	(2.19)	0.16%	(2.20)
	3	0.52%	(2.52)	0.39%	(1.98)	0.18%	(1.29)	0.24%	(1.69)	0.27%	(2.07)	0.22%	(2.06)	0.16%	(1.48)
	6	0.42%	(1.86)	0.28%	(1.31)	0.23%	(1.13)	0.29%	(1.61)	0.30%	(1.75)	0.22%	(1.52)	0.12%	(0.88)
	9	0.54%	(2.63)	0.44%	(1.98)	0.40%	(1.89)	0.46%	(2.26)	0.42%	(2.12)	0.29%	(1.60)	0.17%	(1.04)
	12	0.68%	(3.03)	0.63%	(2.80)	0.61%	(2.83)	0.56%	(2.58)	0.51%	(2.46)	0.36%	(1.70)	0.23%	(1.16)
	24	0.63%	(2.63)	0.62%	(2.50)	0.53%	(2.11)	0.46%	(1.82)	0.44%	(1.71)	0.26%	(1.07)	0.39%	(2.00)
	36	0.56%	(2.19)	0.54%	(2.08)	0.47%	(1.81)	0.48%	(1.96)	0.51%	(2.03)	0.55%	(2.27)	0.49%	(2.51)
Currency (Jan 1987 - May 2013)															
Look-back Period (months)	1	0.38%	(2.35)	0.29%	(2.28)	0.06%	(0.69)	0.11%	(1.36)	0.12%	(1.46)	0.05%	(0.90)	0.01%	(0.25)
	3	0.36%	(2.38)	0.25%	(1.71)	0.07%	(0.59)	0.10%	(0.84)	0.04%	(0.37)	-0.03%	(-0.32)	-0.08%	(-0.92)
	6	0.30%	(1.86)	0.16%	(0.97)	0.17%	(1.02)	0.16%	(1.09)	0.11%	(0.81)	-0.02%	(-0.14)	-0.09%	(-0.86)
	9	0.46%	(2.48)	0.46%	(2.59)	0.36%	(2.11)	0.26%	(1.64)	0.15%	(0.97)	0.00%	(0.01)	-0.08%	(-0.69)
	12	0.36%	(1.89)	0.34%	(1.97)	0.22%	(1.26)	0.11%	(0.70)	0.10%	(0.65)	-0.05%	(-0.32)	-0.14%	(-1.16)
	24	0.16%	(0.83)	0.22%	(1.17)	0.08%	(0.46)	0.02%	(0.11)	-0.04%	(-0.22)	-0.17%	(-1.00)	-0.27%	(-1.58)
	36	0.16%	(0.88)	0.12%	(0.59)	-0.04%	(-0.19)	-0.06%	(-0.33)	-0.11%	(-0.58)	-0.28%	(-1.29)	-0.32%	(-1.56)
Commodity (Jan 1975 - May 2013)															
Look-back Period (months)	1	0.51%	(3.18)	0.28%	(2.94)	0.22%	(3.09)	0.17%	(2.47)	0.18%	(3.11)	0.03%	(0.74)	-0.01%	(-0.48)
	3	0.52%	(3.70)	0.33%	(2.77)	0.29%	(2.84)	0.27%	(2.74)	0.23%	(2.57)	0.01%	(0.11)	-0.02%	(-0.38)
	6	0.47%	(2.96)	0.45%	(3.33)	0.41%	(3.14)	0.37%	(3.01)	0.25%	(2.23)	0.01%	(0.16)	-0.03%	(-0.34)
	9	0.59%	(3.95)	0.58%	(3.82)	0.48%	(3.34)	0.33%	(2.33)	0.17%	(1.33)	-0.03%	(-0.30)	-0.04%	(-0.41)
	12	0.60%	(4.42)	0.46%	(3.14)	0.31%	(2.08)	0.17%	(1.22)	0.12%	(0.93)	-0.07%	(-0.64)	-0.07%	(-0.66)
	24	0.36%	(2.29)	0.18%	(1.14)	0.08%	(0.49)	0.03%	(0.23)	-0.04%	(-0.27)	-0.18%	(-1.29)	-0.14%	(-1.15)
	36	0.07%	(0.40)	0.01%	(0.04)	-0.10%	(-0.60)	-0.17%	(-1.08)	-0.24%	(-1.52)	-0.18%	(-1.25)	-0.09%	(-0.63)

Source: NBIM calculations

Table 4 examines the risk-adjusted performance of a diversified time-series momentum strategy based on a 12-month look-back and 1-month holding period and its factor exposures. We regress the excess return of the equity time-series momentum strategy on the returns of MSCI World and the Fama-French factors, UMD, HML and SMB, representing momentum, value and size premium among individual stocks respectively¹⁴. It is interesting to note that time-series momentum in equity futures remains significantly profitable after controlling for these factors. We also observe that the strategy loads significantly positively on UMD, the cross-sectional momentum on individual stocks, without any significant tilt away from the value premium (HML beta coefficient of -0.05 with corresponding t-statistic of -0.83). We note that results for the diversified time-series momentum strategy do not differ materially from the above observation.

Table 4: 12-1 equity time series momentum strategy exposure to Fama-French factors (From Feb 1991 to May 2013)

	UMD	HML	SMB	MSCI World	Alpha
Coefficient	0,23	-0,05	0,00	0,09	0,45%
Standard Error	0,048	0,062	0,058	0,042	0,002
R-squared	17,3 %				
Coefficient t-stat	4,68	-0,83	0,06	2,20	2,51

Source: Ken French Data Library, MSCI, NBIM calculations

We extend the above monthly analysis and examine the abnormal performance of weekly¹⁵ rebalancing time-series momentum strategies. Table 5 shows the "alphas" of the weekly rebalancing time series momentum strategies with different look-back and holding periods, based on the regression specification as per equation 4. Except for equity futures, we note that the time-series momentum strategy generates a statistically significant "alpha" for weekly rebalancing frequencies. In fact, we observe that equity futures exhibit significant short-term price reversion (weekly rebalancing momentum strategy with a one week look-back period).

13 Newey-West (1987) heteroscedasticity and autocorrelation robust t-statistics

14 An alternative model specification is to regress the time-series momentum returns on a multi-asset class benchmark

15 Wednesday-to-Wednesday weekly returns

Clearly, both the monthly and weekly rebalancing frequency strategies have different frequencies of observations. We further investigate the correlation structure between both strategy types in the following section to see if there are diversification benefits from different trading frequencies.

