# Multi-Asset Seasonality and Trend-Following Strategies[1]

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## Abstract

This paper investigates the seasonality patterns within various asset classes. We find that a strategy that buys the assets with the largest same-calendar-month past average returns (up to ten years) and sells the assets with the smallest same-calendar-month past average returns, earns statistically and economically significant premia within commodity and equity index universes. Capitalising these premia directly appears practically difficult, due to the high strategy turnover and associated costs. We therefore suggest a way to actively incorporate seasonality signals into a trend-following strategy by switching off long and short positions, when the respective seasonality signals argue otherwise. The seasonality-adjusted trend-following strategy constitutes a significant improvement to the raw strategy across both commodities and equity indices. The increased turnover can impact the performance pickup, but the relatively low trading costs of liquid futures contracts as well as methodological amendments that optimise position smoothing can render the improvement genuine.


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# 1. Introduction

Return cyclicality is relatively common within equity returns and the literature on seasonality effects is rather rich. From the famous January effect to the Hallowe'en effect and the lunar cycle, academic studies have documented a multitude of seasonal patterns within equity markets and equity strategy returns. In explaining these patterns, researchers have associated them either to various market-driven incentives, like tax year-end activities and institutional window dressing, or to behavioural effects due to seasonal risk appetite (e.g. investors acquiring a more gambling behaviour in the beginning of the year). What is very common across all these patterns is that it is typically rather expensive to exploit them, and as a consequence, whatever appears to be significantly strong on paper might be impossible to capitalise in practice. Ilmanen (2012, Chapters 25-26) provides a very comprehensive overview of the broad family of seasonal effects and their attempted explanations.

Instead of looking into such month-of-the-year or day-of-the-week type of seasonal patterns, Heston and Sadka (2008) are the first to study in detail the existence of long-run seasonality patterns in the cross-section of US equity returns. They find statistically and economically strong seasonal effects; a winners-losers strategy formed after ranking the stocks based on their average past same-calendar-month performance earns a monthly return that exceeds 50 basis points for lookback periods that go even up to 20 years. This strong long-lasting effect cannot be explained by trading volume or volatility (even though, interestingly enough, both variables exhibit similar seasonal patterns) and remains robust to various methodological permutations[3]. In a follow-up paper, Heston and Sadka (2010) extend their findings to non-US markets and document similarly strong seasonal patterns across Japan, Canada and 12 European countries.

More recently Keloharju, Linnainmaa and Nyberg (2015) extend the findings of Heston and Sadka (2008, 2010) and explore the long-run seasonal patterns within equity anomalies (they focus on 15 strategies based on value, momentum, gross profitability etc.). Interestingly, even though their primary focus is on equity anomalies, they also include a short section where they test for similar seasonality patterns within commodities and international stock market indices.

Motivated by these recent findings, we investigate in detail the existence of any long-run seasonal patterns across various non-equity asset classes, namely commodities, government bonds, FX rates and country equity indices. By using a panel regression framework we document strong statistical evidence of long-run (up to ten years due to limited data availability) seasonal patterns within commodities and equity indices, but nothing of particular significance within government bonds or FX rates[4]. These findings are in line with Keloharju *et al.* (2015).

Commodity markets are traditionally driven by supply and demand shocks between producers and consumers and the seasonal variation of these shocks can potentially be the reason of the seasonal return regularities. For instance, heating energy commodity

[3] In particular, Heston and Sadka (2008) show that the seasonal patterns remain robust across different size or industry bands, and are not concentrated on any particular calendar month of corporate event (like earnings announcement months, dividend announcement months, ex-dividend months or fiscal year-end months).

[4] FX rates exhibit strong seasonal patterns but at a higher frequency and mostly intra-daily; see for example Andersen and Bollerslev (1997) and Ito and Hashimoto (2006).

prices are expected to predictably fluctuate between seasons (winter and summer); indicatively, Todorova (2004) studies the seasonal patterns on crude oil and natural gas futures. Similarly, agricultural commodity prices are expected to predictably fluctuate around (before and after) the harvesting period; indicatively, Sørensen (2002) studies the seasonal patterns on corn, soybean and wheat futures.

In theory, such seasonal variations in commodity prices should be completely predictable and already incorporated in the time-variation of returns, to the extent that no active return ("alpha") could be extracted from these patterns. In practice, there exist various irregularities that render these effects worth exploring. This is indeed the objective of this paper; to identify the conditions under which such seasonal patterns can be exploitable in practice.

In order to capture the seasonality premia across commodity and equity index markets, we construct long-short portfolios that buy assets with the largest same-calendar-month average returns over the past ten years and short assets with the lowest same-calendar-month average returns over the same period. The strategy returns are statistically and economically strong, and fairly uncorrelated with other investment strategies like value or momentum. However, in line with expectations, capitalising on these premia can be very costly due to the high turnover that the respective strategies exhibit. At times, the trading costs can even completely eliminate the positive returns, hence casting doubts on the practical importance of our findings.

Following the above, it appears unlikely to be able to capitalise on commodity and equity index seasonality patterns directly. However, one can potentially extract vital information from seasonal activity when constructing a trend-following strategy. A typical trend-following strategy involves long positions on upward moving assets over the past year and short positions on downward moving assets over the same period. We investigate whether the interaction of seasonality and trend-following signals can improve the performance of the trend-following strategy by effectively switching off any long positions, whose seasonality signal falls on the bottom of the cross-sectional ranking (i.e. same-calendar-month seasonal losers) and similarly switch off any short positions, whose seasonality signal falls on the top of the cross-sectional ranking (i.e. same-calendar-month seasonal winners).

The seasonality-adjusted trend-following strategy constitutes a statistically significant improvement to the original trend-following strategy across both asset classes, namely commodities and equity indices. It is though important to stress that the performance pickup can be substantially reduced by the increased turnover from incorporating the seasonality signals. However, trading on the very liquid front futures contracts and applying some type of cost optimisation overlay can significantly reduce the associated costs.

The paper is organised in three main parts. Section 2 contains the empirical analysis for the identification of seasonality patterns within the various asset classes. Section 3 provides insight upon the existence of the seasonality premia within commodities and equity indices by looking into risk-based or limits-to-arbitrage explanations. Section 4 presents the construction of a typical trend-following portfolio and explores the added value from incorporating seasonality signals. Finally, Section 5 concludes.

## 2. Exploring Seasonality Patterns

Testing for the existence of seasonality patterns in the cross-section of asset returns implies testing whether lagged returns over a certain frequency (e.g. lagged annual returns, lagged semi-annual returns etc.) can forecast future returns. Instead of running univariate regressions of asset returns on their lagged values on an asset-by-asset basis, we can increase the statistical power of the experiment by running panel Fama and MacBeth (1973) regressions. This involves running, first, a cross-sectional regression of the returns of all assets on their respective $k$-month lagged monthly return at the end of each month $t$:

$$r_{i,t} = \alpha_{k,t} + \beta_{k,t} \cdot r_{i,t-k} + \epsilon_{i,t}, \text{ for } i = 1, \dots, N_{k,t} \text{ and each } t \tag{1}$$

and subsequently average across time the regression coefficients $\alpha_{k,t}$ and $\beta_{k,t}$ to estimate the values of $\alpha_k$ and $\beta_k$:

$$\alpha_k = \frac{1}{T}\sum_{t=1}^{T} \alpha_{k,t} \text{ and } \beta_k = \frac{1}{T}\sum_{t=1}^{T} \beta_{k,t}. \tag{2}$$

In equation (1) above, $r_{i,t}$ denotes the return of asset $i$ in month $t$ and $N_{k,t}$ denotes the number of assets at the end of month $t$ that have data up to $k$ months ago.

In order to explore the existence of seasonality patterns in the cross-section of asset returns within various asset classes, we compile a very comprehensive and rich dataset both across assets and across time using data from Datastream. In particular, we collect spot return data for 19 commodities (we use the S&P GSCI or the Thompson Reuters commodity price indices, whichever offers the longest history), 16 government bonds (we use the Datastream benchmark ten-year indices), 10 FX rates (from WM/Reuters or GTIS) and 18 MSCI country equity total return indices. Table 1 lists all the assets in our universe, including the starting month for each asset.

Heston and Sadka (2008, 2010) and Keloharju *et al.* (2015) run the panel regression for lags up to 240 months (20 years). Our significantly smaller multi-asset data sample does not allow for strong statistical power for such long lags and we therefore run the panel regression for lags up to 60 months[5] and separately for each asset class as the seasonal patterns can vary significantly from one asset class to another. This choice for maximum lag implies that our first cross-sectional regression will take place five years after the first month of data in each asset class. As already explained in the previous section, not all assets and asset classes start at the same point in time. Hence, in an effort to have a reasonable balance between cross-sectional and time-series data availability, we conduct the panel regression analysis starting in January 1975 for equity indices (all 19 assets available), in July 1991 for commodities (14 out of the 18 assets available), in July 1994 for government bonds (13 out of the 16 assets available) and in January 1991 for foreign exchange (all ten currencies available).

[5] Moskowitz, Ooi and Pedersen (2012) as well as Baltas and Kosowski (2013, 2015), who run similar panel regressions on a multi-asset space also use lags up to 60 months.

