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Momentum Strategies Across Asset Classes

Risk Factor Approach to Trend Following

Quantitative and Derivatives Strategy

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See page 183 for analyst certification and important disclosures, including non-US analyst disclosures.

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Dear Investor,

In the current environment of low yields and high valuations, interest in Risk Premia strategies continues to grow. In our primer on Systematic Strategies, we developed a framework for Risk Factor investing across assets, and in the subsequent report we provided a detailed overview of Equity Risk Premia Strategies. In this report we focus on **Momentum Strategies Across Assets**.

Momentum Strategies tend to have positive performance in rising markets and can also outperform traditional assets during market corrections. Low or negative correlation during market corrections has been an attractive feature of investing in Momentum Strategies and CTA funds. Momentum Strategies are not without risks – they can suffer during market turning points such as sharp market recoveries and can also underperform in mean reverting markets. As a result, Momentum Strategies tend to have higher Sharpe ratios than traditional assets, but also higher tail risk and negative skewness – a common feature of Risk Premia strategies.

In the first two chapters of the report, we designed and studied prototype Momentum factors across assets. As the virtually unlimited number of possible implementations may confound an investor, we first provide a framework for designing and testing Momentum Strategies. We have examined single asset and multi asset strategies, Absolute and Relative Momentum, various Momentum filters, lookback windows, rebalancing frequencies and investment horizons. The third chapter of this report is dedicated to risk management techniques such as stop-loss, mean reversion signals and diversification across assets and signals. In the last chapter we analyze Seasonality strategies, where we treat Seasonality as Momentum of non-consecutive asset returns.

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Chapter 1

Introduction to Momentum Investing

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Overview of Trend-Following Strategies

The existence of a Price Momentum effect implies that the price of an asset exhibits trends as opposed to being randomly distributed. A trending price means simply that an asset that recently appreciated is more likely to continue moving higher, and an asset that recently declined is more likely to continue moving lower. The existence of Momentum effects would violate the efficient markets hypothesis (which states that past prices cannot predict future performance) and enable Momentum traders to consistently outperform the broad market.

The concept of Momentum trading could be traced back at least to the 18th century, and well elaborated Trend-Following strategies have been known for close to 100 years[1]. A host of academic literature describes and gives potential explanations for the Momentum effect. They include increased loading of high Momentum assets to systematic risk[2], inefficiencies in investor behavior (over/under-reaction to news or investor herding)[3], macroeconomic supply and demand frictions, positive feedback loops between risk assets and economic growth (e.g. strong equity markets can create wealth effects that boost consumer spending, and in turn corporate earnings and equities), and even in the market microstructure. Interested readers can refer to our primer report on Cross Asset Systematic Strategies and Equity Risk Premia Strategies for more discussions and analysis of Momentum premium across different asset classes

Momentum in Equities is a well researched topic. One of the early papers to document equity Momentum was published by Jegadeesh, and Titman (1993). Examples of various equity Momentum improvements can be found in our report Investment Strategies no 89: Equity Momentum. The existence of **Momentum in Commodities** is well known to CTA practitioners over the past 30 years. A detailed review of commodity Momentum strategies can be found in our report: Investment Strategies No. 25: Momentum in Commodities as well as in reports by Erb and Harvey (2006), Miffre and Rallis (2007) and Fuertes, Miffre, and Rallis (2010). Momentum effects have also been documented in the **Fixed Income** space. For instance, our report on Momentum in German government bonds (Investment Strategies No. 27: Euro Fixed Income Momentum Strategy) demonstrates a strong Momentum signal with a 2-3 week time horizon. The existence of fixed income Momentum across global bond markets was also shown in the work of Asness, Moskowitz, Pedersen (2011). The **Momentum effect in Currency Markets** was tested and demonstrated for example in the research of Okunev and White (2003), Burnside, Eichenbaum, and Rebelo (2011) and Menkhoff, Sarno, Schmeling, and Schrimpf (2012). Interested readers can refer to the Appendix on page 171 for a list of academic literature on the Momentum risk premium.

In our previous report on Cross Asset Systematic Strategies, we examined Momentum effects across assets and showed the performance of simple Momentum strategies over the past 40 years. Our prototype Momentum factors were monthly rebalanced portfolios that went long assets with the highest, and sold short assets with the lowest 12-month price returns.[4]

[1] David Ricardo (1772-1823) quoted "Cut short your losses; let your profits run on". Further, see William Dunnigan's 'Trading With the Trend' in 1934, and Richard Donchian's 'Trend-Following Methods in Commodity Price Analysis' in the Commodity Yearbook of 1957.
[2] Liu and Zhang (2008) provide evidence that high Momentum stocks have excess exposure to macro growth risk.
[3] See, for example, Barberis, Sheleifer and Vishny (1998), Hong, Lim and Stein (2000) and Dasgupta, Prat and Verardo (2011)
[4] These non-tradable prototype Momentum Risk Factors are constructed as follows (they are constructed to illustrate long-term risk properties and we later consider more liquid contracts in tradable versions of prototype Momentum Risk Factors in Chapters 2-4):

Equity Momentum Factor: Excess return of a long position in three equity indices with the highest past 12-month returns and a short position in the three equity indices with lowest past 12-month returns (monthly rebalanced). Our index universe of country equity benchmarks was: Australia, Canada, France, Germany, HK, Italy, Japan, Netherlands, Spain, Sweden, Switzerland, the UK, and the US.

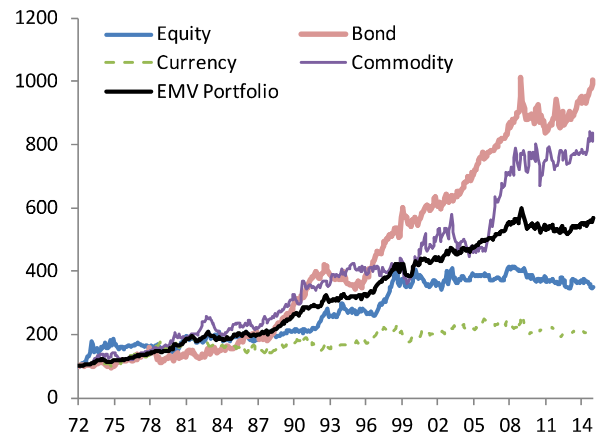
Bond Momentum Factor: Excess return of a long position in the three 10-year government bonds with the highest past 12-month returns and a short position in the three 10-year government bonds with lowest past 12-month returns (monthly rebalanced). The universe was comprised of government bonds from Australia, Belgium, Canada, Germany, Denmark, Japan, Sweden, the UK, and the US.

Currency Momentum Factor: Excess return of a long position in the three G10 currencies with the highest past 12-month returns and a short position in the three G10 currencies with lowest past 12-month returns (monthly rebalanced).

Commodity Momentum Factor: Excess return of a long position in three commodity futures with the highest 12-month returns and a short position in three futures with lowest 12-month returns. The commodity futures universe: Brent and WTI oil, Heating Oil, Gasoil, Gasoline, Natural Gas, Gold, Silver, Cocoa, Coffee, Cotton, Feeder Cattle, Wheat, Lean Hogs, Live Cattle, Soybeans, Sugar, and Wheat.

Even these simple prototype models have delivered positive long-run risk premia across major asset classes as shown in Figure 1. The summary of performance statistics in Table 1 shows that Momentum strategies in various asset classes delivered Sharpe ratios in a 0.2 to 0.6 range. With the benefit of cross asset diversification, an Equal Marginal Volatility (EMV) weighted portfolio of prototype Momentum Risk Factors generated a Sharpe ratio of 0.78 during 1972-2014. [5] These solid Sharpe ratios were at least in part a compensation for the negative skewness and elevated tail risk (positive excess kurtosis) Momentum strategies delivered.

Figure 1: Performance of Prototype Momentum Risk Factors by Asset Class



Source: J.P. Morgan Quantitative and Derivatives Strategy.
* For comparison purpose, Equity, Bond, Currency and Commodity prototype Momentum strategies are scaled to have an ex-post volatility of 10% per annum in the chart.

Table 1: Performance and Risk Statistics for Prototype Momentum Factors

	Equity	*Bond*	*Curncy*	*Comdty*	*EMV*
Excess Ret (%)	4.6	3.5	1.7	7.3	4.1
STDev (%)	17.7	6.2	9.0	15.1	5.3
MaxDD (%)	-37.5	-19.1	-27.9	-33.3	-13.2
MaxDDur (yrs)	16.4	6.0	15.2	5.7	6.0
***t*-Statistic**	**2.2**	**3.9**	**1.5**	**3.6**	**5.2**
Sharpe Ratio	**0.26**	**0.57**	**0.18**	**0.49**	**0.78**
Hit Rate (%)	51.7	63.4	56.8	56.2	63.8
Skewness	0.51	-0.10	-0.33	0.01	-0.32
Kurtosis	6.17	3.67	1.87	1.45	1.13

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Similar to our tests, Ooi, Moscowitz, and Pedersen (2011) documented Momentum effects in global equity index, currency, commodity and bond futures markets since the 1970s. Based on extended datasets, Hurst, Ooi, and Pedersen (2012) validated significant Momentum effects across assets since 1903, while Lemperiere, Derenble, Seager, Potters and Bouchaud (2014) did a similar exercise for Equity index and commodity markets since 1800. We have even reviewed 800-year backtests reported in a book 'Trend-Following with Managed Futures' by A. Greyserman and K. Kaminski that suggests a long-term Sharpe ratio of 1.16 for trend following strategies. However, we do caution against relying on very long backtests (e.g. more than ~50 years) as they often underestimate risks and transaction costs and hence may produce misleading results (see risk section below).

In this report we further expand our analysis of Momentum effects and develop a framework for systematic Trend-Following strategies. We also address the question of risks embedded in Momentum factors by quantifying these risks and analyzing Momentum strategies in the context of Risk Factor investing.