Table 5: Monthly alphas (t-statistics¹⁶) of weekly rebalancing time series momentum strategies with different look-back and holding periods

		Holding Period (weeks)										
		1	2	4	6	8	12					
All assets (Jan 1975 - May 2013)												
Look-back Period (weeks)	1	0.35%	0.65%	0.57%	0.51%	0.46%	0.33%	(2.31)	(5.44)	(6.33)	(6.65)	(5.23)
	2	0.82%	0.80%	0.56%	0.48%	0.44%	0.33%	(5.16)	(6.53)	(5.42)	(5.26)	(4.40)
	4	0.91%	0.82%	0.67%	0.58%	0.51%	0.41%	(6.38)	(6.51)	(5.29)	(5.18)	(3.99)
	6	0.85%	0.87%	0.70%	0.60%	0.50%	0.40%	(5.73)	(6.36)	(4.97)	(4.23)	(3.63)
	8	0.94%	0.93%	0.76%	0.63%	0.55%	0.45%	(6.17)	(7.58)	(5.35)	(4.40)	(3.69)
	12	0.92%	0.92%	0.76%	0.64%	0.57%	0.46%	(6.05)	(6.47)	(4.54)	(4.04)	(3.34)
Equity (Jan 1990 - May 2013)												
Look-back Period (weeks)	1	-0.49%	-0.06%	0.16%	0.12%	0.15%	0.12%	(-2.45)	(-0.39)	(1.64)	(1.33)	(1.86)
	2	-0.06%	0.08%	0.09%	0.08%	0.15%	0.08%	(-0.36)	(0.62)	(0.80)	(0.79)	(1.16)
	4	0.10%	0.13%	0.11%	0.16%	0.19%	0.18%	(0.57)	(0.79)	(1.15)	(1.30)	(1.44)
	6	0.08%	0.17%	0.14%	0.13%	0.15%	0.17%	(0.39)	(0.98)	(0.81)	(1.06)	(1.32)
	8	0.24%	0.38%	0.23%	0.21%	0.24%	0.20%	(1.65)	(2.06)	(1.20)	(1.36)	(1.29)
	12	0.10%	0.22%	0.18%	0.15%	0.10%	0.05%	(0.45)	(1.07)	(0.81)	(0.56)	(0.31)
Bond (Jan 1990 - May 2013)												
Look-back Period (weeks)	1	0.04%	0.31%	0.31%	0.29%	0.28%	0.28%	(0.21)	(2.29)	(2.75)	(2.96)	(3.51)
	2	0.46%	0.60%	0.44%	0.35%	0.33%	0.32%	(2.36)	(4.30)	(3.29)	(3.02)	(3.07)
	4	0.60%	0.66%	0.51%	0.44%	0.38%	0.39%	(3.06)	(3.58)	(3.45)	(3.15)	(2.82)
	6	0.49%	0.52%	0.47%	0.38%	0.34%	0.37%	(2.73)	(2.90)	(2.78)	(2.18)	(2.30)
	8	0.50%	0.55%	0.49%	0.41%	0.41%	0.43%	(2.56)	(2.83)	(2.09)	(2.16)	(2.46)
	12	0.68%	0.67%	0.61%	0.58%	0.54%	0.43%	(3.67)	(3.46)	(2.85)	(2.73)	(2.31)
Currency (Jan 1987 - May 2013)												
Look-back Period (weeks)	1	0.20%	0.38%	0.29%	0.25%	0.18%	0.16%	(1.26)	(2.99)	(3.20)	(2.70)	(2.26)
	2	0.39%	0.25%	0.15%	0.16%	0.09%	0.11%	(2.30)	(1.77)	(1.87)	(1.22)	(1.41)
	4	0.17%	0.20%	0.15%	0.11%	0.14%	0.17%	(1.38)	(1.81)	(1.14)	(1.69)	(1.75)
	6	0.29%	0.23%	0.15%	0.16%	0.14%	0.18%	(2.33)	(2.33)	(1.59)	(1.61)	(1.77)
	8	0.29%	0.32%	0.30%	0.26%	0.25%	0.25%	(2.35)	(3.14)	(2.71)	(2.04)	(2.05)
	12	0.37%	0.48%	0.42%	0.39%	0.38%	0.33%	(2.18)	(3.04)	(2.60)	(2.68)	(2.55)
Commodity (Jan 1975 - May 2013)												
Look-back Period (weeks)	1	0.31%	0.48%	0.42%	0.36%	0.36%	0.24%	(2.21)	(4.76)	(5.53)	(6.27)	(4.78)
	2	0.51%	0.53%	0.35%	0.31%	0.30%	0.22%	(3.71)	(4.26)	(3.93)	(4.41)	(3.51)
	4	0.55%	0.47%	0.40%	0.36%	0.32%	0.24%	(3.60)	(3.39)	(3.48)	(3.25)	(2.85)
	6	0.56%	0.58%	0.49%	0.43%	0.36%	0.26%	(3.62)	(4.24)	(3.98)	(3.48)	(2.82)
	8	0.62%	0.63%	0.52%	0.45%	0.39%	0.31%	(4.51)	(4.80)	(4.00)	(3.65)	(3.10)
	12	0.66%	0.67%	0.55%	0.45%	0.41%	0.35%	(4.57)	(4.83)	(3.78)	(3.37)	(2.96)

Source: NBIM calculations

3.4. Horizon diversification

Having established the abnormal performances associated with both monthly and weekly rebalancing time-series momentum strategies, we examine their correlation profile to see if any diversification benefits exist. Table 6 shows the average correlation between monthly and weekly rebalancing momentum strategies across different look-back periods. Disregarding monthly and weekly strategies which have significant overlap in their look-back periods (e.g. 4-1 weekly and 1-1 monthly), we note the low correlation between the different rebalancing frequencies, implying that they capture distinct phenomena of return continuation. Similar to Baltas and Kosowski (2012), we find that there exist diversification benefits from combining traditional monthly strategies with higher frequency weekly strategies. However, we believe that further research needs to be conducted to study the trade-off between diversification benefits and performance degradation as a result of higher transaction costs and potential market impact due to the potential increase in turnover from mixing both signals¹⁷.