**Table 1: Dataset**

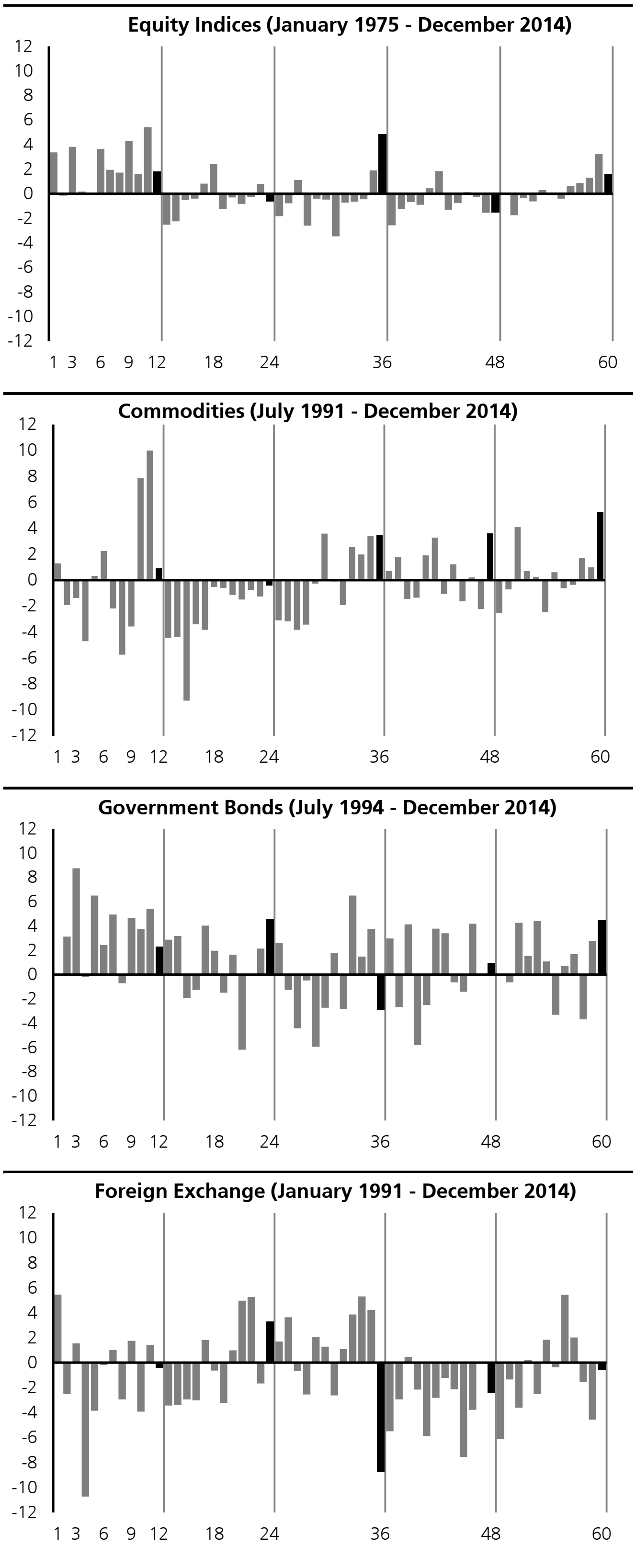
| Commodities | | Government 10Yr Bonds | | Foreign Exchange | | Equity Indices | |
|---|---|---|---|---|---|---|---|
| | *Start date* | | *Start date* | | *Start date* | | *Start date* |
| Brent Crude | Jan-70 | Australia | Mar-87 | AUD | Jan-84 | Australia | Jan-70 |
| Heating Oil #2 | Jan-83 | Austria | Jan-85 | CAD | Jan-86 | Austria | Jan-70 |
| WTI Crude | Jan-83 | Belgium | Jul-89 | CHF | Jan-86 | Belgium | Jan-70 |
| Natural Gas | Apr-90 | Canada | Jan-85 | DKK | Jan-86 | Canada | Jan-70 |
| Gas Oil | Jul-86 | Denmark | Jan-89 | EUR | Jan-70 | Denmark | Jan-70 |
| Corn | Jan-70 | France | Jan-85 | GBP | Jan-70 | France | Jan-70 |
| Soybeans | Jan-70 | Germany | Jan-80 | JPY | Jan-86 | Germany | Jan-70 |
| Cotton #2 | Jan-77 | Italy | Apr-91 | NOK | Jan-86 | Hong Kong | Jan-70 |
| Cocoa | Jan-71 | Japan | Jan-84 | NZD | Jan-86 | Italy | Jan-70 |
| Coffee "C" | Jan-81 | Netherlands | Jan-88 | SEK | Jan-86 | Japan | Jan-70 |
| Sugar #11 | Jan-73 | Norway | Dec-92 | | | Netherlands | Jan-70 |
| Wheat | Jan-70 | Spain | Dec-90 | | | Norway | Jan-70 |
| Live Cattle | Jan-70 | Sweden | Jan-89 | | | Singapore | Jan-70 |
| Aluminium | Jan-91 | Switzerland | Jan-81 | | | Spain | Jan-70 |
| Copper | Jan-77 | UK | Jan-80 | | | Sweden | Jan-70 |
| Nickel | Jan-93 | US | Jan-80 | | | Switzerland | Jan-70 |
| Zinc | Jan-91 | | | | | UK | Jan-70 |
| Gold (100 oz.) | Jan-70 | | | | | US | Jan-70 |
| Silver #11 | Jan-73 | | | | | | |
| *All Available from:* | Jan-93 | | Dec-92 | | Jan-86 | | Jan-70 |

Notes: The table reports the assets that we use for our analysis, including the first month that each data series is available. The last row of the table reports the month after which all assets per asset class are available. The sample period ends in December 2014. All data is obtained from Datastream.

Figure 1 reports the slope coefficients $\beta_k$ for all lags (annual lags are coloured in black) and asset classes and Figure 2 reports the respective t-statistics, which are calculated using Newey and West (1987) standard errors with 12 lags in order to adjust for potential serial-correlation and heteroskedasticity patterns in the error terms. These two Figures should be studied side by side.

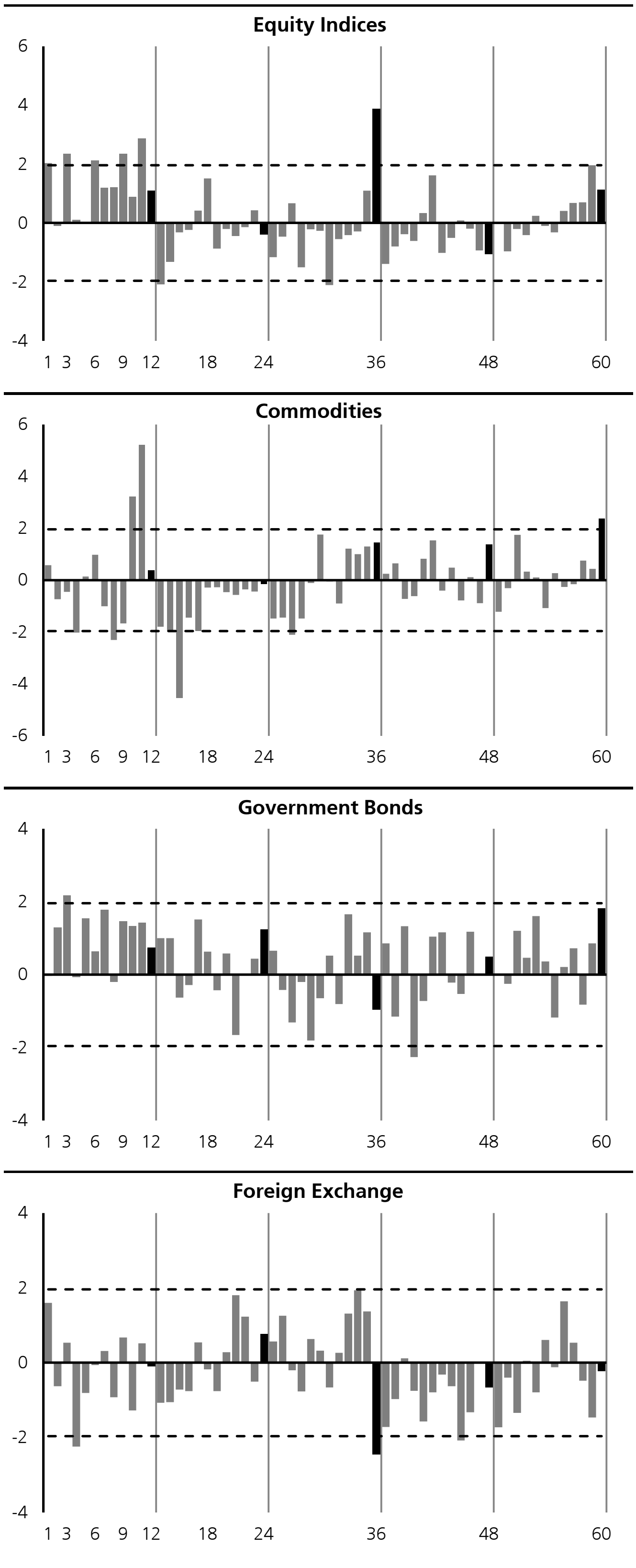
What we look for is a combination of two things. On one hand, we look for a large numerical value for $\beta_k$ (in Figure 1). As Fama (1976, Chapter 9) explains, these slope coefficients can be interpreted as the return of a long-short, zero-cost portfolio of all the assets that are used in the panel regression in equation (1). On the other hand, we look for a large t-statistic for $\beta_k$ (in Figure 2). Critical values of $\pm 1.96$ (5% significance) are denoted with dashed lines in the figure. A more conservative threshold of significance is that of $\pm 1.64$ (10% significance). Several interesting patterns emerge from these Figures, which we discuss separately for each asset class.

**Figure 1: Panel Regression Coefficients**




Notes: The charts report the Fama-MacBeth panel regression coefficients from regressing monthly returns on lagged returns, for lags ranging from 1 to 60 months. The sample period differs for each asset class and is mentioned in the chart titles. All data is obtained from Datastream.

**Figure 2: Panel Regression t-statistics**




Notes: The charts present the Fama-MacBeth t-statistics of the panel regression coefficients from regressing monthly returns on lagged returns, for lags ranging from 1 to 60 months. The t-statistics are adjusted for serial-correlation and heteroskedasticity using the Newey and West (1987) correction with 12 lags. The dashed lines at -1.96 and +1.96 denote the 5% significance thresholds. All data is obtained from Datastream.