An investor looking to design a Momentum strategy may find the large number of possible implementations overwhelming. For instance, one needs to choose the asset universe, type of Momentum signal, signal lookback window, rebalance frequency, and investment horizon, even before considering various risk management methods such as stop loss or volatility targeting. A large number of possible parameters in a Momentum strategy may naturally raise concerns of over-fitting and in-sample choice of parameters.

In this report, we define a framework for designing a Momentum strategy and test a broad range of implementations. Figure 2 below summarizes various elements of a Trend-Following strategy we address in the rest of the report. First, one needs to decide if the strategy will be trading **instruments from one or multiple asset classes** (i.e. specify the asset

[5] At each month-end portfolio rebalancing, each Momentum Risk Factor is weighted inversely with respect to its past 24-month volatility. See Chapter 3 of our report on Cross Asset Systematic Strategies for more details on portfolio allocation methodologies and their applications. Also see the Appendix on page 166 for a brief summary of these methods.

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universe). In this report, we first design 'prototype strategies' in each of the traditional asset classes (i.e. our universe of 10 liquid contracts in each of Equities, Bonds, Currencies and Commodities[6]) and then look at multi-asset Momentum portfolios. Then one can choose between an **Absolute and Relative Momentum approach.** Absolute Momentum applies a Momentum filter on each of the assets while Relative Momentum applies a Momentum filter to relative asset performance. There are virtually an unlimited number of choices for the **trend filtering method**, ranging from simple price returns and moving averages to various relative strength and volatility normalized indicators. When selecting a trend filter one also needs to specify the lookback window that can range from an intraday or daily time horizon to more commonly used 6-12 month lookback windows. The strategy also needs to be **rebalanced with a specified frequency** (e.g. weekly, monthly, or quarterly) and the assets are held over a particular time horizon (based on the half-life of the Momentum signal, but often the same as the rebalance frequency). Both in the next section and in the Appendix, we will backtest a broad range of Momentum strategies that span a range of trend filters and rebalance properties. The third chapter of this report is dedicated to **risk management techniques** that can be implemented both on individual factors, as well as at a portfolio level. In the last chapter we analyze **Seasonality strategies**, where we treat Seasonality as a Momentum of non-consecutive asset returns.

Figure 2: Elements of a Trend-Following Strategy

Underlying Asset	Momentum Type	Trend Filter	Rebalance	Risk Management
Single Asset	Absolute Momentum	Signal Metric	Investment Horizon	Factor Level
Multi Asset	Relative Momentum	Lookback Window	Rebalance Frequency	Portfolio Level

Source: J.P. Morgan Quantitative and Derivatives Strategy

[6] To have equal representation in each asset class, we chose the following underliers (10 liquid underliers in each asset classes):
Equity Index Futures: S&P/TSX 60 (Canada), CAC 40 (France), DAX (Germany), Hang Seng (HK/China), Nikkei 225 (Japan), AEX (Netherlands), IBEX 35 (Spain), Swiss Market (Switzerland), FTSE 100 (UK), and S&P 500 (US).
Fixed Income Futures: Australia 10-year, Canada 10-Year, Germany 5-Year, Germany 10-Year, Japan 10-Year, US 2-Year, US 5-Year, US 10-Year, US 30-Year, and 3M Eurodollar.
G10 Currency Pairs: AUDUSD, CADUSD, CHFUSD, EURUSD, JPYUSD, NZDUSD, SEKUSD, CHFEUR, JPYEUR, and NOKEUR.
Commodity Futures: Wheat, Crude Oil, ULSD, Gasoline, Aluminum, Copper, Gold, Silver, Brent, and Platinum.

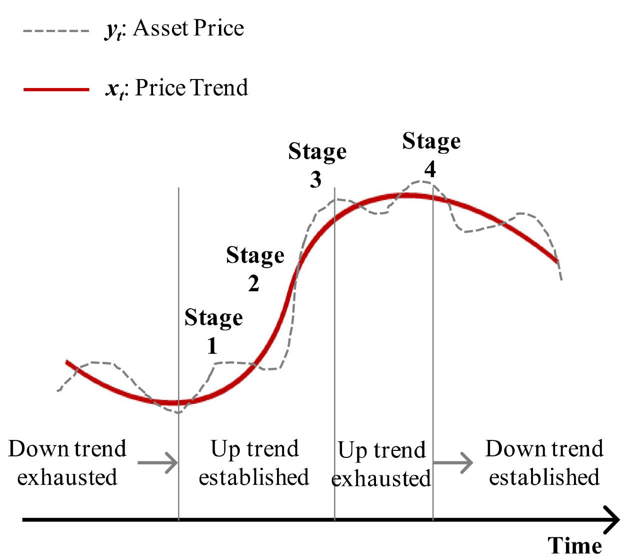
Risks of Momentum Strategies

As we discussed, the existence of Momentum effects over extended periods of time and in various assets is historically established. The question is how effectively and with what risk can a Momentum strategy identify and utilize such price trends. If there was a Momentum strategy that could always precisely identify up and down trends, it would attract unlimited assets and the effect would have to disappear. The main risk of a Momentum strategy will therefore be in incorrectly identifying the trend (e.g. following the trend when trend is about to revert).

Figure 3 below illustrates the typical cycle of a trend[7] : **Turning Point**: Asset price moves up due to an initial catalyst; **Trend Establishment**: price moves further up due to the lagged response of investors or a continuation of the trend in underlying fundamentals; **Trend Continuation**: further inflows due to herding / trend following and investors' over-reaction - asset price is driven above fundamentals; **Trend Exhausting**: Asset price starts moving sideways and downtrend turning point is nearing.

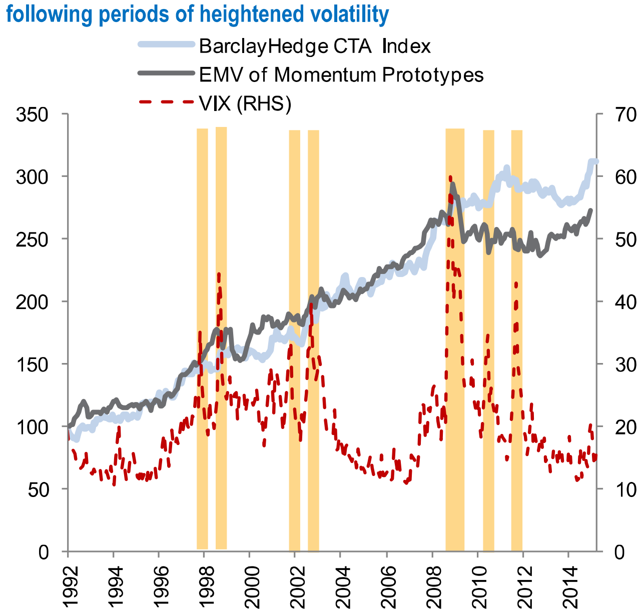
Given that trends often last longer than turning points (e.g. think of a long term bull market, followed by a crash) the return profile of Momentum strategies will typically be characterized by long periods of outperformance, with increased risk during market turning points that occur when a trend is reversed (crashes after long rallies, and sharp recoveries after prolonged bear markets). **For most trend following strategies, tail risk and negative skewness are more likely to occur during market turning points and periods of increased volatility**. Figure 4 below shows that both our prototype models and CTAs underperformed (and/or exhibited higher return volatility) during and after increases in market volatility (as measured by the VIX).

Figure 3: Establishing and exhausting of price trends



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 4: Momentum Strategies and CTAs often underperformed following periods of heightened volatility



Source: J.P. Morgan Quantitative and Derivatives Strategy.
* The EMV portfolio of prototype Momentum Factors is 1.5 leveraged to have a similar volatility level to the BarclayHedge CTA index.

Ultimately a Momentum strategy should be evaluated by the tradeoff between long periods of gains and increased risk and potential losses due to trend mis-identification (typically during turning points). Our view is that Momentum strategies do provide significant risk premia, and a typical Momentum strategy can outperform a buy-and-hold position in traditional assets on a Sharpe ratio basis and underperform it on a skew and kurtosis basis. This is a reason why we have included Momentum strategies as one of the 4 main Risk Factor styles (in addition to Value, Carry and Volatility).

[7] In this case, we illustrate a typical 'Up trend'; similar could be illustrated for a 'Down trend'.

In addition to risk during market turning points, Momentum strategies can **underperform during periods of mean reverting (stationary) markets when no clear asset trend exists**. While most asset prices do exhibit long term trending behavior, during periods of low expected returns (e.g. low bond yields or rich equity valuation) asset prices may turn more stationary, thus hurting Trend-Following strategies.

Another **risk of investing into a Momentum strategy is related to potentially flawed backtests**. Momentum strategies often implement risk management methods (e.g. stop loss) to mitigate losses during market turning points. As the number of market turning points in a typical data sample is not large, devised risk management signals may not have statistical significance (i.e. will look good in a backtest but may not work in the future). Additionally, backtests often underestimate the strategy's risk and the impact of transaction costs. Long term backtests are often derived from cash data (when futures data are not available) sampled at a low frequency. As the term structure of futures often prices in some level of mean reversion, the return of a Momentum strategy calculated from cash prices will overestimate the return of a tradable strategy using futures. A low sampling frequency (e.g. quarterly as opposed to daily) will underestimate tail risk by smoothing out sharp corrections/turning points. These types of backtest idealizations can eventually produce results that don't make much practical sense. For example, the 800-year backtest mentioned in a previous section that delivered a 13% annualized return would imply that 1 penny invested in a Momentum strategy at inception would grow to at least a trillion times the value of all assets that currently exist in the world. Obviously the backtest has used too many idealizations, and something along the way would have gone wrong with that trend following strategy.