Table 6: Average correlation between monthly rebalancing and weekly rebalancing time-series momentum strategies for different look-back periods (daily data from February 1978 to June 2013)

	1-1 Monthly	3-1 Monthly	6-1 Monthly	9-1 Monthly	12-1 Monthly	24-1 Monthly	36-1 Monthly
1-1 Weekly	23%	16%	14%	13%	11%	6%	4%
2-1 Weekly	36%	24%	19%	17%	15%	9%	5%
4-1 Weekly	60%	38%	31%	27%	24%	15%	11%
6-1 Weekly	73%	53%	43%	37%	33%	22%	15%
8-1 Weekly	72%	61%	50%	42%	38%	25%	18%
12-1 Weekly	61%	78%	62%	52%	46%	32%	24%

Source: NBIM calculations

16 Newey-West (1987) heteroscedasticity and autocorrelation robust t-statistics

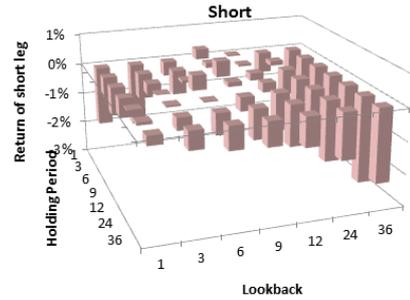
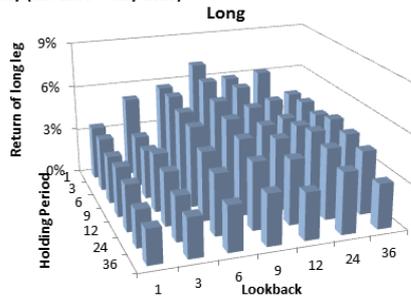
17 We acknowledge that there are different ways to combine signals. One approach could be running both monthly and weekly momentum portfolios simultaneously, while another could be to go long or short only if both the monthly and weekly signals agree with each other.

3.5. The long and short of it

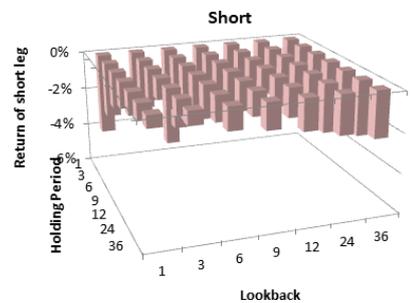
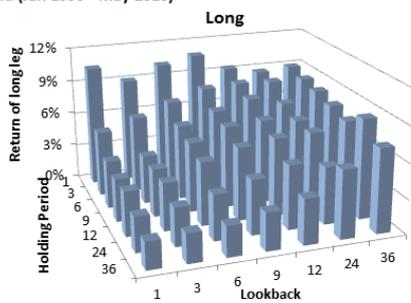
Reverting back to the monthly rebalancing momentum strategies, we decompose total portfolio return into components coming from the long and short legs. Chart 5 shows the return contribution from long and short legs across different look-back and holding periods for the different asset classes. We observe that most of the positive portfolio performance is due to the long signals, while the value-added from the short signals is only apparent in currencies and commodities. In the case of currencies, this result is perhaps expected since currency investing is by definition pairs-driven.

Chart 5: Return contribution from long and short legs across different look-back and holding periods

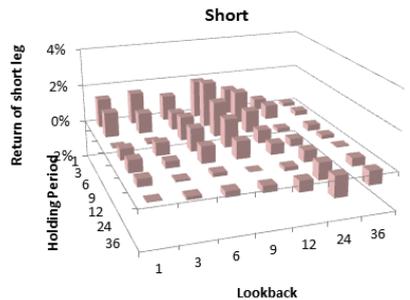
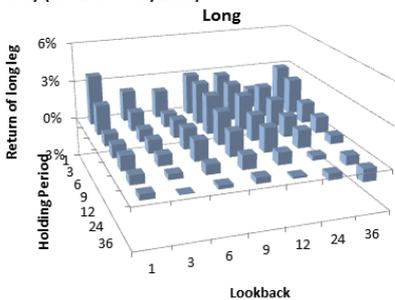
Equity (Jan 1990 - May 2013)



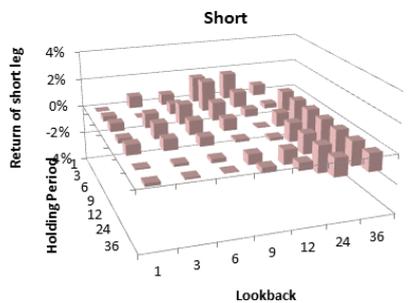
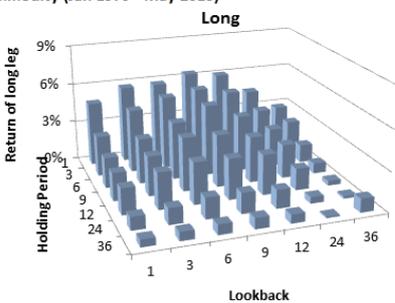
Bond (Jan 1990 - May 2013)



Currency (Jan 1987 - May 2013)



Commodity (Jan 1975 - May 2013)



Source: NBIM calculations

3.6. Volatility regime dependence

As mentioned earlier in the note, Christoffersen and Diebold (2006) and Christoffersen et al. (2007) provide empirical evidence to show that return signs are more (less) predictable in low (high) volatility regimes in some equity markets. We extend their empirical work by looking at the return from the long and short legs separately under different volatility regimes¹⁸ for equities, bonds, currencies and

¹⁸ Determined in-sample

commodities. For each month, we first calculate the trailing 21-day annualised volatility of an asset. Assuming perfect foresight, we then group each asset's volatility time series into regimes as follows: high (top quartile), low (bottom quartile) and medium (between second and third quartiles). Conditioned on the asset volatility regime, we then calculate the inverse-volatility weighted¹⁹ return of each asset arising from the long and short legs separately.

Table 7: Volatility-conditioned return of individual 12-1 time-series momentum for equities, bonds and currencies²⁰

Equity (Jan 1990 - May 2013)

Long Leg	S&P 500	FTSE 100	AEX	TOPIX	CAC	DAX 30	Hang Seng	S&P ASX 200	S&P TSX 60	Average
Low volatility (Bottom quartile)	5,8 %	5,8 %	5,5 %	-0,4 %	3,5 %	4,4 %	11,6 %	14,0 %	11,3 %	6,8 %
Medium volatility	5,6 %	3,2 %	5,3 %	3,9 %	3,6 %	7,6 %	4,5 %	0,8 %	2,2 %	4,1 %
High volatility (Top quartile)	5,2 %	2,7 %	5,5 %	0,4 %	4,1 %	1,9 %	-2,0 %	4,7 %	-2,0 %	2,3 %
Short Leg										
Low volatility (Bottom quartile)	-1,2 %	0,2 %	-1,3 %	0,8 %	0,4 %	-0,6 %	0,1 %	1,3 %	-0,6 %	-0,1 %
Medium volatility	0,9 %	0,3 %	1,8 %	2,0 %	2,2 %	2,9 %	0,0 %	1,5 %	1,7 %	1,5 %
High volatility (Top quartile)	2,6 %	-1,9 %	-0,7 %	1,8 %	-2,1 %	-0,9 %	-1,9 %	-0,2 %	-2,0 %	-0,6 %
Combined										
Low volatility (Bottom quartile)	4,7 %	6,0 %	4,2 %	0,4 %	4,0 %	3,8 %	11,7 %	15,3 %	10,8 %	6,7 %
Medium volatility	6,5 %	3,5 %	7,1 %	5,9 %	5,8 %	10,5 %	4,4 %	2,3 %	3,9 %	5,6 %
High volatility (Top quartile)	7,8 %	0,8 %	4,9 %	2,1 %	2,1 %	0,9 %	-3,9 %	4,5 %	-4,1 %	1,7 %