**Equity Indices:** We document strong serial-correlation effects over the course of the first 12 months, which is a clear indication of trend-following (time-series momentum) patterns. The return predictability becomes economically (judging by the level of $\beta_k$) and statistically (judging by the level of the t-statistic of $\beta_k$) strong in quarterly lags (3, 6 and 9 months). The first-year momentum patterns revert straight after the course of the year in line with the findings of Moskowitz, Ooi and Pedersen (2012). Regarding seasonality, which is the main focus of this paper, we document strong, both statistically and economically, positive return predictability at a lag of 36 months and less significantly so at lags of 12 and 60 months.

**Commodities:** Possibly expected due to the nature of this asset class, commodities appear to exhibit the strongest seasonal patterns across all asset classes. At annual lags of 36, 48 and 60 months (even up to 120 months as it is shown in the Appendix A), there is economically strong return predictability, as deduced by the levels of the regression coefficients $\beta_k$, with the 60-month lagged return also enjoying very strong statistical significance with a t-statistic of 2.5. We also document very strong end-of-first-year trend-following patterns, followed by strong reversals after the course of the year, in line with the findings of Moskowitz *et al.* (2012).

**Government Bonds:** The fixed income market exhibits strong times-series return predictability over the first 12 months, which constitutes evidence of the profitability of trend-following strategies within fixed income markets over the recent decades; see Baltas, Jessop, Jones and Zhang (2013). However, following the first year, there is hardly any significant pattern worth documenting. No seasonal patterns emerge.

**Foreign Exchange:** We fail to document any statistically or even economically strong patterns across any subperiod or specific lag within the FX universe, at least for the given dataset and the respective sample period. A statistically strong reversal effect at a lag of 36 months constitutes, to our view, more of an artefact of data fitting and less so of any practical use.

In summary, we document significant seasonality patterns within commodity indices and –less significantly so– within equity indices. These results are in line with Keloharju *et al.* (2015), who similarly document some significant seasonality patterns in commodity futures and country equity indices, but do not present any analysis within the fixed income and foreign exchange markets. Based on this analysis and for the remainder of this paper, we solely focus on commodity and equity index markets.

For additional robustness and after acknowledging any data limitation issues, we present in Appendix A the results of our panel regression framework for lags up to 120 months (ten years) for equity index and commodity markets (Figures A.1 and A.2 respectively). The evidence of long-term seasonality for commodities is overwhelming with $\beta_k$ for all annual lags between three and ten years (excluding the lag of nine years) being the largest across the respective years and statistically significant for lags above five years. In contrast, the evidence for equity indices is not so statistically strong; all annual lags between five and ten years are all positive, but lack statistical significance. The strongest effect remains at a lag of three years as already documented in Figures 1 and 2.

## 3. Capturing the Seasonality Premium

In order to evaluate the investment implications of the documented patterns within commodities and equity indices, we next construct long-short portfolios between past same-calendar-month winners and past same-calendar-month losers. The analysis is conducted separately for each of the two asset classes of interest.

In order to construct these portfolios, we first rank all assets of the same asset class at the end of each month based on their average past same-calendar-month return for a lookback period of ten years (we require at least five years of data for an asset in order to be included in the ranking). As an example, at the end of December 2000, we are expected to form a portfolio that will be held over January 2001 and for that reason we rank the available assets based on their average return over the past ten Januaries (1991 to 2000). Based on this ranking we then split the universe of assets into quintiles and we construct a long-short portfolio by taking a long position on the top quintile and a short position on the bottom quintile, equally weighting the respective constituents. Using the terminology of Heston and Sadka (2008, 2010), we call this portfolio the "annual" strategy.

As a point of reference, we similarly construct a long-short portfolio based on the past five-year average monthly return of the assets, after excluding the same-calendar-month returns from the calculation. In the context of the example given above, this implies sorting all the assets on their average return between January 1991 and December 2000, after first removing all the Januaries from the sample. To contrast this against the annual strategy, we call this portfolio the "non-annual" strategy.

Before proceeding with the presentation of the results, we have to note that for the construction of annual and non-annual strategies we switch to a futures dataset for commodities. So far, for the purposes of the panel regression analysis in the previous section we have used spot commodity price index data mainly due to the longer data availability (compared, say, to a futures universe). Estimating regressions with lags up to five or ten years requires a relatively long history and cross-section of assets, hence our decision to use spot return data. More importantly, a regression captures serial dependence of returns and does not focus on the absolute level of asset returns.[6]

Contrary to a regression analysis, the construction and back-testing of trading strategies requires precise estimates for the absolute level of returns that would have been experienced by an investor in practice. Futures contracts constitute the most appropriate vehicle in order to implement such trading strategies, especially for commodities, where the cash settlement of futures contracts is definitely preferred from the physical delivery of spot transactions.

Other than the practical implications of physical versus cash settlement, commodity spot return data typically differ significantly from futures returns due to the level of the cost of carry in the calculation of futures prices. The nature of commodity markets (ranging widely from energy, softs, metals etc.) suggests that commodities constitute an asset class with relatively large (if not the largest across all asset classes) costs of

[6] Given asset pricing principles (and skipping any further details at this stage), spot price returns and returns of the first-to-expire (and therefore most liquid) futures contract should be largely correlated. However, large correlation does not imply anything about the underlying levels of returns, which can be significantly different, if the cost of carry in the calculation of the futures price is large. As an example, consider how different the spot and futures returns are in a market of an asset that exhibits strong contango or backwardation behaviour for a long period.

carry, which includes storage costs and convenience yields. Our expectation (which is confirmed in unreported results) is that spot returns and futures returns for commodities differ largely in practice. For this reason, in order to construct seasonality strategies that can approximate closely the returns that an investor would experience, we use daily commodity front futures price data, collected from Bloomberg.[7] Table B.1 in the Appendix compares the spot and futures dataset in terms of data availability; clearly, the only downside from using futures data is that the sample periods of the contracts are generally smaller compared to the spot data.

The construction of the long-short seasonality portfolios, as outlined above, uses one fifth of assets on the long side and another fifth of assets on the short side, whilst requiring at least five years of data for each asset in order to be included in the cross-sectional rankings. Given these restrictions and the data availability, we form commodity portfolios from January 1992 onwards, at which point the portfolio has two assets long and two assets short; from August 1994 the portfolio contains three assets long and three assets short, in line with Keloharju *et al.* (2015), who construct similar seasonality strategies within commodity futures markets.

Contrary to commodities, equity country indices are relatively liquid in spot transactions (e.g. through ETFs), which are anyway always cash settled. More importantly, equity index futures returns only differ from spot returns due to any dividend yield, which can be assumed to have relatively small magnitude during the course of the life of a front futures contract. This renders spot and futures returns for equity indices not only highly correlated but also relatively similar in levels.[8] This observation allows us to continue using our spot equity index dataset for the construction of the seasonality strategies. This is important, because the available data on equity futures contracts have a relatively shorter history and a relatively smaller coverage compared to commodity futures.

Given our spot equity index dataset, all 18 assets are available from January 1970 and we can therefore construct long-short seasonality portfolios starting from January 1980 that would have three assets long and three assets short.

Overall, for the construction of long-short annual and non-annual seasonality strategies, we use a futures dataset for commodities (Table B.2 in Appendix B) and a spot total return dataset for equity indices (Table 1), with the simulations starting in January 1992 and January 1980 respectively.

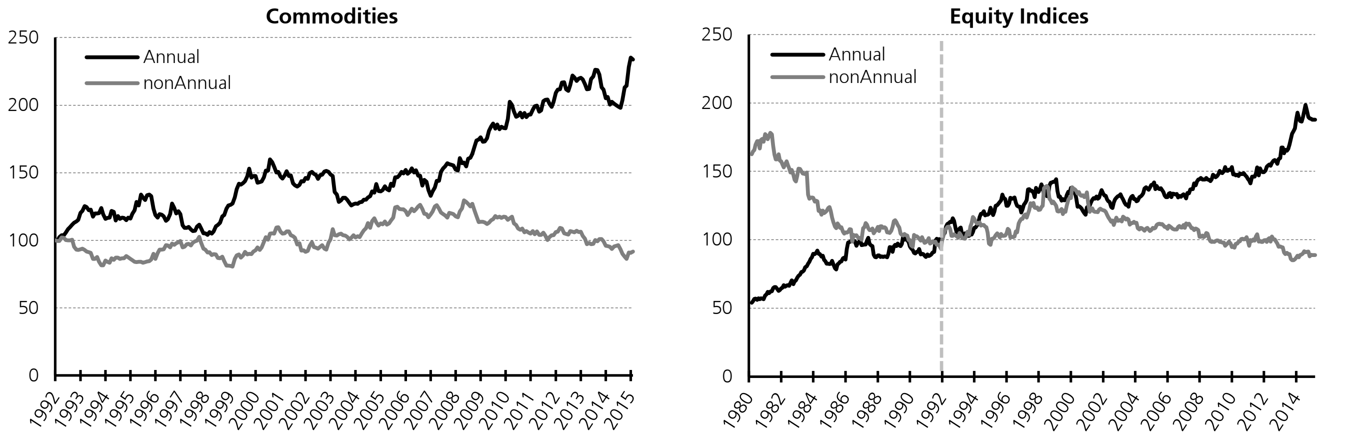
7 In particular, we use generic continuous-price series provided by Bloomberg, which are constructed in a way that we always trade the most liquid contract (typically the "front" contract), and we calculate for each futures contract fully-collateralised monthly returns in excess of the prevailing risk-free rate as shown in Baltas *et al.* (2013) and Baltas and Kosowski (2015).

8 de Roon, Nijman and Veld (2000) and Moskowitz *et al.* (2012) document that equity index returns calculated using spot price series or front futures series are highly correlated.