In addition to the generic risks discussed above that are common to all trend following strategies, there are also **risks that are specific to each Asset** (e.g. market turning points in equities often occur at different times than the turns in commodity cycles). Asset specific risks tend to exhibit low correlation, and for this reason combining Momentum strategies in different assets can significantly improve the performance of trend following strategies (e.g. see Figure 1, Table 1). Later in the report, we show that multi asset Momentum strategies almost always outperform single asset Momentum strategies. Our analysis also shows that most CTA funds allocate to Momentum strategies across assets, in order to diversify asset specific risk. **High levels of cross-asset correlations, such as the ones we experienced in 2010-2012 can erode this benefit and cause multi-asset trend following strategies to underperform**.

Momentum strategies often employ different methods to address these risks. Market turning points can be addressed with various degrees of efficiency using stop losses, volatility control methods or adding exposure to Value (Reversion) factors. Asset specific risk is addressed by building a cross-asset Momentum portfolio. We discuss these techniques in some detail in Chapter 3 of this report.

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CTAs and Momentum Strategies

Managed Futures Hedge Funds, also known as 'CTAs' (short for Commodity Trading Advisors), often trade futures contracts based on **Trend-Following techniques**.[8] In this report, we provide a quantitative link between the performance of CTA benchmarks and the exposure CTAs have to our prototype Momentum strategies. These analyses can be used to replicate or actively manage the exposure of a broad CTA benchmark to specific asset classes or Momentum signal types.

Historically, CTAs provided steady absolute returns and their performance had low correlation with traditional assets. In particular, CTAs outperformed risky asset classes during the market crises of 1997/1998, 2001/2002, and the Global Financial Crisis of 2008/2009. Table 2 below shows the performance of CTAs during the 10 worst performance months for each of the main asset classes. CTAs' strong performance during these crises makes a case for using them as an effective overlay to traditional asset portfolios.

Table 2: Average total returns during the worst 10 months[9] for major asset classes during 1990-2014 (%)

	CTA	Equity	Bond	Commodity	REIT	HFRI	Best Performance
Worst 10 Months for Equity	1.4	-11.0	0.2	-10.6	-10.8	-3.7	CTA
Worst 10 Months for Bonds	-0.5	-2.0	-2.1	-1.6	-3.2	-0.6	CTA
Worst 10 Months for Commodities	0.0	-6.5	0.6	-14.7	-5.3	-2.7	Bond
Worst 10 Months for REITs	1.2	-8.1	0.1	-6.5	-15.7	-2.8	CTA
Worst 10 Months for Hedge Funds	1.3	-9.7	0.5	-7.6	-6.3	-4.4	CTA

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* We used MSCI World Net Total Return Index for 'Equity', Barclays US Aggregate Total Return Index for 'Bond', S&P GSCI Commodities Total Return Index for 'Commodities', Dow Jones REIT Total Return Index for 'REITs', Barclay CTA Index for 'CTA' and HFRI Weighted Composite Index for 'Hedge Funds'.
** Using other CTA benchmarks does not change the results materially.

Figure 5 below shows the cumulative performance of CTA funds since 1990. We used BarclayHedge and CISDM indices as they have longer track record compared with other benchmarks[10]. Given the positive long term performance and attractive hedging properties, assets in CTA funds grew dramatically over the past 2 decades (Figure 6).

[8] Earlier CTAs mainly traded Currencies and Commodity futures. Nowadays, CTAs trade a broad range of financial instruments (cash, forwards, futures, options, etc) across different asset classes and geographies.

[9] The worst performing months in our analysis are (during 1990-2014):
Equities (MSCI World Index): October 2008, August 1998, September 2008, September 2002, February 2009, May 2010, September 2001, January 2009, September 2011, and May 2012;

Bonds (Barclays US Aggregate Index): July 2003, April 2004, March 1994, October 2008, May 2013, February 1999, February 1996, February 1994, March 2002, and December 2009;

Commodities (S&P GSCI Index): October 2008, November 2008, March 2003, December 2014, December 2008, May 2010, May 2012, September 2008, July 2008, and September 2011;

REITs (Dow Jones REIT Index): October 2008, November 2008, February 2009, January 2009, April 2004, September 2011, June 2008, August 1998, November 2007, and June 2007;

Hedge Funds (HFRI Composite Index): August 1998, October 2008, September 2008, September 2011, November 2000, August 2011, May 2010, July 2002, April 2000, and September 2001.

[10] Both BarclayHedge and CISDM benchmarks for CTA funds are based on equally-weighted returns for the eligible funds. Despite differences in reporting universe and inclusion criteria, the correlation between the BarclayHedge and CISDM CTA indices was close to 100% since the 1990s. Other popular choices of CTA benchmarks are provided by BTop 50, DJCS, BAIF, HFR, Newedge and Eurekahedge. Moreover, instead of tracking CTA funds, the Mount Lucas (MLM) index is another recognized benchmark of managed futures that directly implement a simple Trend-Following strategy on 22 Fixed Income, Currency and Commodity futures. See the Appendix on 124 for a short introduction of the CTA industry and related benchmark indices.

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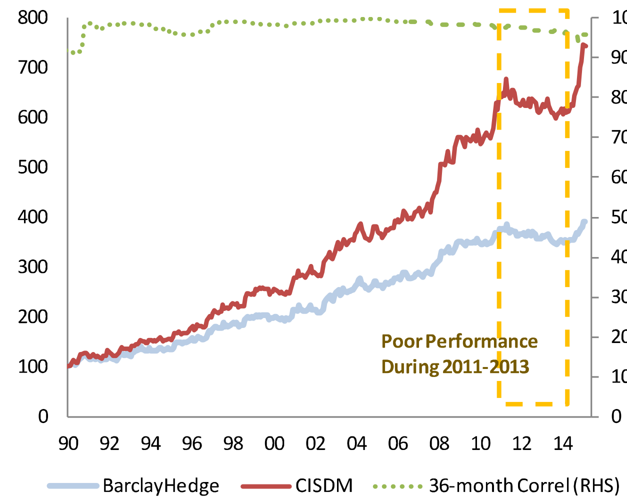
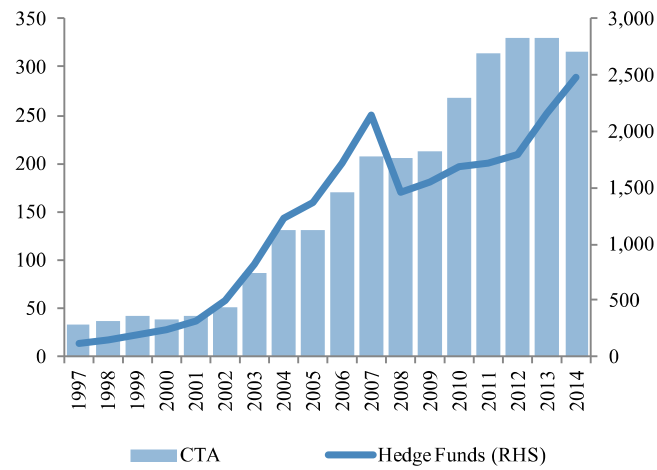
Figure 5: CTA performance during Jan 1990 – Feb 2015



Source: Bloomberg, J.P. Morgan Quantitative and Derivatives Strategy.

Figure 6: AUM (USD bn) of CTAs and Hedge Funds (ex CTAs)



Source: BarclayHedge, J.P. Morgan Quantitative and Derivatives Strategy.

According to BarclayHedge, the AUM of CTA funds stood at USD 316.8bn as of 4Q 2014. During 2014, CTA assets declined by ~4%, in sharp contrast to their average ~25% growth rate during 1980-2011.

During the 2011-2013 period, CTA funds delivered relatively poor performance (Figure 5). This was perhaps the main reason behind the slowdown in asset inflows since 2011 (Figure 6). Many investors asked us to explain this underperformance and provide an opinion on the future CTA performance.We did not have to wait long to see CTA performance sharply rebound in 2014 and 2015 with a +11.8% return over the past 12 months for the BarclayHedge CTA index – the best 12 month return since 2008[11]. It is widely believed that strong outperformance reflects the ability of Momentum strategies to capture the strong recent trends in commodities (particularly the ~50% oil drop over the past 6 months) and currencies (in particular the ~25% USD rally against various global currencies).

To analyze the key drivers of the poor performance during the 2011-2013 time period, and recent strong performance of CTAs, we replicated a CTA benchmark with a set of exposures to our prototype Momentum strategies in Equities, Bonds/Rates, Currencies, and Commodities (see details in the next Chapter) as well as to isolate the cash return component.

Figure 7 (with further details in the section 'CTA Exposure to Prototype Momentum Factors' on page 48), shows that after-fee CTA returns to investors fell from an average of +7.4% (of which +4.1% were due to cash returns) during 1994-2010 to -1.9% during the 2011-2013 time period. A main driver of the decline was the **dramatic reduction in cash yields** since the 2008 crisis from an average of +4.1% to +0.6% per annum, which significantly affected the 'cash-rich' managed futures' ability to generate absolute returns. The decline in cash yields was related to the secular decline in bond yields, reinforced by central banks' counter-deflationary actions. This demonstrates how low yields find its way into every segment of the financial system (in this case central bank actions reduced the total return of a specific risk premia strategy).

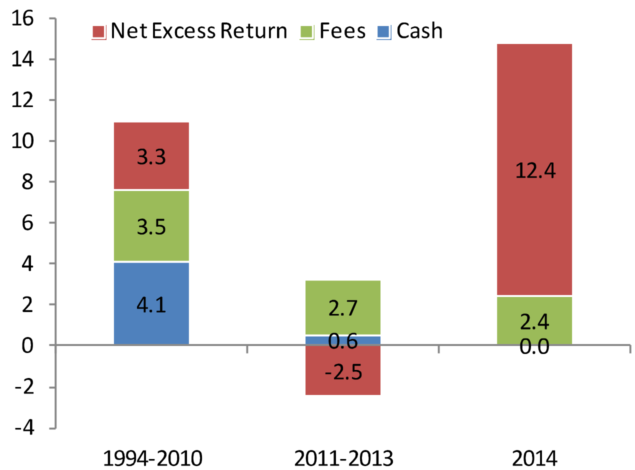
Figure 8, shows the breakdown of CTA performance into individual asset Momentum strategies. [12] One can notice that the 2011-2013 deterioration of CTA fund excess returns during the recent 3 years was mostly due to the poor performance of Currency, Commodity and Bond related Trend Risk Factors and weak alpha. These exposures were also responsible for the

[11] Similar conclusion could be reached for other CTA benchmark indexes.