Bond (Jan 1990 - May 2013)

Long Leg	Euro 2-Year	Euro 5-Year	Euro 10-Year	Euro 30-Year	Canada 10-Year	Japan 10-Year	UK 10-Year	US 2-Year	US 5-Year	US 10-Year	US 30-Year	Average
Low volatility (Bottom quartile)	0,0 %	2,7 %	8,6 %	0,5 %	-1,2 %	11,5 %	2,7 %	7,0 %	9,7 %	10,8 %	9,0 %	5,6 %
Medium volatility	6,7 %	9,0 %	6,5 %	6,4 %	6,9 %	8,8 %	6,0 %	10,6 %	7,9 %	3,8 %	3,1 %	6,9 %
High volatility (Top quartile)	4,3 %	4,7 %	4,0 %	0,4 %	8,1 %	5,4 %	4,1 %	5,2 %	5,0 %	7,0 %	3,5 %	4,7 %
Short Leg												
Low volatility (Bottom quartile)	1,2 %	1,2 %	1,6 %	0,2 %	-1,1 %	0,5 %	1,1 %	0,1 %	0,4 %	0,3 %	0,1 %	0,5 %
Medium volatility	-1,0 %	-1,7 %	-2,5 %	-3,3 %	-2,7 %	-1,0 %	-1,0 %	0,7 %	-1,1 %	-2,1 %	-2,1 %	-1,6 %
High volatility (Top quartile)	-2,6 %	-2,0 %	-0,7 %	-3,6 %	-1,8 %	-1,8 %	-2,9 %	-1,3 %	-0,7 %	-1,2 %	-1,0 %	-1,8 %
Combined												
Low volatility (Bottom quartile)	1,1 %	3,9 %	10,2 %	0,7 %	-2,4 %	12,1 %	3,9 %	7,0 %	10,1 %	11,1 %	9,1 %	6,1 %
Medium volatility	5,7 %	7,2 %	4,1 %	3,1 %	4,2 %	7,8 %	5,0 %	11,3 %	6,8 %	1,7 %	1,0 %	5,3 %
High volatility (Top quartile)	1,7 %	2,7 %	3,3 %	-3,2 %	6,3 %	3,6 %	1,3 %	3,9 %	4,3 %	5,7 %	2,5 %	2,9 %

Currency (Jan 1987 - May 2013)

Long Leg	EURUSD	CADUSD	JPYUSD	NZDUSD	CHFUSD	GBPUSD	Dollar Index	Average
Low volatility (Bottom quartile)	5,8 %	2,6 %	2,1 %	2,1 %	2,6 %	3,5 %	4,3 %	3,3 %
Medium volatility	0,4 %	4,4 %	3,0 %	5,0 %	2,3 %	-0,5 %	-2,1 %	1,8 %
High volatility (Top quartile)	-7,4 %	-2,7 %	-0,8 %	5,2 %	-4,7 %	-1,3 %	-0,8 %	-1,8 %
Short Leg								
Low volatility (Bottom quartile)	-4,2 %	4,5 %	8,3 %	-1,7 %	1,6 %	1,0 %	1,2 %	1,5 %
Medium volatility	-2,1 %	0,3 %	1,7 %	-0,4 %	-0,1 %	-2,4 %	2,7 %	0,0 %
High volatility (Top quartile)	0,3 %	-1,8 %	-0,8 %	1,3 %	-1,6 %	0,3 %	-3,4 %	-0,8 %
Combined								
Low volatility (Bottom quartile)	1,6 %	7,1 %	10,5 %	0,4 %	4,2 %	4,5 %	5,5 %	4,8 %
Medium volatility	-1,7 %	4,7 %	4,7 %	4,6 %	2,2 %	-3,0 %	0,6 %	1,7 %
High volatility (Top quartile)	-7,1 %	-4,5 %	-1,6 %	6,5 %	-6,2 %	-1,0 %	-4,2 %	-2,6 %

Source: NBIM calculations

Table 7 decomposes the volatility-conditioned return of the individual time-series momentum strategies due to long and short legs. For all asset classes, we see that the combined return of an instrument generally decreases as its volatility increases. Examining the performance attributed to long and short legs independently, we find that the return profile generally deteriorates as we enter high volatility regimes, consistent with the findings of Christoffersen and Diebold (2006) and Christoffersen et al. (2007). Assuming reasonable predictability of the volatility regime an asset is in, the general inverse relationship between asset volatility and asset predictability provides confidence levels on the individual time-series momentum signals, which can help contribute to risk budgeting decisions in portfolio construction. Forecasting of volatility regimes at different horizons is challenging and is outside the scope of this note. However, we advocate further research on transforming naïve momentum strategies to better adapt to turning points and trend reversals based on volatility regimes.

3.7. Time-series vs. cross-sectional momentum

Moskowitz et al. (2012) show empirically that there exists a significant relationship between time-series and cross-sectional momentum²¹ and argue that time-series momentum is not fully captured by its cross-sectional counterpart. In this section, we explore this relationship further and show that the time-series momentum effect is related to bottom-up asset selection (cross-sectional momentum),

19 For ease of comparison across different volatility regimes, we size each position to have constant ex-ante 10% volatility so that we have equal risk contribution (excluding correlations) from each asset.

20 For brevity, we omit the results for commodities, which are in general similar to the other asset classes.

21 See section 2.3 for the definition of cross-sectional momentum and portfolio construction approach

top-down asset rotation (market timing) and exposure to passive long positions (“market”). To extend the analysis even further, one could study the effect of correlation between contracts on both types of momentum, but is beyond the scope of this note.