### 3.1. Performance Evaluation

We next present our main empirical findings regarding the performance of long-short strategies that aim to capitalise on the documented seasonal patterns within commodity and equity index markets. Figure 3 presents the cumulative returns for the annual and the non-annual portfolios for both asset classes. In order to have the same point of reference between the two asset classes, January 1992 has been set equal to 100 for both of them (this is denoted by the vertical dashed line in the equities chart). Finally, in order to allow for visual comparison between the two strategies (annual and non-annual), they have both been dynamically adjusted at end of every month in order to target a prescribed level of volatility equal to 7%.[9]

**Figure 3: Seasonality Patterns in Commodities and Equity Indices (Top vs. Bottom Quintile with volatility target at 7%)**




Notes: The figure presents the cumulative returns of long-short seasonality portfolios (top versus bottom quintile) within commodity and equity index markets. The annual strategy ranks all available assets by the average same-month return over the past ten years (minimum five years of data are required for each asset). The non-annual strategy ranks the available assets by their past ten year average return (minimum five years of data are again required) after excluding for the same-month returns. All strategies in this figure employ a 7% volatility target. The rebalancing takes place at the end of each month and the assets of all top and bottom quintiles are equally weighted. The sample period is January 1992 to February 2015 for commodities and January 1980 to February 2015 for equity indices. The commodity dataset is obtained from Bloomberg, whereas the equity index dataset is obtained from Datastream.

Focusing first on the annual strategy, it is evident that assets with the largest same-calendar-month past returns outperform their peers with the lowest same-calendar-month past returns, both within commodities and equity indices. Setting the annual strategies against their non-annual counterparties, the effects become stronger. The annual strategies outperform their non-annual counterparties especially during the most recent decade and also during the 80's for the equities universe. The relative benefit (annual versus non-annual) was significantly smaller or even non-existent during the 90's for both asset classes. Table 2 reports various performance statistics for these strategies.

All annual seasonality strategies (within both asset classes and across sample periods) generate strong and statistically significant positive returns. Focusing on the common sample period (January 1992 to February 2015), the annualised arithmetic returns are close to 4% for commodities and 3% for equity indices (both statistically significant at 5%), hence resulting to Sharpe ratios of 0.49 and 0.45. On the contrary, the non-

[9] In order to implement a constant-volatility ($CV$) overlay on a portfolio with monthly returns denoted by $r_t$ in month $t$, we scale the exposure to it (by effectively employing dynamic leverage) based on an estimate of its running volatility at the end of the previous month $\sigma_{t-1}$; we use a rolling window of 100 days for our analysis. The returns of the $CV$ strategy are given by:

$$r_t^{CV} = \frac{7\%}{\sigma_{t-1}} \cdot r_t$$

annual seasonality strategies fail to deliver any positive and statistically significant returns. As a consequence, the spread return between the two strategies, annual minus non-annual (presented in the last two rows of the table) is always positive and it is statistically significant for commodities (at 10%) and for equity indices, but only over the longer sample period (at 1%).

**Table 2: Performance Statistics for Seasonality Strategies (vol. target at 7%)**

| | Commodities | | Equity Indices | | Equity Indices | |
|---|---|---|---|---|---|---|
| | **Annual** | **non Annual** | **Annual** | **non Annual** | **Annual** | **non Annual** |
| **Sample Period** | *Jan. 1992 - Feb. 2015* | | | | *Jan. 1980 - Feb. 2015* | |
| **Geometric Mean (%)** | 3.70 | -0.34 | 2.75 | -0.23 | 3.78 | -2.52 |
| **Arithmetic Mean (%)** | 3.97** | -0.05 | 2.93** | 0.03 | 3.96*** | -2.20 |
| **t-stat** | (2.36) | (-0.03) | (2.18) | (0.02) | (3.31) | (-1.58) |
| **Volatility (%)** | 8.11 | 7.73 | 6.49 | 7.18 | 7.10 | 8.30 |
| **Sharpe Ratio** | 0.49 | -0.01 | 0.45 | 0.00 | 0.56 | -0.27 |
| **Max Drawdown (%)** | 22.31 | 33.40 | 17.88 | 39.01 | 17.88 | 61.02 |
| **Calmar Ratio** | 0.17 | -0.01 | 0.15 | -0.01 | 0.21 | -0.04 |
| | **Annual - non Annual** | | **Annual - non Annual** | | **Annual - non Annual** | |
| **Arithmetic Mean (%)** | 4.05* | | 2.76 | | 6.07*** | |
| **t-stat** | **(1.92)** | | (1.36) | | **(3.25)** | |

Notes: The table reports various performance statistics for annual and non-annual seasonality long-short (top versus bottom quintile) strategies within commodities and equity indices. The geometric mean, the arithmetic mean, the volatility and the Sharpe ratio are annualised. The sample period is January 1992 to February 2015; for equities, the results for a longer period starting in January 1980 are also reported. The t-statistics are calculated using White (1980) heteroskedasticity robust standard errors. Statistical significance at 1%, 5% and 10% levels is denoted by ***, ** and * respectively. The last 2 rows of the table report average arithmetic return and the respective t-statistic for the return different between annual and non-annual strategies. The commodity dataset is obtained from Bloomberg, whereas the equity index dataset is obtained from Datastream.

## 3.2 Explaining the Seasonality Premium

The empirical analysis presented so far documents a relatively sizeable seasonality return premium for commodities and equity indices with the largest average same-calendar-month past returns against their peers with the lowest average same-calendar-month past returns, for lookback periods that extend even up to ten years. We next explore the sources of this large return premium.

From a risk-based perspective, we aim to investigate whether this return premium constitutes compensation for bearing some known source of systematic risk or captures a known return premium like momentum. If there is no statistical evidence of such an exposure (which proves indeed to be the case), we then explore whether the size and statistical significance of the seasonality return premium are both strong just because the premium cannot be arbitraged away by an investor due to portfolio rebalancing constraints and turnover implications in a limits-to-arbitrage explanation.

### 3.2.1 Factor analysis

Is the seasonality premium a proxy for some other factor, like value or momentum? To answer this question, we perform a time-series factor analysis by regressing the monthly excess returns of the annual seasonality strategies on monthly excess returns of (a definition of) a market and a number of other factor premia for each asset class. The factors that we use are taken from Baltas, Jessop and Jones (2014) and are constructed using futures contracts; for further details see the aforementioned paper as well as Asness, Moskowitz and Pedersen (2013) and. Briefly, we use the following three factors for each asset class:

- **Market (MKT):** equally-weighted portfolios of commodity and equity index futures. Given that holding returns of futures contracts are already expressed in excess format[10], the respective market factors are consequently in excess format by construction.
- **Momentum (MOM):** long-short momentum factors within commodity and equity index markets, constructed by ranking the available assets at the end of each month based on their past 12-month return (skipping the most recent month) and then taking a long position on the top third and a short position on the bottom third, equally weighting each one of them.
- **Value (VAL):** following the same methodology as for momentum, long-short value factors are constructed for both markets. The ranking criterion for the equity universe is the book-to-price ratio of the respective country MSCI indices (data collected from Bloomberg, starting from January 1995) whereas for the commodity universe the ranking criterion is the five-year logarithmic return of the spot commodity prices.

Our results remain qualitatively and quantitatively unchanged to various methodological permutations e.g. using spot price data instead of futures data to construct the factors or using linear weights (instead of top third versus bottom third) for the momentum and value factors.

Panel A of Table 3 presents the results of the following monthly regression over the period January 1992 to February 2015 for commodities and January 1995 to February 2015 for equity indices:

$$r_t = \alpha + \beta \cdot MKT_t + \gamma \cdot VAL_t + \delta \cdot MOM_t + \epsilon_t \tag{3}$$

Notice that for this analysis we make use of the raw returns of the seasonality strategies, without employing any volatility target.

The evidence shows that the returns from the annual seasonality long-short strategy cannot be explained through exposure to existing return factors. All regression coefficients for both asset classes are small in magnitude and statistically insignificant. This finding can also be supported by the very low correlations between the seasonality strategies and the rest of the factors in Panel B of Table 3. Very interestingly, the seasonality strategies do not exhibit any beta with the underlying market (they are effectively market neutral strategies). The only statistically strong (at 10% level) parameter in Panel A of Table 3 is the alpha of the seasonality strategies.

[10] See Baltas and Kosowski (2015).

**Table 3: Factor Decomposition of Seasonality Strategies**

**Panel A: Regression Results using raw Seasonality Strategies**

| | Ann. alpha (%) | MKT | VAL | MOM | Adj. $R^2$ |
|---|---|---|---|---|---|
| **Commodities** | 12.30* | 0.07 | 0.01 | 0.18 | 0.77% |
| *Jan 1992 – Feb 2015* | **(1.89)** | (0.41) | (0.13) | (1.48) | |
| **Equity Indices** | 4.66* | 0.02 | -0.05 | -0.07 | -0.49% |
| *Jan 1995 – Feb 2015* | **(1.80)** | (0.41) | (-0.49) | (-0.82) | |

**Panel B: Correlation Matrices**

| **Commodities** | **Seasonality** | **MKT** | **VAL** | **MOM** |
|---|---|---|---|---|
| **Seasonality** | 1.00 | | | |
| **MKT** | 0.04 | 1.00 | | |
| **VAL** | -0.06 | -0.23 | 1.00 | |
| **MOM** | 0.13 | 0.11 | -0.47 | 1.00 |
| **Equity Indices** | | | | |
| **Seasonality** | 1.00 | | | |
| **MKT** | 0.02 | 1.00 | | |
| **VAL** | -0.01 | 0.46 | 1.00 | |
| **MOM** | -0.07 | -0.10 | -0.36 | 1.00 |

Notes: The figure presents in Panel A the results of time-series regressions of annual seasonality strategies on a market factor (equally-weighted), a value factor and a momentum factor. The t-statistics are calculated using White (1980) heteroskedasticity robust standard errors. Statistical significance at 1%, 5% and 10% levels is denoted by ***, ** and * respectively. Panel B reports the correlation matrix of the factors for each asset class. The commodity dataset is obtained from Bloomberg, whereas the equity index dataset is obtained from Datastream.