[12] Alpha and performance attribution were calculated assuming the average exposure of CTA funds to our prototype 'Trend Factors' didn't change during 1994-2014. The result is based on 10bps one-way turnover cost and 15bps monthly slippage cost assumptions. Lower (higher) cost assumptions would increase (decrease) Alpha. See more details on page 48 for our analysis of 'CTA Exposure to Prototype Momentum Factors'.

record performance of CTAs in the second half of 2014. In addition, we see CTAs delivered Alpha of +7.1% in 2014 before fee Alpha and estimated fee at +9.5% and +2.4% respectively.

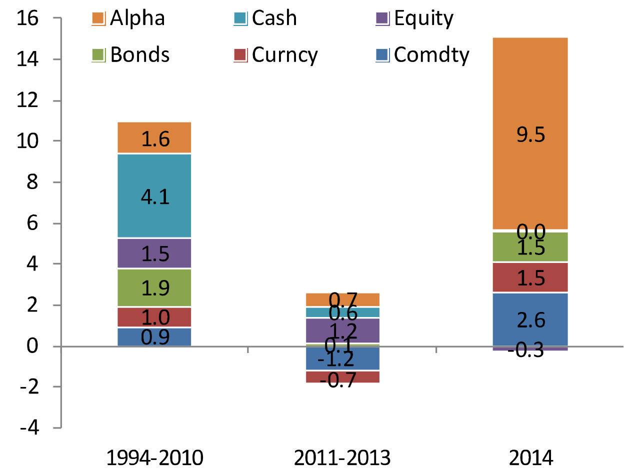
Figure 7: CTA gross return breakdown by distribution destination (%)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

* Based on the average of Barclay CTA Index, BTop 50 Index, DJCS CTA Index and CISDM CTA Index. ** Cash returns are based on the J.P. Morgan 3-Month US$ Cash Index.

Figure 8: CTA gross return breakdown by asset class (%)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

* Based on the average of Barclay CTA Index, BTop 50 Index, DJCS CTA Index and CISDM CTA Index. ** Cash returns are based on the J.P. Morgan 3-Month US$ Cash Index.

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Chapter 2

Prototype Momentum Factors

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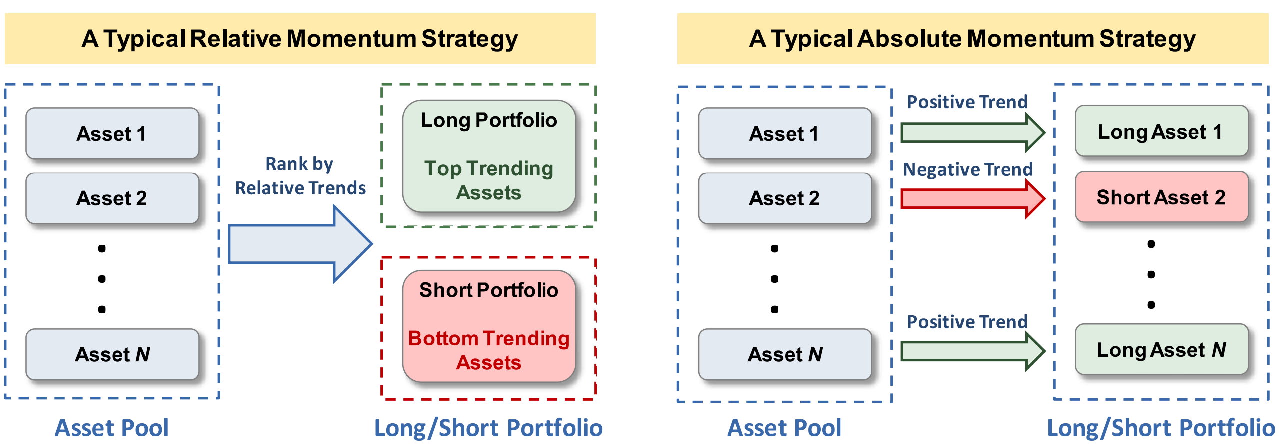
Introduction

In this section we outline different implementations of a Momentum strategy, and study the historical properties of a range of simple Momentum strategies (prototype factors). Designing a factor entails the selection of underlying assets, choice of metrics used to identify Momentum, as well as various technical aspects of implementation such as rebalance frequency, investment horizon and transaction costs. Our prototype factors are based on 3, 6, and 12 month price return signals and are implemented in each of the traditional asset classes: Equities, Bonds, Currencies and Commodities. In addition to historical performance, we analyze correlation properties of these prototype factors in some detail.

As we outlined in the previous section, the first step in designing a Momentum strategy is deciding whether to employ Absolute or Relative Momentum filters. **Absolute Momentum Strategies** (also called Time Series Momentum, or TSM in short) use trend indicators to determine the price trends of each asset individually, based on which a long (or short) position is established. An example is to use a simple 12-month price return: go long an asset with positive 12-month return; stay in cash (or short) asset with negative 12-month return. **Relative Momentum Strategies** (also called Cross Sectional Momentum, or CSM in short) employ trend indicators to rank assets on a relative basis. An example is to use past 6-month return to rank assets, then go long a portfolio of the top-performing assets and short a portfolio of the bottom-performing assets. If there is persistence in the relative asset returns, such a long/short portfolio would deliver a positive return.

Figure 9 below compares a typical long/short Relative Momentum strategy with a long/short Absolute Momentum strategy: while a Relative Momentum strategy performs cross-sectional ranking of assets during each rebalancing, an Absolute Momentum strategy runs through each asset and determines long/short positions on an individual basis[13].

Figure 9: Comparing a Relative Momentum Strategy with an Absolute Momentum Strategy



Source: J.P. Morgan Quantitative and Derivatives Strategy

Absolute Momentum could also be characterized as a special case of Relative Momentum by comparing the relative trends of only two assets: a risky asset and a risk-free asset.

[13] While long/short Relative Momentum Strategies could be designed to be market neutral, a long/short Absolute Momentum Strategy usually comes with time-varying market exposure depending on the trends of underlying assets. In addition to long/short Momentum strategies, one could also design long-only and hybrid Momentum strategies. See Chapter 2-3 of the report for more details.

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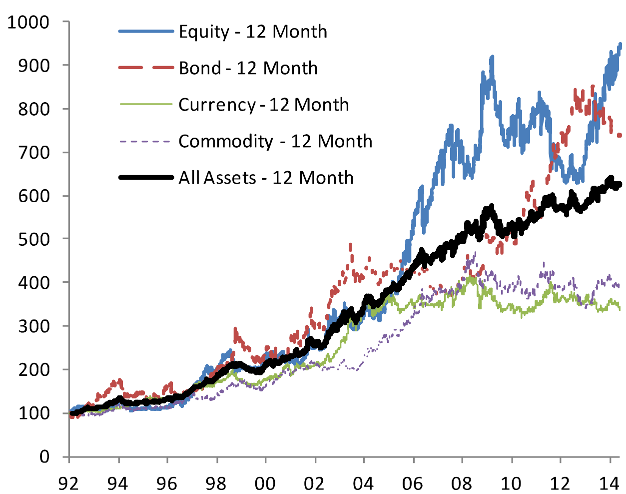
Absolute Momentum Prototypes

We begin by designing and testing Absolute Momentum strategies and then compare their properties to Relative Momentum strategies in the next section. While the two types of Momentum strategies are closely correlated we find that Absolute Momentum strategies are better positioned to capture the Momentum effect and hence tend to perform better than Relative Momentum strategies.

For a single asset, we calculate its 'Momentum signal' at each month-end rebalance date using the price return data up to one business day before. We start with 'Price Return' - the most commonly used 'trend signal' and design time series for each 12-, 6-, 3- and 1-month lookback window. We have currency hedged returns of all assets into US$ and assumed 10bps one-way transaction cost for every asset.[14] Later in the report, we also test various other signals for trend filtering, the effect of non-month-end rebalances and other re-balance frequencies including Weekly and Daily rebalances, the impact of higher transaction costs, and other alternative implementations.

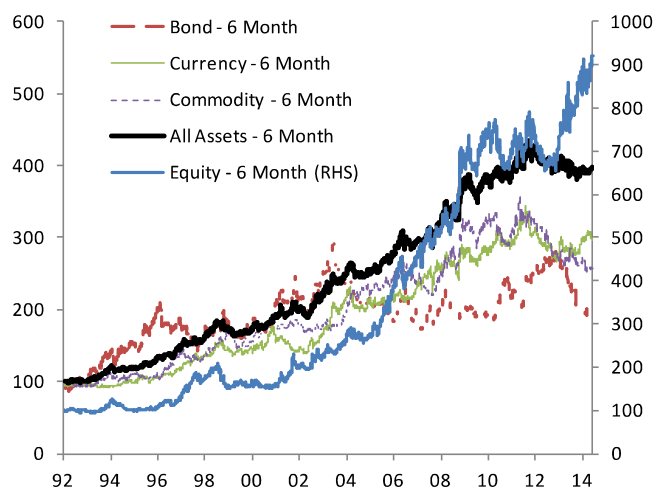
After the cumulative return of a single asset is calculated according to its rebalance weights (+100% during uptrend and -100% in downtrends), we combine different strategies together to form Absolute Momentum strategy benchmarks for each asset class and different signal lookback windows. For example, the 'Equity-12 Month' index aggregates all the Absolute Momentum signals for Equity Index Futures with 12-month window (i.e. the trend is determined by its past 12-month return). While there are different ways to combine individual indices together, we use a version of the Equal Marginal Volatility (EMV) method which gives the same marginal risk assignments[15] to each underlying strategy. Figure 10-Figure 13 below show the historical backtest performance of prototype Absolute Momentum strategies in different asset classes, as well as the average performance of Momentum strategies across all asset classes.