Table 8: 12-1 time-series momentum explained by 12-1 cross-sectional momentum and market timing (monthly returns)

	Independent variable				Independent variable			
	XSMOM	Market	Alpha		Market Timing	XSMOM	Market	
All assets (Jan 1976 - May 2013)								
Coefficient estimate	0,81	0,11	0,14%	Coefficient estimate	0,57	0,80	0,10	0,09%
Standard error	0,025	0,025	0,001	Standard error	0,556	0,025	0,026	0,001
Regression R-squared	70,9 %			Regression R-squared	71%			
T-Statistic	32,43	4,23	1,69	T-Statistic	1,02	32,36	3,99	0,88
Equity (Jan 1991 - May 2013)								
Coefficient estimate	0,54	0,21	0,43%	Coefficient estimate	5,65	0,49	0,27	-0,15%
Standard error	0,069	0,053	0,002	Standard error	1,106	0,067	0,052	0,002
Regression R-squared	22,8 %			Regression R-squared	29,7 %			
T-Statistic	7,86	3,98	2,59	T-Statistic	5,11	7,42	5,26	-0,77
Bond (Jan 1991 - May 2013)								
Coefficient estimate	0,42	0,56	0,22%	Coefficient estimate	1,04	0,43	0,54	0,13%
Standard error	0,046	0,038	0,001	Standard error	0,817	0,046	0,040	0,001
Regression R-squared	66,6 %			Regression R-squared	66,8 %			
T-Statistic	9,22	14,60	2,04	T-Statistic	1,28	9,31	13,43	0,99
Currency (Jan 1988 - May 2013)								
Coefficient estimate	0,90	-0,05	0,08%	Coefficient estimate	1,00	0,90	-0,06	-0,01%
Standard error	0,030	0,029	0,001	Standard error	0,607	0,030	0,029	0,001
Regression R-squared	74,4 %			Regression R-squared	74,7 %			
T-Statistic	29,50	-1,82	0,89	T-Statistic	1,64	29,49	-2,06	-0,13
Commodity (Jan 1976 - May 2013)								
Beta	0,68	-0,08	0,31%	Beta	2,77	0,69	-0,10	0,06%
SE	0,038	0,036	0,001	SE	0,808	0,038	0,036	0,001
R-Squared	41,8 %			R-Squared	43,3 %			
T-Statistic	17,87	-2,32	2,85	T-Statistic	3,42	18,24	-2,84	0,46

Source: NBIM calculations

We first extend the work of Moskowitz et al. (2012) by regressing the 12-1 time-series momentum on the 12-1 cross-sectional momentum and the “market” factor, where the “market”, for consistency, is defined as the inverse-volatility weighted average return of instruments. For example, if we conduct this analysis within the equity asset class, then the market will be defined as the inverse-volatility weighted average return of all the equity futures contracts in our sample. The left panel of table 8 presents the results of our regressions which show that time-series momentum still exhibits significant “alpha” after controlling for the passive exposures to cross-sectional momentum and the “market” factor in equities, bonds and commodities.

Extending on the work of Treynor and Mazuy (1966), we test for the strategy’s market timing abilities by adding a quadratic “market” term and cross-sectional momentum to the commonly referenced one-factor model:

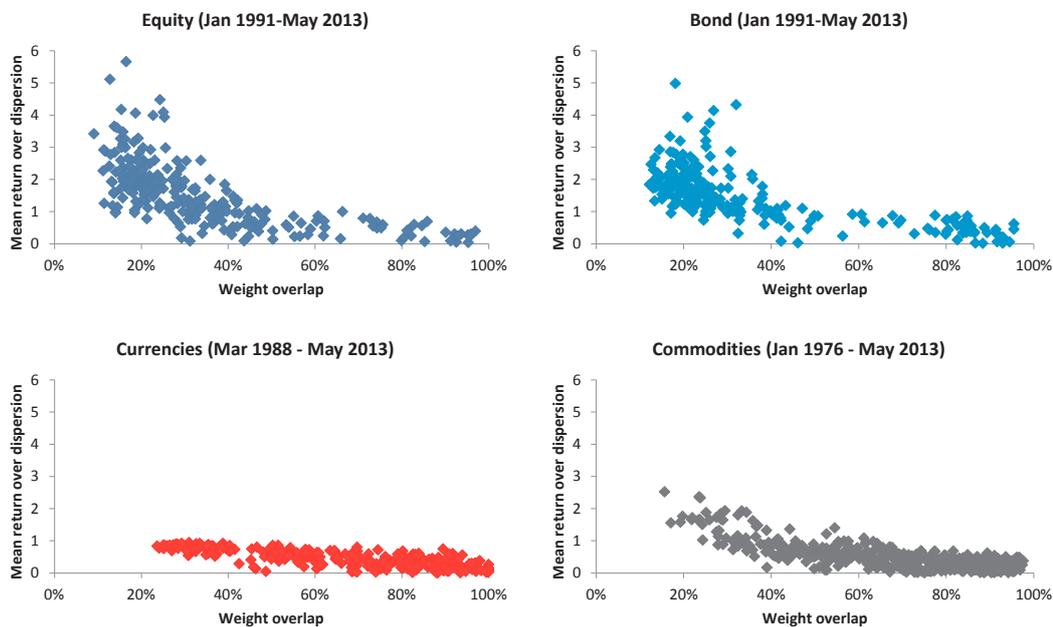
$$TSMOM_t^{J,K} = \alpha + \beta_1 r_{m,t} + \beta_2 r_{m,t}^2 + \beta_3 XSMOM_t^{J,K} \quad (5)$$

where $TSMOM_t^{J,K}$ and $XSMOM_t^{J,K}$ are the time-series momentum and cross-sectional momentum returns respectively based on J -month look-back and K -month holding period, and $r_{m,t}$ is the inverse-volatility weighted average return of instruments (“market”). The coefficient of the above quadratic term reflects the convexity achieved by the strategy in its exposure to the “market” and is positive if it exhibits timing ability.

The right panel of table 8 presents the results of the above regression specification across all assets and for each asset class. We first observe that market timing is a significant component (at the 95% confidence interval) of time-series momentum for both equities and commodities. This is further corroborated by the meaningful increase in R-squared when we add the market timing variable for both equities and commodities, which we do not see in bonds and currencies. Within bonds, we further observe the statistically significant positive exposure of the momentum portfolio to the “market”. As mentioned previously, the relatively stable positive bond performance over our back-testing period between Jan 1990 and May 2013 meant few turning points historically and hence the much greater positive contribution from the “market” relative to market timing.

By construction, the signals generated by time-series momentum will more closely resemble that of cross-sectional momentum when the past cross-sectional average return is near zero. In other words, the long or short bias associated with time-series momentum strategies will be more significant if the cross-sectional average return over a certain look-back period deviates further from zero and the dispersion of returns over the same look-back period is lower. Chart 6 shows the scatterplots of portfolio weight overlap between time-series and cross-sectional momentum²², and the average past 12-month return normalized by its corresponding cross-sectional standard deviation for the different asset classes. We readily observe that there is a great deal of weight overlap between both types of momentum strategies within currencies driven by the past average return being closer to zero. As noted earlier, currency investing is by definition pairs-driven which implies less variable bias in time-series momentum portfolios in this asset class. On the other hand, we see much lower weight overlaps in equities and bonds due to the stronger price trends in these asset classes.