### 3.2.2 Turnover and Limits-to-Arbitrage

Given that the performance of the seasonality strategies cannot be attributed to exposure to conventional return premia such as momentum or value, another possible explanation is that it only exists in the data because it cannot be arbitraged away due to limits-to-arbitrage (in the spirit of Shleifer and Vishny, 1997). Along these lines, we investigate whether the seasonality strategies have relatively large turnover and therefore the associated level of trading costs can swamp the respective premia.

For that purpose, Table 4 reports the average annualised arithmetic return and the respective Sharpe ratio before and after transaction costs for the annual seasonality strategy of each asset class, as well as for the list of factors that were used in the factor analysis of the previous section (market, value and momentum). For comparison purposes, we also include a trend-following (TF) strategy, which is formed by long and short positions on assets with positive or negative 12-month excess returns respectively on an inverse-volatility weight basis. Further details on the construction of trend-following strategies follow in the next section.

Panel A of Table 4 reports statistics for raw strategies, whereas Panel B reports statistics for their respective constant-volatility counterparts that employ dynamic leverage in order to target ex-ante a volatility of 7%. Employing dynamic leverage and targeting a certain level of volatility can scale a strategy to the risk-target of a portfolio manager, but this requires additional turnover and therefore transaction costs. This is why we report results both for the raw strategies and their constant-volatility versions. Our aim is to evaluate the after-costs performance of the strategies when reasonable practical levels of target volatility are employed.

In order to estimate the realised costs, we use a very simplistic rule (our after-costs illustrative results should therefore be treated with the required caution), suggested by Frazzini, Israel and Moskowitz (2012), based on which the realised costs are the product of portfolio turnover and an average level of market impact:

$$Realised\ Costs = Turnover\ \times Market\ Impact \quad (4)$$

Frazzini *et al.* (2012) report an average market impact cost for conventional equity styles (value, momentum, short-term reversals) around 15-25 basis points. We decide to use a reasonable, yet conservative level of 25 basis points (trading liquid commodity futures or equity indices using ETFs is typically substantially cheaper).

**Table 4: The Effect of Turnover and Transaction Costs (assuming Market Impact costs of 25 basis points)**

**Panel A: Raw Strategies**

| | Commodities | | | | | Equity Indices | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | MKT | VAL | MOM | TF | Annual | MKT | VAL | MOM | TF | Annual |
| *Before costs:* | | | | | | | | | | |
| Arithmetic Mean (%) | 4.45 | 4.69 | 15.09*** | 6.45*** | 15.36** | 7.58** | 3.85 | 4.27 | 8.06*** | 4.80** |
| Volatility (%) | 14.46 | 25.35 | 23.59 | 9.11 | 31.18 | 15.59 | 12.98 | 15.06 | 12.30 | 11.23 |
| Sharpe Ratio | 0.31 | 0.19 | 0.64 | 0.71 | 0.49 | 0.49 | 0.30 | 0.28 | 0.66 | 0.43 |
| *Costs:* | | | | | | | | | | |
| Monthly Turnover (%) | 6.48 | 39.36 | 41.40 | 33.04 | 160.05 | 4.59 | 16.19 | 46.32 | 22.18 | 164.35 |
| Realised Costs (%) | 0.19 | 1.18 | 1.24 | 0.99 | 4.80 | 0.14 | 0.49 | 1.39 | 0.67 | 4.93 |
| *After costs:* | | | | | | | | | | |
| Arithmetic Mean (%) | 4.25 | 3.51 | 13.85 | 5.46 | 10.56 | 7.45 | 3.36 | 2.88 | 7.40 | -0.14 |
| Sharpe Ratio | 0.29 | 0.14 | 0.59 | 0.60 | 0.34 | 0.48 | 0.26 | 0.19 | 0.60 | -0.01 |

**Panel B: Dynamic Leveraged Strategies (Volatility Target at 7%)**

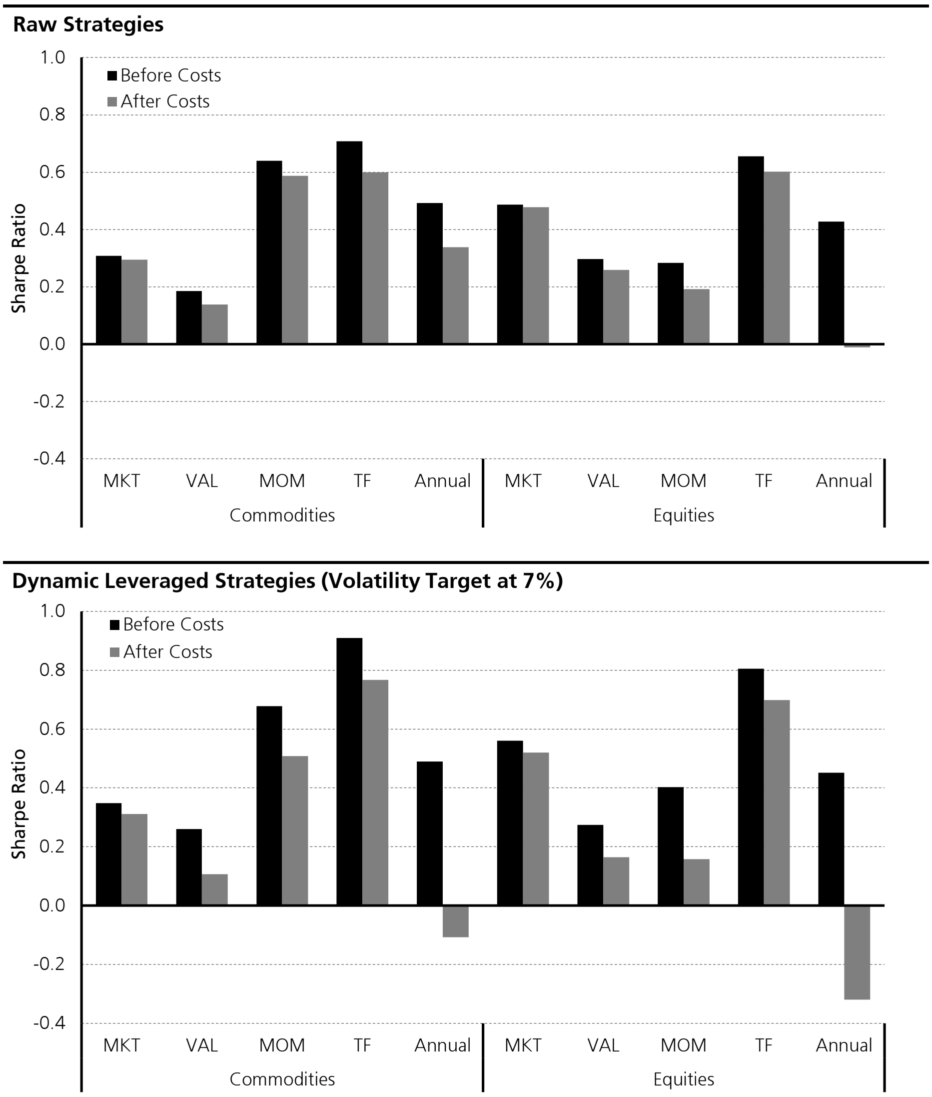
| | Commodities | | | | | Equity Indices | | | | |
|---|---|---|---|---|---|---|---|---|---|---|
| | MKT | VAL | MOM | TF | Annual | MKT | VAL | MOM | TF | Annual |
| *Before costs:* | | | | | | | | | | |
| Arithmetic Mean (%) | 2.66* | 2.14 | 5.22*** | 6.88*** | 3.97** | 4.43** | 1.56 | 2.50* | 6.23*** | 2.93** |
| Volatility (%) | 7.65 | 8.23 | 7.70 | 7.56 | 8.11 | 7.90 | 5.70 | 6.20 | 7.74 | 6.49 |
| Sharpe Ratio | 0.35 | 0.26 | 0.68 | 0.91 | 0.49 | 0.56 | 0.27 | 0.40 | 0.81 | 0.45 |
| *Costs:* | | | | | | | | | | |
| Monthly Turnover (%) | 9.39 | 42.01 | 43.42 | 35.89 | 161.29 | 10.58 | 20.91 | 50.59 | 27.37 | 166.74 |
| Realised Costs (%) | 0.28 | 1.26 | 1.30 | 1.08 | 4.84 | 0.32 | 0.63 | 1.52 | 0.82 | 5.00 |
| *After costs:* | | | | | | | | | | |
| Arithmetic Mean (%) | 2.38 | 0.88 | 3.92 | 5.80 | -0.87 | 4.11 | 0.96 | 0.98 | 5.41 | -2.07 |
| Sharpe Ratio | 0.31 | 0.11 | 0.51 | 0.77 | -0.11 | 0.52 | 0.16 | 0.16 | 0.70 | -0.32 |

Notes: The figure presents the average annualised arithmetic return, volatility and Sharpe ratio for a market (MKT) factor (equally-weighted), a value (VAL) factor, a momentum (MOM) factor, a trend-following (TF) factor and an annual seasonality long-short (top versus bottom quintile) strategy before and after trading costs within commodities and equity indices. The realised costs are estimated as the product of the annualised turnover and an assumed level of average market impact equal to 25bps. Panel A presents the statistics for raw strategies and Panel B presents the statistics for constant-volatility (at 7%) strategies. The sample period is January 1992 to February 2015; the only exception is the equity value strategy, which starts in January 1995. All the strategies have been constructed using futures contracts except for the annual seasonality strategy within equities which has been constructed using MSCI country total return indices. The statistical significance of the average arithmetic returns before costs are tested using White (1980) heteroskedasticity robust standard errors; statistical significance at 1%, 5% and 10% levels is denoted by ***, ** and * respectively. The commodity dataset is obtained from Bloomberg, whereas the equity index dataset is obtained from Datastream.

It is fairly obvious from both Panels of Table 4 that the annual seasonality strategy exhibits at least one order of magnitude larger turnover than any other strategy that we study. This was –to some extent– expected, as the seasonality strategy buys every month the same-calendar-month past winners and sells the same-calendar-month past losers and as a consequence almost the entire portfolio has to be liquidated and re-constructed (monthly turnover estimates for the long-short portfolio exceed 160%).