Figure 10: Absolute Momentum Strategies: 12-month return



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 11: Absolute Momentum Strategies: 6-month return



Source: J.P. Morgan Quantitative and Derivatives Strategy.

[14] We used cash return indices to backfill the data when there is no futures data available and assumed covered interest rate parity in hedging the currency risk of the collateral in foreign currency Equity/Bond futures contracts.

[15] Interested readers can refer to our primer report on Cross Asset Systematic Strategies p. 63-88 for more details on EMV and related Cross-Sectional Risk Allocation Methods. Our use of EMV is also consistent with academic practices. For instance, Moskowitz, Ooi, and Pedersen (2012) used similar methods in constructing their benchmark indices. In our backtest of strategies, we used a target volatility of 20% for each underlier and exponentially weighted standard deviation with a horizon mass of 63 days for ex-ante volatility.

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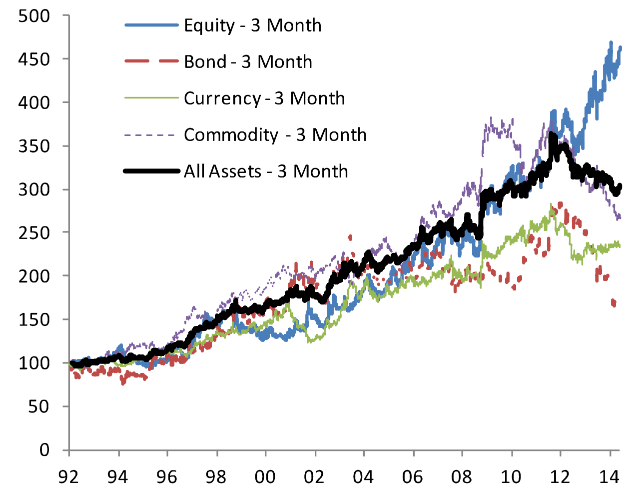
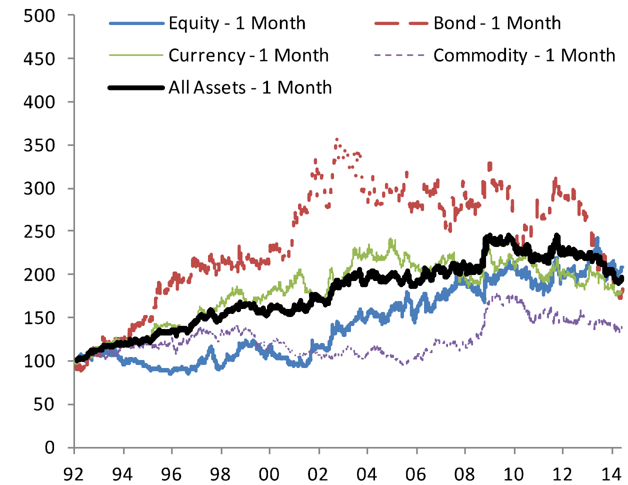
Figure 12: Absolute Momentum Strategies: 3-month return



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 13: Absolute Momentum Strategies: 1-month return



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 3 below summarizes performance and risk statistics[16] for prototype Absolute Momentum (TSM) strategies. We find that the annual returns and volatilities of Equity TSM Strategies generally increase with the trend signal horizon from 1 month to 12 months. For instance, the annualized average return and volatility for the 12-month Equity strategy are +10.9% and 13.4%, respectively, whereas the annualized average return and volatility for the 1-month Equity strategy are +4% and 11.9%, respectively. On the other hand, strategy volatility is not greatly affected by the change in signal lookback window. In addition, a shorter trend horizon of 1-3 months usually has a larger max drawdown and longer drawdown durations. As a result, a 6-12 month trend horizon delivered better risk-adjusted performance than a 1-3 month trend horizon for most Absolute Momentum strategies. Besides the effectiveness of trend signals, another reason for the outperformance of 6-12 month trend horizons relates to their lower turnover, and hence lower transaction costs[17].

Table 3: Performance and Risk of Absolute Momentum Strategies during 1992-2014: 12-month and 6-month Trend Horizons

Trend Horizon	Asset Class	Ann. Return	Ann. Volatility	Max Drawdown	MaxDDur (in years)	Sharpe Ratio	Hit Rate	Return Skewness	Return Kurtosis
12-Month	Equity	10.9	13.4	-31.6	4.9	0.82	53.5	-0.3	3.3
	Bond	9.8	13.1	-28.7	5.5	0.75	53.4	-0.2	2.6
	Curncy	6.0	10.3	-23.1	6.1	0.58	53.9	-0.3	2.8
	Comdty	6.8	10.7	-28.0	5.9	0.63	54.2	-0.3	2.5
	All-Asset	**8.5**	**7.0**	**-12.6**	**2.1**	**1.21**	**55.6**	**-0.3**	**2.1**
6-Month	Equity	10.7	12.8	-28.0	3.1	0.84	53.6	-0.3	3.2
	Bond	4.0	13.1	-43.9	11.0	0.31	51.9	-0.2	2.3
	Curncy	5.4	10.1	-22.5	2.8	0.53	53.1	-0.2	2.1
	Comdty	4.8	10.4	-29.1	3.1	0.46	53.2	-0.2	2.5
	All-Asset	**6.4**	**7.0**	**-12.4**	**2.7**	**0.92**	**53.9**	**-0.3**	**2.2**

Source: J.P. Morgan Quantitative and Derivatives Strategy.

[16] Exact definitions of these performance-risk analytics are summarized in the Appendix on page 63. Similar sets of statistics were used throughout our guide to Cross Asset Systematic Strategies and Equity Risk Premia Strategies.
[17] See the section 'Investment Horizon, Rebalance Frequency, and Transaction Costs' on page 42 for more analysis on the impact of transaction cost assumptions.

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Table 4: Performance and Risk of Absolute Momentum Strategies during 1992-2014: 3-month and 1-month Trend Horizons

Trend Horizon	Asset Class	Ann. Return	Ann. Volatility	Max Drawdown	MaxDDur (in years)	Sharpe Ratio	Hit Rate	Return Skewness	Return Kurtosis
3-Month	Equity	6.9	12.5	-24.4	3.0	0.56	53.0	-0.2	3.5
	Bond	5.4	13.1	-39.7	7.1	0.42	51.5	-0.1	2.3
	Curncy	4.6	10.2	-27.1	2.8	0.45	52.3	-0.1	3.0
	Comdty	5.2	10.3	-31.3	3.1	0.51	52.8	-0.2	2.6
	All-Asset	**5.7**	**7.0**	**-20.1**	**2.7**	**0.81**	**53.8**	**-0.1**	**4.0**
1-Month	Equity	4.0	11.9	-26.1	3.9	0.33	50.7	0.0	3.3
	Bond	3.5	12.9	-52.2	11.7	0.27	51.2	0.1	2.8
	Curncy	3.1	9.7	-27.5	9.5	0.32	51.2	-0.1	2.8
	Comdty	1.9	10.2	-33.4	10.0	0.19	51.8	-0.2	2.6
	All-Asset	**3.2**	**6.7**	**-22.4**	**5.4**	**0.48**	**51.7**	**-0.1**	**3.1**

Source: J.P. Morgan Quantitative and Derivatives Strategy.

We note in the performance chart for Momentum prototype indices that 12- month Equity, Currency and Commodity strategies all suffered significant drawdowns since 2009 as the asset price trends reversed (while the 12-month Bond strategy fared relatively well until 2013). We also note the underperformance of various Momentum strategies after 2011 (with the exception of Equity Momentum strategies and the 12-month Bond Momentum strategy). The tables also show that although all strategies had **significantly positive Sharpe ratios, they had negative skewness and high kurtosis[18] which indicates that the Momentum risk premium is most likely compensation for taking 'Momentum crash' risk.**[19]

Shorter trend lookback windows (e.g. 1 month or shorter), have more volatile signals resulting in higher transaction costs. On balance, a 6-12 month trend horizon achieves low turnover and a reasonably fast response to market regime shifts. Empirically, shorter (< 1-3 months) and longer (> 3-5 years) time horizons often relate to mean-reversion effects, giving rise to 'Value' risk premia. As we show in the next chapter, short term reversion effects can be incorporated into Momentum strategies to reduce the risk of market turning points.

Similar to the analysis in our guide to Cross Asset Systematic Strategies and Equity Risk Premia Strategies, below we report exposures of prototype Momentum Factors to macro regimes of Growth, Inflation, market Volatility and Funding Liquidity indicators[20].

[18] The reported 'Kurtosis' in Table 3 is a finite sample estimation of the excess kurtosis relative to a normal distribution:

$$\mathbf{Kurt}_R = \frac{T(T+1)}{(T-1)(T-2)(T-3)}\sum_{i=1}^{T}\left(\frac{r_i-\bar{r}}{s_R}\right)^4 - \frac{3(T-1)^2}{(T-2)(T-3)}$$

where T is the sample size and $\boldsymbol{R} = (r_1, \dots, r_T)'$ is the excess return time series. Refer to the Appendix 'Performance-Risk Analytics' on page 163 for more information.

[19] Please note that some authors report positive skewness for Momentum strategies over long periods of time – see Y. Lemperiere, C. Deremble, P. Seager, M. Potters, J.P. Bouchaud: "Two Centuries of Trend Following", April 2014.

[20] The macro/market regime indicators are defined as follows. Growth is defined as YoY change of OECD leading indicator; Inflation is defined as OECD global consumer price inflation indicator; Volatility is defined as the VIX indicator; Liquidity is defined as the difference between 3-month Treasury Bill rate and 3-month US$ Libor rate (the Ted spread defined as such is shown to be closely linked to both market and funding Liquidity). See more details in the Appendix 'Macro and Market Regimes' on page 161.