Chart 6: Weight overlap between 12-1 time-series and 12-1 cross-sectional momentum as a function of normalized cross-sectional average return



Source: NBIM calculations

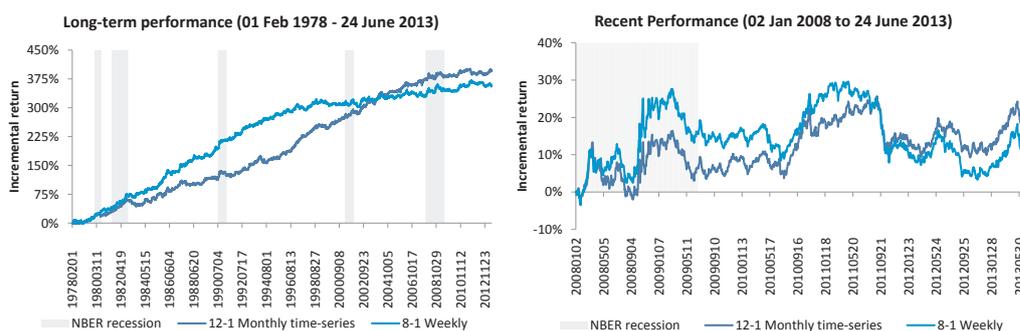
3.8. Recent performance

In recent years, the performance of “trend-following” hedge funds or so-called CTAs has been subpar, leading some to speculate that such strategies may have become too crowded. We note that CTAs may be using a variety of statistical techniques, beyond the vanilla momentum strategies described so far. However, it is still worth looking at the recent performance of our stylized momentum strategies. Chart 7 presents both the long-term and recent historical performance of the 12-1 monthly and 8-1 weekly time-series momentum strategies using daily returns.

During all five NBER recession periods over the entire sample period from February 1978 to June 2013, both monthly and weekly time-series momentum strategies have exhibited relatively stable positive returns. This finding is similar to Moskowitz et al. (2012) and Baltas and Kosowski (2012) who document positive time-series momentum performance during NBER recessions. Chart 8 shows the net exposure by asset class for the 12-1 monthly time-series momentum strategy over time. We find that, on average, the monthly diversified strategy exhibits a net long bias in both government bonds and equities due to their positive price trends during our sample period. As noted in section 3.7, due to the nature of currency investing which is pairs-driven by construction, the net exposure of currencies is flatter than that of other asset classes. Another observation that stands out is the weaker recent performance of time-series momentum strategies since January 2008.

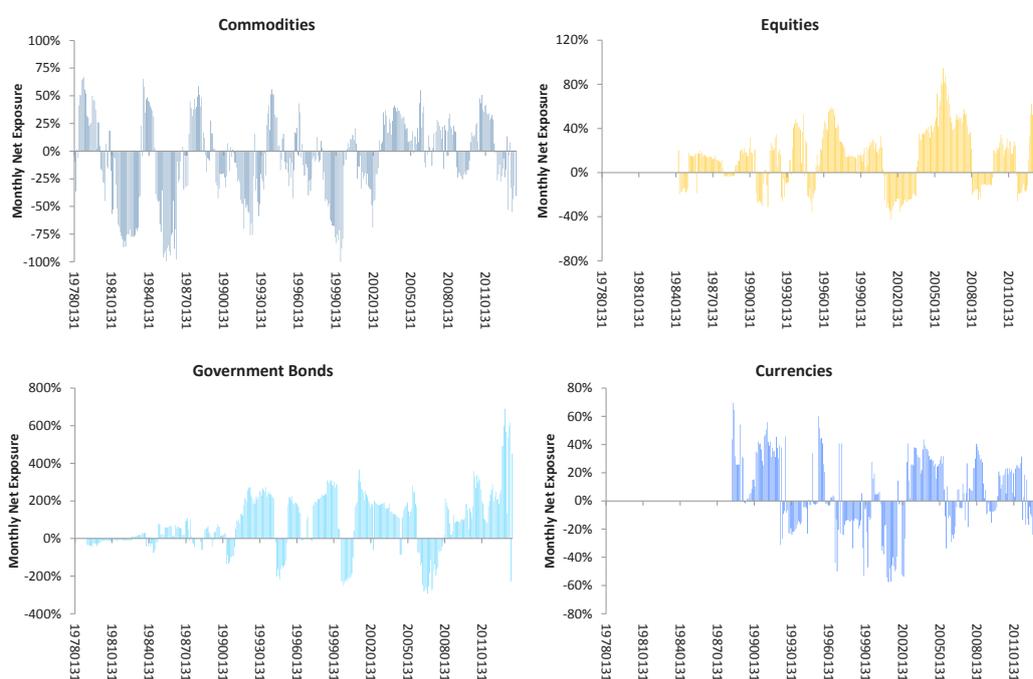
22 Using cross-sectional momentum portfolio as the base

Chart 7: Long-term and recent performance of 12-1 monthly and 8-1 weekly diversified time-series momentum strategy



Source: NBER, NBIM calculations

Chart 8: Net exposure²³ of 12-1 monthly diversified time-series momentum strategy by asset class



Source: NBIM calculations

To investigate the recent lacklustre performance of time-series momentum, we examine the difference in value-added from market timing for two distinct periods, pre and post January 2008. Given the increasing frequency of central bank interventions as well as sensitivity to macro-economic news, markets trends have become less persistent as they fluctuate with policy changes. In section 3.7, we showed empirically that time-series momentum is driven by both cross-sectional momentum and market timing. If trends become less persistent, then we would expect market timing to be more challenging. Table 9 shows the regression results using the specification as per section 3.7. Over the most recent period between January 2008 and May 2013, we observe that market timing has become statistically insignificant at the 5% level for equities. Whilst market timing for commodities remains statistically significant at the 5% level, its corresponding t-statistic dropped from 3.2 pre-January 2008 to 2.14 post-January 2008. We also note that market timing has recently been detrimental to time-series momentum for bonds (negative t-statistic of -1.51 vs. positive t-statistic of 1.48 pre January 2008). The results in Table 9 indicate that time-series momentum is as much related to

23 Note that the small net exposure of bonds prior to 1990 is due to smaller number of active bond contracts. For the same reason, the strategy has zero exposure to both equities and currencies prior to April 1983 and April 1987 respectively. See Table 1 for the data start date for each contract.

cross-sectional momentum before and after 2008, but that the additional return from market timing has become less pronounced.