The substantially larger turnover of the seasonality strategy turns out to be detrimental as the after-costs Sharpe ratios turn negative in most cases. On the contrary, all other premia remain relatively strong even after incorporating trading costs. To obtain a visual perspective on the before-costs and after-costs Sharpe ratios, both for the raw and the constant-volatility strategies, we present our estimates in Figure 4.

**Figure 4: The Effect of Transaction Costs on Sharpe Ratios**




Notes: The figure presents the before-costs and after-costs Sharpe rations for a market (MKT) factor (equally-weighted), a value (VAL) factor, a momentum (MOM) factor, a trend-following (TF) factor and an annual seasonality long-short (top versus bottom quintile) strategy within commodities and equity indices. The realised costs are estimated as the product of the annualised turnover and an assumed level of average market impact equal to 25bps. The top chart presents the results for raw strategies and the bottom chart presents the results for constant-volatility (at 7%) strategies. The sample period is January 1992 to February 2015; the only exception is the equity value strategy, which starts in January 1995. All the strategies have been constructed using futures contracts (obtained from Bloomberg) except for the annual seasonality strategy within equities which has been constructed using MSCI country total return indices (obtained from Datastream).

The bottom-line of this analysis is that the seasonality premium within commodity and equity index markets might appear positive and statistically significant on paper, but in practice it might be completely eliminated by trading costs due to the very large associated turnover. This constitutes one plausible explanation as to why the seasonality premium has not been arbitraged away.

Following from these results, it is obvious that seasonality signals cannot be traded directly by an investor. However, as the next section of the paper illustrates, these signals bear important information that can be incorporated in the construction of trend-following strategies.

## 4. Seasonality-adjusting a Trend-Following Strategy

As already briefly explained in the previous section, trend-following strategies are constructed by taking long positions on all assets with positive past 12-month returns and a short position on all assets with negative past 12-month returns.

More formally, let $N_t$ denote the number of available assets at time $t$. A trend-following strategy involves taking a long or short position on each asset $i$, based on the sign of the past excess return over a prescribed lookback period that is typically equal to 12 months.[11] The weighting scheme that is typically employed (especially if assets of the same asset class comprise the portfolio) is the inverse-volatility weighting scheme.[12,13] The return of the strategy is given by:

$$r_{t,t+1}^{TF} = \sum_{i=1}^{N_t} sign\left(r_{t-12,t}^{i}\right) \cdot \frac{\left(\sigma_t^i\right)^{-1}}{\sum_{j=1}^{N_t}\left(\sigma_t^j\right)^{-1}} \cdot r_{t,t+1}^{i} \tag{5}$$

For further details on the construction and dynamics of trend-following strategies see Moskowitz, Ooi and Pedersen (2012), Hurst, Ooi and Pedersen (2012, 2013), Baltas, Jessop, Jones and Zhang (2013) and Baltas and Kosowski (2013, 2015).

Trend-following strategies are typically implemented using a constant-volatility[14] overlay by targeting ex-ante a prescribed level of volatility $\sigma_{TGT}$. This requires employing dynamic leverage that is equal to the ratio between the running realised volatility of the unlevered trend-following strategy of equation (5), denoted by $\sigma_t^{TF}$, and the target level, $\sigma_{TGT}$. The return of the constant-volatility trend-following ($CVTF$) strategy is therefore given by:

$$r_{t,t+1}^{CVTF} = \frac{\sigma_{TGT}}{\sigma_t^{TF}} \cdot \sum_{i=1}^{N_t} sign\left(r_{t-12,t}^{i}\right) \cdot \frac{\left(\sigma_t^i\right)^{-1}}{\sum_{j=1}^{N_t}\left(\sigma_t^j\right)^{-1}} \cdot r_{t,t+1}^{i} \tag{6}$$

---

[11] Moskowitz *et al.* (2012), Baltas and Kosowski (2013) and Baltas, Jessop, Jones and Zhang (2013) find that a 12-month horizon generates the largest Sharpe ratio for trend-following strategies within each asset class.

[12] It can be shown that the inverse-volatility weighting scheme can split portfolio volatility equally across portfolio constituents as long as all pairwise correlations are equal.

[13] As highlighted in Baltas, Jessop, Jones and Zhang. (2013, 2014) and Baltas (2015), working with assets across multiple asset classes can qualify risk-parity (equal risk contribution) as a more appropriate weighting scheme, especially in periods of extreme asset co-movement. For the purposes of this paper, this point is not relevant as we only construct trend-following strategies using assets of the same asset class.

[14] A similar technique has been employed by Barroso and Santa-Clara (2014) and Daniel and Moskowitz (2014), who focus on cross-sectional winners-minus-losers momentum strategies. See also Hallerbach (2012, 2014).

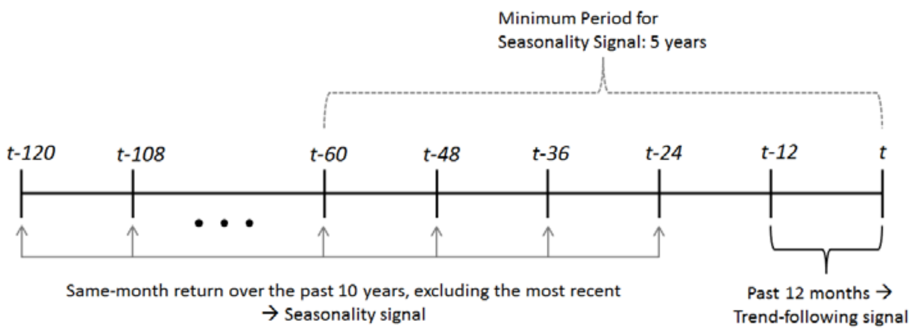
The dynamic leverage equals the ratio $\sigma_{TGT}/\sigma_t^{TF}$ . As an example, if $\sigma_{TGT} = 10\%$ and at the end of some month the running volatility of the unlevered strategy is 5%, then all positions for the forthcoming month should be doubled (a 2x leverage ratio).

One way to incorporate the seasonality signals into the construction of trend-following portfolios is to avoid taking a certain long or short position, if there exists a contradicting seasonality signal. In particular:

- Switch off a long position if the asset belongs in the bottom seasonality basket (i.e. it has one of the lowest same-calendar-month average past returns).
- Switch off a short position if the asset belongs in the top seasonality basket (i.e. it has one of the largest same-calendar-month average past returns).

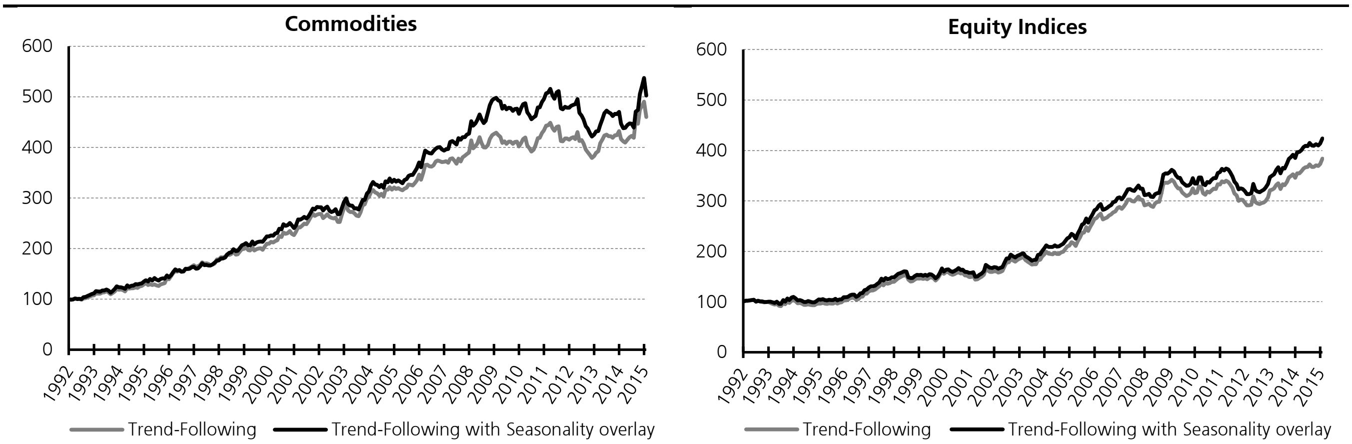
As we have done throughout this paper, we measure the seasonality signals over the course of the past ten years and require at least five years for an asset to be included in the cross-sectional ranking. Given that the trend-following signal uses information from the past 12 months, we exclude the past year's same-month return from the seasonality calculation in order to safeguard against any correlation between the two signals. Figure 5 illustrates the trend-following and seasonality signals generation. Using these signal conventions, Figure 6 presents the cumulative returns of a simple trend-following strategy and its seasonality-adjusted variant within commodities and equity indices. All strategies in Figure 6 incorporate a 7% volatility target.

**Figure 5: Trend-following and Seasonality Signals**




Notes: The figure describes the signal generation for the seasonality-adjusted trend-following strategy.

**Figure 6: Incorporating Seasonality Signals in Trend-Following Strategies (Volatility Target at 7%)**




Notes: The figure presents the cumulative returns of a trend-following strategy and its variant that incorporates seasonality information within commodity and equity index markets. All strategies in this figure employ a 7% volatility target. The sample period is January 1992 to February 2015. The commodity dataset is obtained from Bloomberg, whereas the equity index dataset is obtained from Datastream.

What is fairly obvious from these plots is that the seasonality overlay improves the performance of the trend-following strategies before any transaction costs are taken into account. Table 5 presents performance statistics before accounting for any transaction costs, as well as after accounting for different levels of costs.