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Table 5 below summarizes annualized average returns (and related *t*-statistics, in parenthesis) of each Risk Factor under "Low", "Mid" and "High" regimes of Growth, Inflation, Volatility and Liquidity, respectively.

Table 5: Performance (t-statistics*) of Cross Asset Prototype Absolute Momentum Factors under different macro/market regimes

	Growth			Inflation			Volatility			Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Equity - 12 Months	2.87	15.97	14.10	5.32	17.48	9.05	19.14	11.53	2.21	8.81	6.99	17.03
	(-2.04)	(1.25)	(0.79)	(-1.34)	(1.75)	(-0.47)	(2.06)	(0.14)	(-2.21)	(-0.54)	(-0.99)	(1.53)
Bond - 12 Months	17.24	12.98	-0.25	12.41	6.05	12.05	9.71	-2.73	22.81	14.88	0.61	14.33
	(1.70)	(0.69)	(-2.41)	(0.54)	(-0.98)	(0.47)	(-0.06)	(-2.98)	(3.04)	(1.14)	(-2.18)	(1.02)
Curncy - 12 Months	-0.20	10.47	7.66	2.02	10.82	4.29	7.99	6.60	3.30	4.07	3.00	10.77
	(-2.06)	(1.49)	(0.57)	(-1.25)	(1.73)	(-0.54)	(0.67)	(0.21)	(-0.89)	(-0.63)	(-0.97)	(1.61)
Comdty - 12 Months	3.21	9.51	7.65	5.18	9.04	5.76	11.07	5.90	3.34	7.08	4.11	9.08
	(-1.14)	(0.87)	(0.28)	(-0.48)	(0.77)	(-0.32)	(1.38)	(-0.28)	(-1.10)	(0.10)	(-0.84)	(0.74)
Equity - 6 Months	9.05	17.00	6.28	5.41	12.85	13.55	16.41	10.10	5.73	8.47	5.65	18.09
	(-0.45)	(1.63)	(-1.17)	(-1.33)	(0.59)	(0.71)	(1.49)	(-0.17)	(-1.32)	(-0.60)	(-1.33)	(1.93)
Bond - 6 Months	9.17	7.15	-3.84	1.80	2.54	8.23	8.28	-10.56	14.57	8.96	0.74	2.72
	(1.19)	(0.71)	(-1.90)	(-0.53)	(-0.41)	(0.94)	(0.98)	(-3.53)	(2.50)	(1.14)	(-0.80)	(-0.34)
Curncy - 6 Months	-0.18	10.74	5.52	6.42	8.01	1.29	7.48	6.41	2.14	5.08	1.43	9.47
	(-1.94)	(1.88)	(0.06)	(0.36)	(1.00)	(-1.38)	(0.75)	(0.37)	(-1.12)	(-0.09)	(-1.36)	(1.45)
Comdty - 6 Months	5.84	3.16	5.35	4.75	4.89	4.71	3.66	6.40	4.35	8.10	-1.02	7.16
	(0.34)	(-0.52)	(0.18)	(-0.01)	(0.03)	(-0.02)	(-0.36)	(0.51)	(-0.14)	(1.06)	(-1.84)	(0.76)
Equity - 3 Months	7.42	11.48	3.91	5.41	6.98	10.39	12.21	4.53	6.01	3.08	4.44	15.22
	(-0.05)	(1.06)	(-1.01)	(-0.57)	(-0.18)	(0.75)	(1.27)	(-0.83)	(-0.44)	(-1.24)	(-0.86)	(2.11)
Bond - 3 Months	7.50	6.28	-2.71	2.43	2.14	6.63	3.48	-8.55	15.97	7.92	2.63	0.48
	(0.89)	(0.60)	(-1.49)	(-0.28)	(-0.38)	(0.67)	(-0.05)	(-2.85)	(2.90)	(0.99)	(-0.24)	(-0.74)
Curncy - 3 Months	1.56	6.62	4.62	6.14	5.04	1.56	6.29	2.70	3.77	6.10	-0.10	6.72
	(-0.96)	(0.84)	(0.13)	(0.64)	(0.30)	(-0.94)	(0.72)	(-0.55)	(-0.17)	(0.66)	(-1.55)	(0.88)
Comdty - 3 Months	3.30	6.29	5.11	3.23	4.24	7.27	4.63	7.24	2.87	9.49	3.85	1.32
	(-0.53)	(0.46)	(0.07)	(-0.52)	(-0.23)	(0.76)	(-0.09)	(0.76)	(-0.67)	(1.53)	(-0.34)	(-1.19)
Equity - 1 Month	7.95	8.24	-4.32	8.00	3.52	0.50	2.54	5.00	4.28	0.96	0.16	10.66
	(1.18)	(1.25)	(-2.45)	(1.13)	(-0.13)	(-0.99)	(-0.41)	(0.31)	(0.10)	(-0.88)	(-1.10)	(1.99)
Bond - 1 Month	9.13	2.35	-0.71	-0.55	2.37	8.96	8.53	-4.56	6.72	7.32	5.39	-1.91
	(1.38)	(-0.31)	(-1.07)	(-0.98)	(-0.32)	(1.30)	(1.23)	(-2.02)	(0.78)	(0.93)	(0.44)	(-1.37)
Curncy - 1 Month	2.05	7.56	-0.46	-1.09	4.56	5.30	5.23	0.59	3.27	1.38	5.25	2.50
	(-0.36)	(1.66)	(-1.29)	(-1.45)	(0.60)	(0.81)	(0.81)	(-0.90)	(0.09)	(-0.61)	(0.81)	(-0.20)
Comdty - 1 Month	3.79	1.89	0.08	-1.13	-2.05	9.46	3.47	2.82	-0.48	4.70	2.42	-1.33
	(0.63)	(-0.01)	(-0.62)	(-0.98)	(-1.43)	(2.47)	(0.52)	(0.29)	(-0.81)	(0.93)	(0.16)	(-1.09)

Source: J.P. Morgan Quantitative and Derivatives Strategy. *Performances are annualized and in US$ %.
** The *t*-statistics shown in parentheses is from a two-sample *t*-test from comparing factor performance under the particular regime versus factor performance out of the regime.

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Table 6 summarizes the exposure of prototype Absolute Momentum (TSM) Factors to macro/market regime indicators over the full backtest period during 1992-2014. We report both regression coefficients (Beta to the corresponding regime indicator) and related *t*-statistics.

Table 6: Cross Asset Prototype Absolute Momentum (TSM) Factors' exposures (t-stats*) to macro/market regime factors

	Growth	Inflation	Volatility	Liquidity		Growth	Inflation	Volatility	Liquidity
Equity - 12 Months	0.19 (0.81)	0.27 (1.16)	-0.46 (-1.94)	-0.07 (-0.32)	**Equity - 6 Months**	-0.27 (-1.18)	0.21 (0.92)	-0.16 (-0.70)	-0.10 (-0.44)
Bond - 12 Months	-0.39 (-1.54)	0.05 (0.20)	0.91 (3.66)	-0.30 (-1.19)	**Bond - 6 Months**	-0.09 (-0.37)	0.22 (0.89)	0.51 (2.04)	-0.17 (-0.67)
Curncy - 12 Months	0.24 (1.36)	0.06 (0.32)	-0.06 (-0.33)	0.18 (1.02)	**Curncy - 6 Months**	0.19 (1.12)	-0.14 (-0.81)	0.01 (0.07)	-0.07 (-0.43)
Comdty - 12 Months	0.22 (1.20)	-0.01 (-0.05)	-0.35 (-1.93)	0.16 (0.88)	**Comdty - 6 Months**	-0.04 (-0.19)	0.05 (0.29)	0.26 (1.38)	-0.46 (-2.53)
Equity - 3 Months	-0.26 (-1.20)	0.03 (0.12)	0.16 (0.72)	-0.05 (-0.23)	**Equity - 1 Month**	-0.42 (-2.08)	-0.30 (-1.48)	0.40 (2.01)	0.05 (0.26)
Bond - 3 Months	-0.06 (-0.22)	0.17 (0.66)	0.77 (3.07)	-0.18 (-0.70)	**Bond - 1 Month**	-0.25 (-1.04)	0.38 (1.59)	0.29 (1.22)	-0.29 (-1.20)
Curncy - 3 Months	0.04 (0.24)	-0.16 (-0.96)	0.21 (1.29)	-0.18 (-1.09)	**Curncy - 1 Month**	0.01 (0.06)	0.25 (1.54)	0.11 (0.69)	-0.17 (-1.03)
Comdty - 3 Months	-0.17 (-0.97)	0.09 (0.50)	0.22 (1.22)	-0.63 (-3.62)	**Comdty - 1 Month**	-0.32 (-1.81)	0.30 (1.72)	0.20 (1.12)	-0.54 (-3.12)

Source: J.P. Morgan Quantitative and Derivatives Strategy. *Performances are annualized and in US$ %.
** The *t*-statistics shown in parentheses is from a two-sample *t*-test from comparing factor performance under the particular regime versus factor performance out of the regime.

Table 5 and Table 6 provide insights into the historical macro exposures of Momentum Factors. One can see that over the full sample period Momentum strategies tend to behave similarly to their underlying traditional asset class. For instance:

1) Most Equity Momentum strategies perform well in high Liquidity/low Volatility regimes, while Bond Momentum (risk-off asset) performs well in a high Volatility/low Liquidity environment.

2) Bond Momentum also fared well in a low Growth regime (and performed poorly during high Growth and mid Volatility regimes);

3) Longer term Commodity/Currency Momentum tends to be positively correlated with Liquidity – it performed well during a high Liquidity regime. Short term Commodity Momentum (1M) is positively correlated with Inflation and negatively correlated with Liquidity.

Based on these results, an investor who uses a top-down approach for exposures to Trend-Following strategies could first make a forecast of macro variables such as Growth and Inflation, and then make an appropriate choice of asset class and trend signal horizon based on such forecasts.