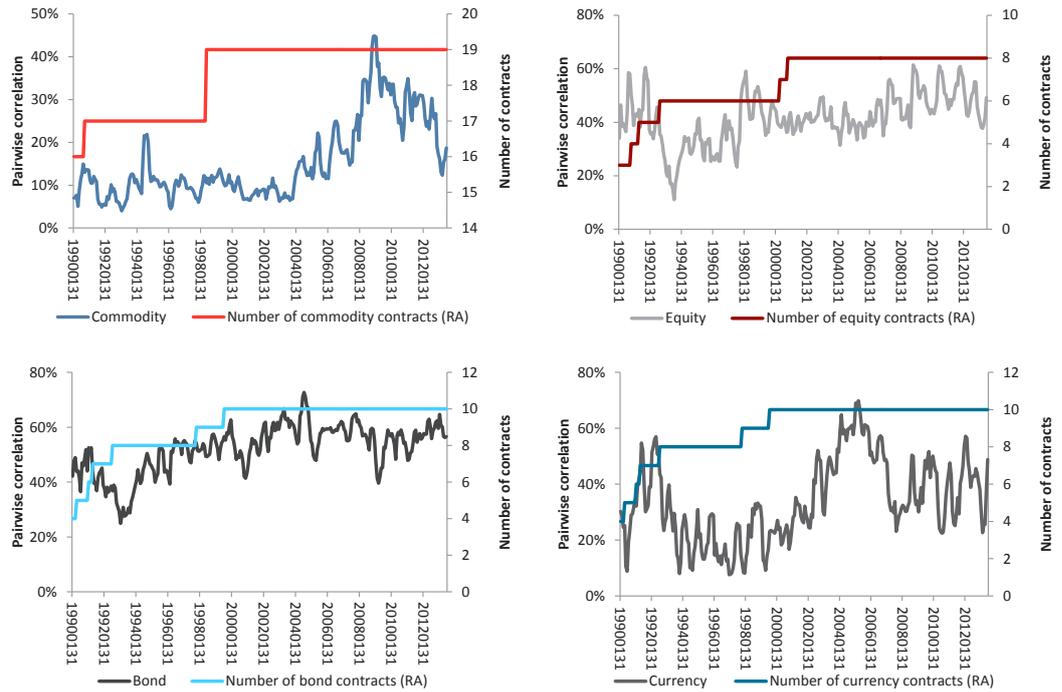
Table 9: Evolution of value-added from market timing to 12-1 monthly diversified time-series momentum

	Jan 2008 - May 2013				Before Jan 2008			
	Independent variable				Independent variable			
	Market Timing	XSMOM	Market	Alpha	Market Timing	XSMOM	Market	Alpha
All assets								
Coefficient estimate	0,26	0,84	0,15	0,02%	0,74	0,80	0,09	0,10%
Standard error	0,793	0,044	0,041	0,002	0,687	0,029	0,030	0,001
Regression R-squared	88,2 %				67,9 %			
T-Statistic	0,32	19,30	3,77	0,10	1,07	27,96	2,94	0,85
	Market Timing	XSMOM	Market	Alpha	Market Timing	XSMOM	Market	Alpha
Equity								
Coefficient estimate	3,01	0,66	-0,08	0,17%	5,26	0,46	0,36	-0,15%
Standard error	2,285	0,180	0,137	0,004	1,333	0,070	0,055	0,002
Regression R-squared	23,9 %				35,9 %			
T-Statistic	1,32	3,67	-0,55	0,41	3,94	6,53	6,56	-0,72
	Market Timing	XSMOM	Market	Alpha	Market Timing	XSMOM	Market	Alpha
Bond								
Coefficient estimate	-1,73	0,24	0,79	0,09%	1,48	0,47	0,50	0,14%
Standard error	1,150	0,062	0,061	0,002	0,997	0,056	0,048	0,002
Regression R-squared	86,8 %				62,5 %			
T-Statistic	-1,51	3,97	12,82	0,59	1,48	8,29	10,39	0,86
	Market Timing	XSMOM	Market	Alpha	Market Timing	XSMOM	Market	Alpha
Currency								
Coefficient estimate	0,87	1,05	-0,08	0,01%	1,18	0,86	-0,05	0,00%
Standard error	1,386	0,088	0,068	0,003	0,687	0,032	0,032	0,001
Regression R-squared	70,4 %				76,3 %			
T-Statistic	0,63	11,87	-1,24	0,05	1,71	27,07	-1,56	-0,02
	Market Timing	XSMOM	Market	Alpha	Market Timing	XSMOM	Market	Alpha
Commodity								
Beta	3,86	0,66	0,21	-0,63%	2,87	0,68	-0,16	0,17%
SE	1,808	0,112	0,097	0,004	0,898	0,039	0,038	0,001
R-Squared	45,4 %				45,4 %			
T-Statistic	2,14	5,92	2,18	-1,74	3,20	17,44	-4,33	1,19

Source: NBIM calculations

Another possible explanation for the recent weaker performance is the use of volatility-parity weighting in time-series momentum strategies and the higher correlations between futures contracts. Chart 9 shows the average pairwise correlation, as well as the number of corresponding assets, over time within each asset class. In general, we see that correlations within each asset class have increased over time, which in turn reduced diversification benefits. In such an environment, volatility-parity, which assumes no correlation between risky assets, becomes a sub-optimal risk allocation methodology. Assuming equal asset volatilities, an asset that exhibits a lower (higher) correlation with the rest of the universe should optimally have a larger (lower) weight than that implied by volatility-parity.

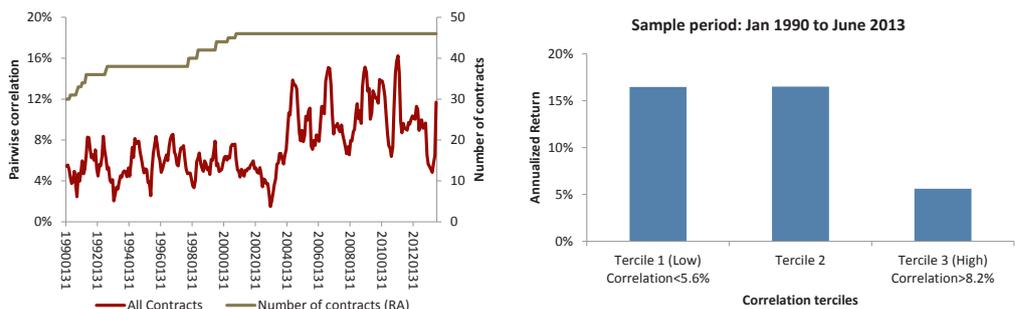
Chart 9: Rolling average pairwise correlation²⁴ within each asset class



Source: NBIM calculations

In order to empirically investigate this hypothesis, we construct a correlation event study where we group all months of the dataset in three average pairwise correlation buckets and evaluate the performance of our 12-1 diversified monthly time-series momentum strategy. Looking at both panels of chart 10 in tandem, we see that the performance of volatility-parity trend-following strategy deteriorates significantly during periods of high average pairwise correlation which exist after 2004.