**Table 5: Combining Trend-Following with Seasonality**

**Panel A: Raw Strategies**

| | **Commodities** | | **Equity Indices** | |
|---|---|---|---|---|
| | **TF** | **Enhanced TF** | **TF** | **Enhanced TF** |
| ***Before costs:*** | | | | |
| **Arithmetic Mean (%)** | 6.45*** | 7.52*** | 8.06*** | 8.72*** |
| **Volatility (%)** | 9.11 | 9.32 | 12.30 | 12.32 |
| **Sharpe Ratio** | 0.71 | 0.81 | 0.66 | 0.71 |
| **Monthly Turnover (%)** | 33.04 | 55.79 | 22.18 | 44.90 |
| ***Wilcoxon Paired Test p-values:*** | | | | |
| **Two-Sided** | 15.32% | | 10.12% | |
| **One-Sided** | 7.66% | | 5.08% | |
| *After Costs:* | | | | |
| **Sharpe Ratio (for 5 bps)** | 0.69 | 0.77 | 0.64 | 0.69 |
| **Sharpe Ratio (for 10 bps)** | 0.66 | 0.74 | 0.63 | 0.66 |
| **Sharpe Ratio (for 15 bps)** | 0.64 | 0.70 | 0.62 | 0.64 |
| **Sharpe Ratio (for 20 bps)** | 0.62 | 0.66 | 0.61 | 0.62 |
| **Sharpe Ratio (for 25 bps)** | 0.60 | 0.63 | 0.60 | 0.60 |

**Panel B: Dynamic Leveraged Strategies (Volatility Target at 7%)**

| | **Commodities** | | **Equity Indices** | |
|---|---|---|---|---|
| | **TF** | **Enhanced TF** | **TF** | **Enhanced TF** |
| ***Before costs:*** | | | | |
| **Arithmetic Mean (%)** | 6.88*** | 7.27*** | 6.23*** | 6.65*** |
| **Volatility (%)** | 7.56 | 7.42 | 7.74 | 7.80 |
| **Sharpe Ratio** | 0.91 | 0.98 | 0.81 | 0.85 |
| **Monthly Turnover (%)** | 35.89 | 58.01 | 27.37 | 49.90 |
| *After Costs:* | | | | |
| **Sharpe Ratio (for 5 bps)** | 0.88 | 0.93 | 0.78 | 0.81 |
| **Sharpe Ratio (for 10 bps)** | 0.85 | 0.89 | 0.76 | 0.78 |
| **Sharpe Ratio (for 15 bps)** | 0.82 | 0.84 | 0.74 | 0.74 |
| **Sharpe Ratio (for 20 bps)** | 0.80 | 0.79 | 0.72 | 0.70 |
| **Sharpe Ratio (for 25 bps)** | 0.77 | 0.75 | 0.70 | 0.66 |

Notes: The figure presents the average annualised arithmetic return, volatility and Sharpe ratio for a trend-following (TF) strategy and its variant that incorporates information from seasonality signals (Enhanced TF) within commodities and equity indices. After-costs Sharpe ratio estimates are also presented for different levels of average market impact (5, 10, 15, 20 and 25 basis points). The realised costs are estimated as the product of the annualised turnover and the assumed level of average market impact. Panel A presents the statistics for raw strategies and Panel B presents the statistics for constant-volatility (at 7%) strategies. Panel A also reports the p-values from two-sided and one-sided paired Wilcoxon (1945) signed-rank tests for the difference in the monthly average arithmetic returns between the Enhanced TF strategy and the simple trend-following strategy. The one-sided test has been designed in a way to test whether the returns of the Enhanced TF strategy are greater than the returns of the simple TF strategy. The sample period is January 1992 to February 2015. The strategies have been constructed using futures contracts obtained from Bloomberg. The statistical significance of the average arithmetic returns before costs are tested using White (1980) heteroskedasticity robust standard errors; statistical significance at 1%, 5% and 10% levels is denoted by ***, ** and * respectively.

The results show that before costs the improvement for the trend-following strategy is indeed genuine. The Sharpe ratio of the strategy increases from 0.71 to 0.81 for commodities and from 0.66 to 0.71 for equity indices; the respective changes for constant-volatility versions of the strategies are 0.91 to 0.98 and 0.81 to 0.85 respectively. Importantly enough, one-sided paired Wilcoxon (1945) signed-rank tests confirm that the enhanced trend-following strategies generate significantly larger average returns than the plain trend-following strategies; the p-values are 7.7% for commodities and 5.1% for equity indices.

This performance pickup does not come at no cost. The turnover of the trend-following strategies almost doubles after incorporating the seasonality signals. This results in substantial degradation of the risk-adjusted performance after incorporating trading costs. Assuming various levels of average market impact, between 5 and 25 basis points, we find that the break-event level of market impact is around 25 basis points for the raw trend-following strategies (Panel A in Table 5), whereas for the constant-volatility versions of the strategies (Panel B in Table 5), which anyway exhibit even larger turnover, the break-even level is around 15 basis points. On a positive note, these cost estimates might be relatively conservative in practice. Typically, futures contracts are very liquid and tend to have low trading costs. To put things in perspective, Hurst *et al.* (2012), who also study trend-following strategies, report one-way transaction costs of 1 bp for government bonds, 3 bps for FX rates, 6 bps for equity indices and 10 bps for commodities for the period 2003 to 2012.

Finally, it's worth noting than in our implementation of the trend-following strategy, we applied no cost optimisation or position smoothing techniques that in practice would be employed to reduce rebalancing costs. As an example, instead of switching off the inconsistent long or short positions of a trend-following strategy as instructed by the respective seasonality signals, one suggestion would be to just halve the positions. We empirically tested this and the turnover of the enhanced strategies falls significantly with the performance pickup remaining strong. Baltas and Kosowski (2015) discuss various other ways to reduce portfolio turnover and therefore improve the after-costs performance of the strategy.

## 5. Concluding Remarks

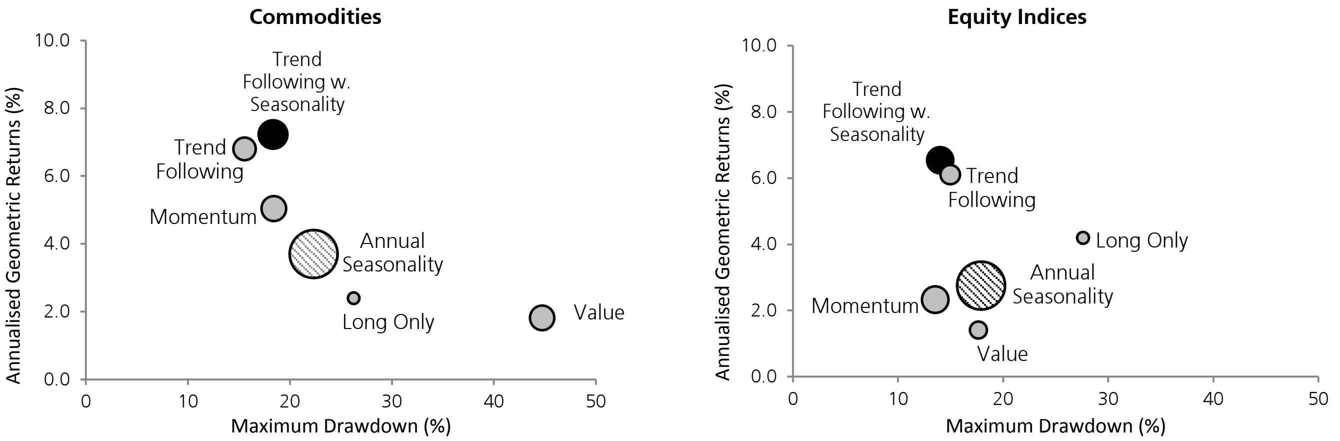
The purpose of this paper has been to investigate the existence of seasonality patterns in the cross-section of asset returns within different asset classes (commodities, FX rates, government bonds and equity indices). Using panel regression framework, we identify strong seasonality patterns within commodities and equity indices and for that reason the rest of the analysis focuses mainly on these two asset classes.

The seasonality premium, which can be captured by a long-short portfolio that buys / sells the assets with the largest / smallest same-calendar-month past average returns (up to ten years), is statistically and economically significant for both asset classes and does not appear to proxy for some known systematic source of risk. Instead, our interpretation for its persistent behaviour over time draws from a limits-to-arbitrage perspective. The seasonality strategies exhibit very large turnover and some reasonable trading costs are enough to completely eliminate the premium, especially when the strategies are run with a realistic volatility target overlay.

An attempt to make practical use of the seasonality signals is to actively use them to switch off inconsistent long and short positions in a trend-following framework. Our back-tests have shown statistically significant improvement of the plain trend-following strategy within both commodities and equity indices. The increased turnover, caused by the incorporation of the seasonal signals, can strongly impact the performance pickup. However, given that these strategies are mainly constructed using liquid front futures contracts and sophisticated position smoothing techniques, the respective trading costs can be relatively managed to remain at low levels.

To conclude, Figure 7 presents a risk (proxied by maximum drawdown) and return plane for a list of commodity and equity index strategies that were discussed in this paper, including of the annual seasonality strategy, the trend-following strategy and the seasonality-adjusted trend-following strategy. All strategies employ a 7% volatility target. The area of each bubble is equivalent to the turnover of the strategies (reported in Tables 4 and 5).