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Relative Momentum Strategies

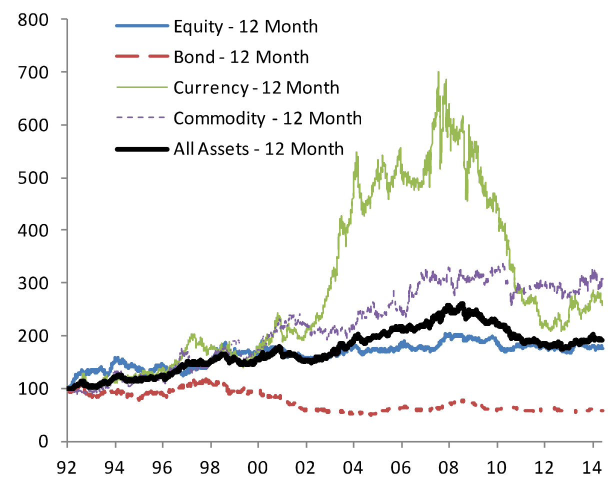
Relative Momentum strategies employ a Momentum signal that is established relative to a group of assets (as opposed to the asset's own performance in Absolute Momentum strategies).[21] Relative Momentum strategies are also called Cross-sectional Momentum strategies (CSM in short).

The main conceptual difference between the two Momentum approaches is that a Relative Momentum strategy may be buying an asset with negative Absolute Momentum, as long as this asset is one of the best performing within a group of assets. Similarly, the strategy may be selling an asset with positive Absolute Momentum in case all assets have positive Momentum. As we show below, this will in some cases hurt performance when there is a broad market rally or a selloff within an asset class (or across asset classes).

To construct and test Relative Momentum strategies, we used the same set of 40 liquid tradable global currencies and futures as the underlying instruments. Within a specific asset group (Equities, Bonds, Currencies, and Commodities), a Relative Momentum strategy goes long the *N* top performing assets and short the *N* bottom performing assets based on their past returns at each month-end rebalance date (based on data up to one business day before). In addition, to be consistent with our study of Absolute Momentum strategies, each asset in the long/short portfolio was Equal Marginal Volatility (EMV) weighted[22] and we assume 10bps one-way transaction costs for all the assets.

Figure 14 shows the performance of prototype Relative Momentum strategies (long/short) in different asset classes with *N* = 3 and Table 7 calculates related return-risk metrics. Significant performance was found before 2009 for Equity Index Futures, Currencies and Commodities Futures.

Figure 14: Cumulative Performance of Relative Momentum Strategies based on past 12-month returns (Long/Short)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 7: Performance-Risk Analytics of Relative Momentum Strategies based on past 12-month returns

	Equity	Bond	Curncy	Comdty	All-Asset
Ann. Ex Ret (%)	3	-1.9	5.8	6.1	3.2
CAGR (%)	2.6	-2.5	4.3	5.1	2.9
STDev (%)	10	10.9	17.5	14.6	7.2
MaxDD (%)	-22.1	-57.2	-70.2	-26.2	-33.2
MaxDDur (in yrs)	7.5	16.6	6.9	4.2	5.9
***t*-Statistic**	**1.4**	**-0.8**	**1.6**	**2**	**2.1**
Sharpe Ratio	**0.3**	**-0.18**	**0.33**	**0.42**	**0.44**
Hit Rate (%)	51	50.4	52.3	52.7	52.3
Skewness	-0.04	-0.17	-0.26	-0.22	-0.21
Kurtosis	2.51	2.86	4.03	2.13	1.43

Source: J.P. Morgan Quantitative and Derivatives Strategy.

[21] The simplest and most commonly used example of a Relative Momentum strategy is the one popularized by Jegadeesh and Titman (1993) and Carhart (1997): Jegadeesh, Narasimhan, and Sheridan Titman (1993), "Returns to buying winners and selling losers: Implications for stock market efficiency", Journal of Finance 48, 65–91; Carhart, Mark M. (1997), "On persistence in mutual fund performance," Journal of Finance 52, 57-82.
[22] Given less asset diversification achieved by Cross Sectional Momentum strategies, we used 15% target volatility in the EMV weights.

The Relative Momentum strategy based on global government bond futures didn't show significant risk-adjusted performance throughout the backtest period during 1992-2014. [23] As in the case of Absolute Momentum, Relative Momentum strategies had negative skewness and positive excess Kurtosis.

It is not surprising that the **prototype Relative Momentum strategies broke down in Feb 2009**, when global equities and commodities troughed. After the 2009 bottom most risky assets rallied, and the strategy was short the assets that were most depressed and hence rallied hardest during the recovery. Subsequently – when all risky assets rallied – the strategy didn't reap the benefit due to both long and short positions in rising asset classes.

Similarly, bond based Relative Momentum didn't work for most of the backtest period during which bond markets were in a secular bull market. The strategy goes long the best performing bonds and shorts the worst performing bonds - since both groups rallied in the secular bull market, the performance of the strategy was roughly flat. The main differentiating property of Relative Momentum strategies (from Absolute Momentum strategies) in the described examples above led to significant underperformance during the past two decades.

In addition to a 12-month strategy, we also tested the Relative Momentum strategies based on past returns of various other window sizes including 6-, 3- and 1-months. We find that performance generally erodes as the time horizons for calculating the trend signals get shorter, similar to our results based on Absolute Momentum strategies. For example, the Sharpe ratio is only 0.09 (*t*-statistics is insignificant at 0.4) for a multi-asset Relative Momentum strategy based on past 3-month returns.

As discussed above, the poor performance of prototype Relative Momentum strategies was largely due to the fact that the short portfolio most often contributed a drag on returns during secular asset rallies (which often last longer than bear markets). For example, the after fee Sharpe ratio is -0.26 for the short leg of a multi-asset Relative Momentum strategy based on past 12-month returns and -0.36 for the short leg of a similar strategy based on past 6-month returns. While a reduction of returns from the short portfolio may be worthwhile (and expected) for a typical long/short strategy if its inclusion could reasonably reduce the risk of overall market-neutral strategy[24], we find the short portfolios in prototype Relative Momentum strategies typically increased overall strategy risk.

To improve the performance of Relative Momentum strategies, one could address this risk in a short portfolio by overlaying an element of Absolute Momentum. Specifically, in each portfolio rebalancing, we include the bottom-3 performing assets only if they returned negatively over the past 3 months. In other words, the short portfolio combines Relative Momentum and Absolute Momentum. We introduce hybrid long-only Momentum models and multi-variate Momentum models which also incorporate both Relative and Absolute Momentum in Chapter 3 of the report.

Figure 15 and Figure 16 show the historical performance of Relative Momentum strategies that include the Absolute momentum filter described above. The related performance/risk analytics are summarized in Table 8 and Table 9 – we do see better performance from these 'enhanced prototypes' than the prototypes without Absolute Momentum on the short portfolio. For instance, the Sharpe ratio improved from 0.44 (original strategy) to 0.82 (enhanced strategy) for the multi-asset composite of 12-month Relative strategies, while maximum drawdown reduced from -33.2% to -12.2%. Comparing the results with Table 3, we find the prototype Absolute Momentum strategies often performed better than their Relative Momentum counterparts on risk-adjusted terms within each asset class. In the section 'Risk Adjusted Momentum' in Chapter 3, we discuss risk-adjustment in the Momentum signal which could help improve the performance/risk profiles of prototype Relative Momentum strategies.

[23] This result does not necessarily contradict with academic studies confirming positive risk premia from trading global government bonds through Relative Momentum models (see the non-tradable prototype bond Momentum model in Figure 1). For liquidity, tradability and consistency considerations, we have only used liquid government bond futures in our strategy back-tests, while most academic studies [e.g. Asness et. al (2013)] on government bond Momentum used cash bond indices (many of which are relatively illiquid and difficult to short) or implied bond returns from bond yields, and many previous academic studies ignored transaction costs.
[24] Note that the Sharpe ratio of a long-only strategy could be well above that of a long/short strategy by additional exposures to various market risks. However, the strategy 'Alpha' of the long-only strategy may be lower after controlling for related market risk factors (betas).

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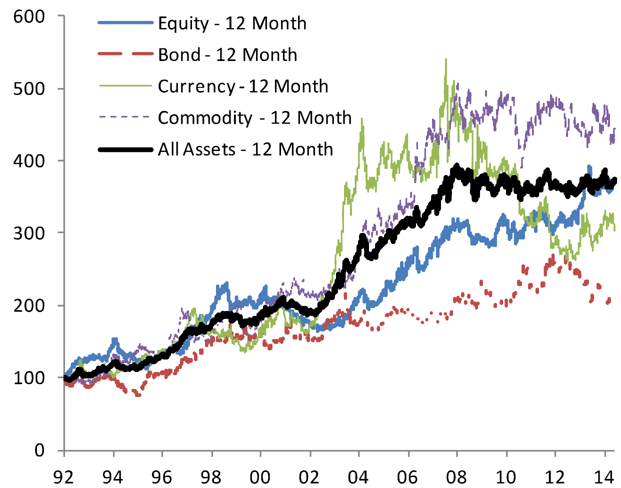
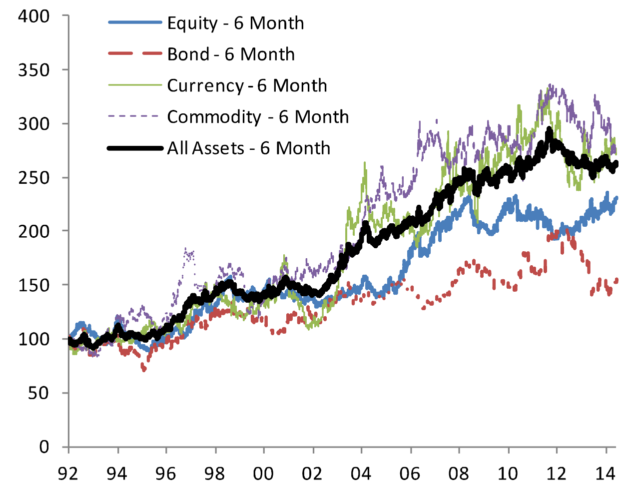
Figure 15: Relative Momentum Strategies: 12-month return (Enhanced)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 16: Relative Momentum Strategies: 6-month return (Enhanced)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 8: Performance-Risk Analytics of Relative Momentum Strategies (Enhanced) based on past 12-month returns