Chart 10: Rolling average pairwise across all futures contracts (left panel) and correlation event study on diversified time-series momentum strategy returns (right panel)



Source: NBIM calculations

24 Using a 90-day estimation window

4. Conclusions

We find a significant time-series momentum effect that is remarkably consistent across the 47 diverse futures contracts studied. Our empirical results are consistent with Baltas and Kosowski (2012) and Moskowitz et al. (2012).

Our results indicate that trading on momentum signals generates substantial turnover. Further research is required to assess the trade-off between the improvement in risk-return characteristics and the transaction and potential market impact costs associated with higher turnover.

Throughout the note, we used a naïve portfolio construction method that takes the inverse of the volatility as a weighting scheme. While such volatility parity approach takes into account the different asset volatilities, the method also has the drawbacks of substantial leverage in low-risk assets and asset correlations not guiding the portfolio construction process. More research on more sophisticated portfolio construction methodologies is warranted to enhance risk-adjusted performance.

We show empirically that the performance of time-series momentum strategies depends on volatility regimes. For example, the time-series momentum performance is lower in times when underlying asset volatility is high. On the other hand, time-series momentum performance is high during US recession periods. It seems that predicting when momentum works well is a fruitful area for further research.

References

- Asness, C.S., T.J. Moskowitz, L.H. Pedersen (2013): "Value and momentum everywhere", *Journal of Finance*, Volume 68, Issue 3, pages 929-985, June 2013.
- Baltas, A. and R. Kosowski (2012): "Momentum strategies in futures markets and trend-following funds", SSRN working paper, June 2012.
- Baltas, A., D. Jessop, C. Jones, H. Zhang (2013): "Trend-following meets risk parity", UBS Global Quantitative Research Monographs, 2 December 2013.
- Barroso, P. and P. Santa-Clara (2012): "Managing the risk of momentum", SSRN working paper, April 2012.
- Chordia, T. and L. Shivakumar (2002): "Momentum, business cycle, and time-varying expected returns", *The Journal of Finance* Vol. LVLL, No. 2, April 2002.
- Christoffersen, P. F. and F.X. Diebold (2006): "Financial asset returns, direction-of-change forecasting, and volatility dynamics", *Management Science* 52 (2006), 1273-1287.
- Christoffersen, P.F., F.X. Diebold, R.S. Mariano, A.S. Tay and Y.K. Tse (2007): "Direction-of-change forecasts based on conditional variance, skewness and kurtosis dynamics: international evidence", *Journal of financial forecasting* (1-22), Volume 1/ Number 2, Fall 2007.
- Daal, E., J. Farhat, P. Wei (2006): "Does futures exhibit maturity effect? New evidence from an extensive set of US and foreign futures contracts", *Review of Financial Economics*, Vol. 15, No. 2, 2006.
- Fama, E.F. (1970): "Efficient capital markets: A review of theory and empirical work", *Journal of Finance* 25, 383-417.
- Fama E.F. (1991): "Efficient capital markets: II", *Journal of Finance* 46(5), 1575-1617.
- Gorton, G.B, F. Hayashi, K.G. Rouwenhorst (2012): "The fundamentals of commodity futures returns", *Review of Finance*, 10.1093/rof/rfs019.
- Hong, H. and J. C. Stein (1999): "A unified theory of underreaction, momentum trading and overreaction in asset markets", *Journal of Finance* 54, 2143-2184.

- Hong, H. and J.C. Stein (2007): "Disagreement and the stock market", *The Journal of Economic Perspective* 21, 109-128.
- Jacobs, B.I. and K.N. Levy (2012): "Leverage aversion, efficient frontiers and the efficient region", forthcoming, *The Journal of Portfolio Management*, Vol. 39, No. 3, Spring 2013.
- Johnson, T. C. (2002): "Rational momentum effects", *The Journal of Finance* Vol. LVII, No. 2, April 2002.
- Korajczyk, R.E. and R. Sadka (2004): "Are momentum profits robust to trading costs?", *Journal of Finance* 59, 1039-1082.
- Kroencke, A.T., F. Schindler and A. Schrimpf (2013): "International diversification benefits with foreign exchange investment styles", *Review of Finance* (2013) pp. 1-37.
- Lesmond, D.A., M.J. Schill and C. Zhou (2004): "The illusory nature of momentum profits", *Journal of Financial Economics* 71, 349-380.
- Liu, L. X. and Z. Lu (2008): "Momentum profits, factor pricing and macroeconomic risk", *The Review of Financial Studies*/ v 21 n 6 2008.
- Luu B.V. and P. Yu (2012): "Momentum in government-bond markets", *The Journal of Fixed Income*, Fall 2012.
- Miffre, J., A. Fuertes and A. Fernandez-Perez (2012): "Commodity futures returns and idiosyncratic volatility", SSRN working paper, 31 July 2012.
- Miffre, J. and G. Rallis (2007): "Momentum strategies in commodity futures markets", *Journal of Banking and Finance* 31, 1863-1886.
- Mouakhar, T. and M. Roberge (2010): "The optimal approach to futures contract roll in commodity portfolios", *The Journal of Alternative Investments*, Winter 2010, Vol. 12, No. 3: pp 51-60.
- Moskowitz, Y., H. Ooi and H., P. Pedersen (2012): "Time series momentum", *Journal of Financial Economics* 104 (2012) 228-250.
- Polbennikov, S., A. Desclee and J. Hyman (2010): "Horizon diversification: Reducing risk in a portfolio of active strategies", *The Journal of Portfolio Management*, Winter 2010, Vol. 36, No. 2: pp. 26-38.
- Samuelson, P.A. (1965): "Proof that properly anticipated prices fluctuate randomly", *Industrial Management Review*, 6, 41-49.
- Shen, Q., A.C. Szakmary and S.C. Sharma (2007): "An examination of momentum strategies in commodity futures markets", *Journal of Futures Markets* 27, 227-256.
- Szakmary, A.C., Q. Shen and S.C. Sharma (2010): "Trend-following trading strategies in commodity futures: A re-examination", *Journal of Banking & Finance* 34 (2010) 409-426.
- Treynor, J. and K. Mazuy (1966): "Can mutual funds outguess the market?", *Harvard Business Review* 44 (July-August): 131-136.
- Vayanos, D. and P. Woolley (2013): "An institutional theory of momentum and reversal", *Review of Financial Studies*, Society for Financial Studies, vol. 26(5), pages 1087-1145.

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