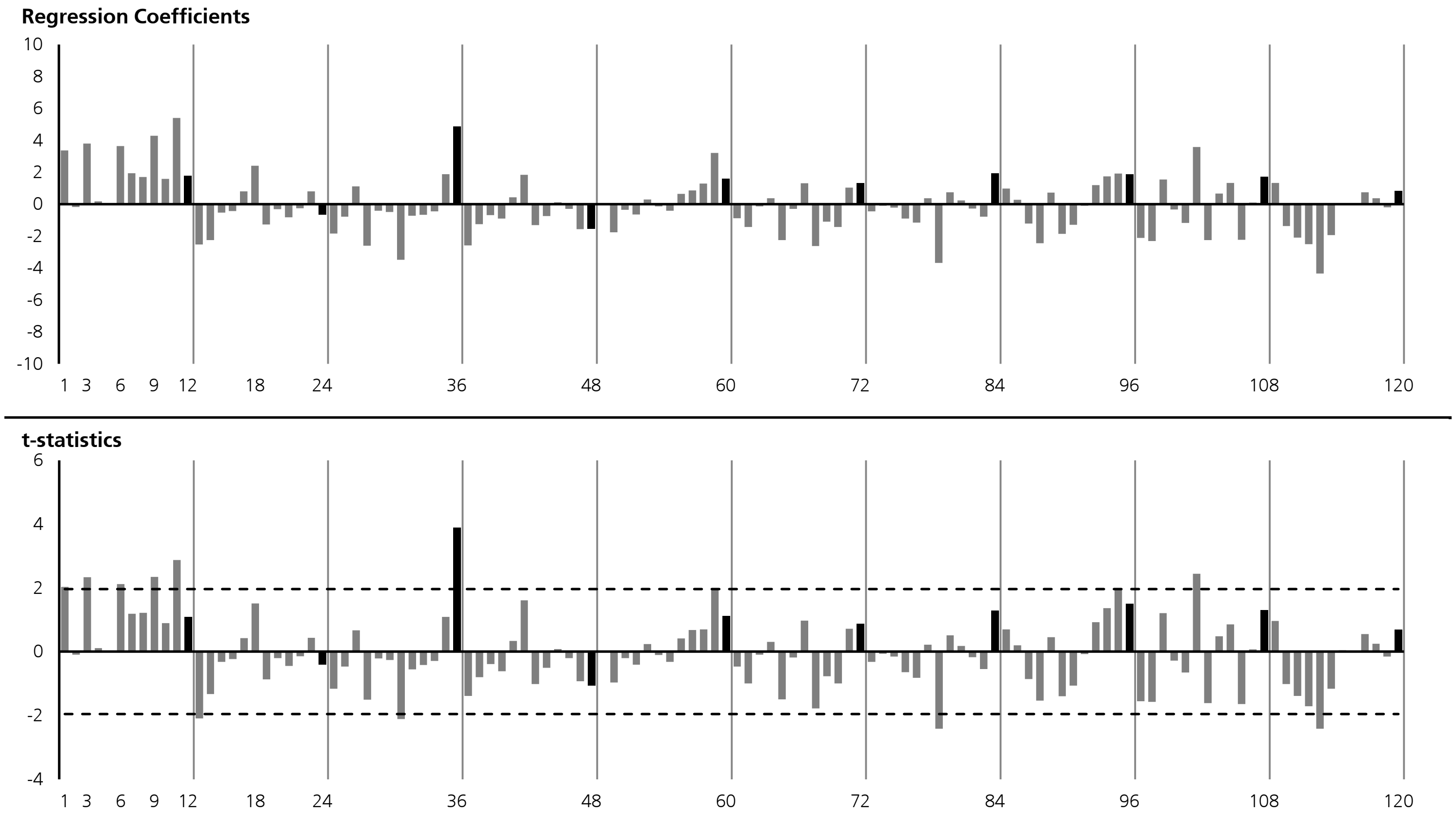
**Figure 7: Risk & Return for Dynamic Leveraged Commodity and Equity Index Strategies (with volatility target at 7%)**




Notes: The area of each bubble is equivalent to the turnover of each strategy. All strategies employ a 7% volatility target and have been constructed using futures contracts (obtained from Bloomberg) except for the annual seasonality strategy within equities which has been constructed using MSCI country total return indices (obtained from Datastream). The sample period is January 1992 to February 2015; the only exception is the equity value strategy, which starts in January 1995.

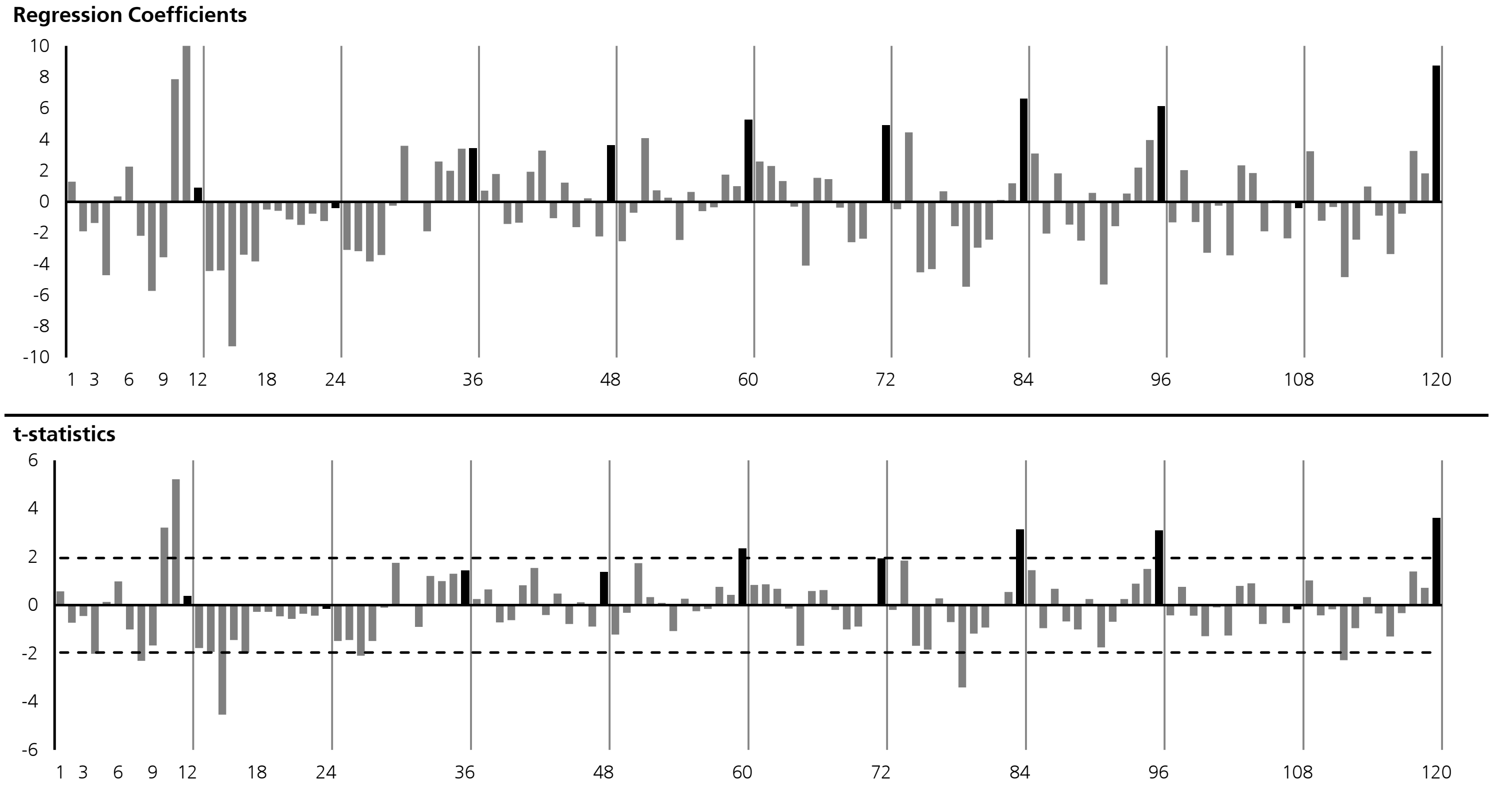
# APPENDIX A - Panel Regressions with lags up to 120 months

**Figure A.1: Panel Regression for Equity Indices – Lags up to 120 months**




Notes: The charts report the Fama-MacBeth panel regression coefficients and respective t-statistics from regressing monthly returns of 18 equity index spot price indices on their respective lagged returns, for lags ranging from 1 to 120 months. The t-statistics are adjusted for serial-correlation and heteroskedasticity using the Newey and West (1987) correction with 12 lags. The dashed lines at -1.96 and +1.96 denote the 5% significance thresholds. The sample period is from January 1980 to December 2014. The dataset is obtained from Datastream.

**Figure A.2: Panel Regression for Commodities – Lags up to 120 months**




Notes: The charts report the Fama-MacBeth panel regression coefficients and respective t-statistics from regressing monthly returns of 19 commodity spot price indices on their respective lagged returns, for lags ranging from 1 to 120 months. The t-statistics are adjusted for serial-correlation and heteroskedasticity using the Newey and West (1987) correction with 12 lags. The dashed lines at -1.96 and +1.96 denote the 5% significance thresholds. The sample period is from July 1991 to December 2014. The dataset is obtained from Datastream.

## APPENDIX B – Commodities dataset for strategy construction

**Figure B.1: Commodity Datasets**

| | *Spot* | *Futures* |
|---|---|---|
| Brent Crude | Jan-70 | Jun-88 |
| Heating Oil #2 | Jan-83 | Jun-86 |
| WTI Crude | Jan-83 | Apr-84 |
| Natural Gas | Apr-90 | Apr-90 |
| Gas Oil | Jul-86 | Jul-89 |
| Corn | Jan-70 | Jan-71 |
| Soybeans | Jan-70 | Jan-71 |
| Cotton #2 | Jan-77 | Jan-71 |
| Cocoa | Jan-71 | Jan-71 |
| Coffee "C" | Jan-81 | Aug-72 |
| Sugar #11 | Jan-73 | Jan-71 |
| Wheat | Jan-70 | Jan-71 |
| Live Cattle | Jan-70 | Jan-71 |
| Aluminium | Jan-91 | Jul-97 |
| Copper | Jan-77 | Dec-88 |
| Nickel | Jan-93 | Jul-97 |
| Zinc | Jan-91 | Jul-97 |
| Gold (100 oz.) | Jan-70 | Jan-75 |
| Silver #11 | Jan-73 | Jan-75 |

Notes: The table reports the starting month for each asset in our spot price index dataset (from Datastream – used for the panel regression analysis) and the futures price dataset (from Bloomberg – used for strategy construction and back-testing).

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