	Equity	Bond	Curncy	Comdty	All-Asset
Ann. Ex Ret (%)	6.5	4.3	6.3	7.6	6.2
CAGR (%)	6.1	3.6	5.1	6.8	6.1
STDev (%)	11.2	12.3	16.3	14.3	7.5
MaxDD (%)	-28.6	-32.6	-52.0	-24.6	-12.2
MaxDDur (in yrs)	6.5	4.8	6.9	6.4	6.4
***t*-Statistic**	**2.8**	**1.7**	**1.8**	**2.5**	**3.9**
Sharpe Ratio	**0.58**	**0.35**	**0.39**	**0.53**	**0.82**
Hit Rate (%)	53.1	52.2	52.5	53.5	54.1
Skewness	-0.29	-0.25	-0.26	-0.27	-0.30
Kurtosis	2.16	2.69	4.55	2.21	1.68

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 9: Performance-Risk Analytics of Relative Momentum Strategies (Enhanced) based on past 6-month returns

	Equity	Bond	Curncy	Comdty	All-Asset
Ann. Ex Ret (%)	4.3	2.7	5.9	5.6	4.6
CAGR (%)	3.8	2.0	4.6	4.7	4.4
STDev (%)	10.9	12.2	16.7	14.4	7.5
MaxDD (%)	-27.6	-35.3	-38.4	-35.6	-15.3
MaxDDur (in yrs)	5.7	4.2	3.3	6.4	2.7
***t*-Statistic**	**1.9**	**1.0**	**1.7**	**1.8**	**2.9**
Sharpe Ratio	**0.40**	**0.22**	**0.35**	**0.39**	**0.61**
Hit Rate (%)	52.9	51.6	52.7	53.3	53.6
Skewness	-0.25	-0.30	-0.34	-0.32	-0.27
Kurtosis	1.72	2.69	4.09	3.27	1.35

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Similar to the exercise in our analysis of cross-asset prototype Absolute Momentum Factors in the previous section, we next report prototype (enhanced) Relative Momentum Factors' exposure to global economic Growth, Inflation, market Volatility and Funding Liquidity indicators.

Table 10 below summarizes the annualized average returns (and related *t*-statistics, in parenthesis) of each Risk Factor under "Low", "Mid" and "High" regimes of Growth, Inflation, Volatility and Liquidity, respectively. In addition, Table 11 summarizes the exposure of prototype Absolute Momentum (TSM) Factors to macro/market regime indicators over the full backtest period during 1992-2014. We report both regression coefficients (Beta to the corresponding regime indicator) and related *t*-statistics.

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Table 10: Performance (t-statistics*) of Cross Asset Prototype Relative Momentum Factors under different macro/market regimes

	Growth			Inflation			Volatility			Liquidity		
	Low	Mid	High	Low	Mid	High	Low	Mid	High	Low	Mid	High
Equity - 12 Months	3.06	17.73	5.02	6.59	8.66	10.37	16.56	10.38	-1.22	5.99	10.79	8.95
	(-1.37)	(2.28)	(-0.88)	(-0.47)	(0.03)	(0.44)	(2.00)	(0.45)	(-2.46)	(-0.64)	(0.55)	(0.09)
Bond - 12 Months	6.79	17.67	-6.80	4.34	7.22	5.74	9.00	-9.07	17.44	6.51	2.33	8.66
	(0.19)	(2.33)	(-2.51)	(-0.28)	(0.29)	(-0.02)	(0.62)	(-2.96)	(2.30)	(0.13)	(-0.69)	(0.55)
Curncy - 12 Months	-3.29	21.23	7.10	5.64	20.76	-3.18	20.02	9.68	-4.79	-1.11	7.24	18.75
	(-1.87)	(2.07)	(-0.19)	(-0.40)	(2.15)	(-1.80)	(1.89)	(0.22)	(-2.11)	(-1.51)	(-0.17)	(1.68)
Comdty - 12 Months	7.74	8.02	14.92	7.90	14.23	7.99	18.10	10.06	2.54	9.12	16.05	5.60
	(-0.43)	(-0.38)	(0.80)	(-0.38)	(0.73)	(-0.38)	(1.35)	(-0.03)	(-1.32)	(-0.19)	(0.99)	(-0.80)
Equity - 6 Months	1.49	13.14	2.41	4.61	6.79	5.37	11.40	8.48	-2.90	3.77	8.55	4.66
	(-1.05)	(1.87)	(-0.81)	(-0.25)	(0.30)	(-0.07)	(1.45)	(0.70)	(-2.16)	(-0.47)	(0.72)	(-0.25)
Bond - 6 Months	6.14	13.46	-8.55	-1.40	7.11	4.62	5.32	-11.57	17.02	0.78	3.99	6.18
	(0.50)	(1.95)	(-2.46)	(-0.96)	(0.74)	(0.19)	(0.33)	(-3.06)	(2.70)	(-0.57)	(0.07)	(0.50)
Curncy - 6 Months	-4.25	18.84	8.59	11.10	12.81	-1.39	15.22	6.61	1.20	4.38	2.69	15.92
	(-1.88)	(1.74)	(0.14)	(0.51)	(0.86)	(-1.39)	(1.18)	(-0.17)	(-1.01)	(-0.52)	(-0.77)	(1.29)
Comdty - 6 Months	7.05	2.46	13.13	4.73	12.71	4.50	11.61	9.87	1.24	4.07	10.33	8.32
	(-0.09)	(-0.86)	(0.94)	(-0.45)	(0.93)	(-0.50)	(0.68)	(0.39)	(-1.07)	(-0.59)	(0.46)	(0.13)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* The *t*-statistics shown in parentheses is from a two-sample *t*-test from comparing factor performance under the particular regime versus factor performance out of the regime.

Table 11: Cross Asset Prototype Relative Momentum (CSM) Factors' exposures (t-stats*) to macro/market regime factors

	Growth	Inflation	Volatility	Liquidity		Growth	Inflation	Volatility	Liquidity
Equity - 12 Months	0.06	-0.10	-0.80	0.33	Equity - 6 Months	0.05	-0.20	-0.67	0.27
	(0.24)	(-0.41)	(-3.44)	(1.40)		(0.22)	(-0.84)	(-2.88)	(1.13)
Bond - 12 Months	-0.04	0.18	0.61	-0.09	Bond - 6 Months	-0.03	0.29	0.52	0.06
	(-0.14)	(0.59)	(2.03)	(-0.29)		(-0.11)	(0.98)	(1.74)	(0.22)
Curncy - 12 Months	0.21	-0.28	-0.38	0.57	Curncy - 6 Months	0.27	-0.42	0.20	0.00
	(0.56)	(-0.77)	(-1.02)	(1.55)		(0.72)	(-1.10)	(0.52)	(0.00)
Comdty - 12 Months	0.22	0.02	-0.58	0.01	Comdty - 6 Months	0.11	0.03	-0.29	0.12
	(0.63)	(0.06)	(-1.68)	(0.02)		(0.32)	(0.07)	(-0.83)	(0.35)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
*The *t*-statistic shown in parentheses is from regression of factor return versus respective macro/market regime indicator.

From these two tables, we note the following:

1) Equity and Currency Relative Momentum (CSM) strategies performed best during mid-Growth, low Volatility and high Liquidity regimes (and underperformed in low Growth, high Inflation, high Volatility and low Liquidity regimes).

2) Bond Relative Momentum strategies performed best in a high Volatility regime and delivered negative performance in high Growth and mid Volatility regimes;

3) Commodity strategies performed best in high Growth, mid Inflation, low Volatility and mid Liquidity regimes.

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Performance of Relative Momentum (CSM) strategies in various macro regimes is broadly similar to their Absolute Momentum (TSM) counterparts[25]. This was expected given that two types of strategies are closely related by design. In the next section we analyze the correlation between these strategies.

The Momentum signal for Relative Momentum strategies often needs to be normalized by asset volatility[26]. While this adjustment is not likely to make a big difference for an Absolute Momentum strategy[27], it can significantly impact Relative Momentum strategy performance. An example of this scaling when applied to an Equity Momentum portfolio can be found in our report on Enhanced Price Momentum. A similar signal scaling by asset volatility is popular in 'carry' strategies which rank assets according to their ex-ante yields (e.g. see Investment Strategies No. 12: JPM Carry to Risk Primer). We discuss risk-scaling in Momentum signals in the section 'Risk Adjusted Momentum' on page 66 (Chapter 3).

Additionally, while a multi-asset Absolute Momentum strategy linearly combines individual asset/security-level strategies into a composite portfolio, there are at least **two ways to create a multi-asset Relative Momentum strategy**: (1) combining asset-level Relative strategies in a portfolio; (2) pooling all assets together and performing a cross-asset ranking of trend strength in each portfolio rebalance. In other words, the first method first creates a Relative Momentum index for each asset class and combines them in a portfolio, whereas the second method comes up with a multi-asset long-short portfolio in one pass. Empirically, the second method often outperformed due to a more prominent dispersion across asset classes as opposed to typically lower dispersion within each asset class.

Given higher dispersion across asset classes, assets that are selected by Relative Momentum in the second approach are more likely to also have Absolute Momentum. This helps the model to avoid the pitfall of shorting the worst performing underlyings that may still have positive Absolute Momentum (i.e. the worst performing asset within an asset class that is in the midst of a secular bull market). For example, a multi-asset Relative Momentum 12-month strategy (long/short 12 assets) based on the second method delivered a Sharpe ratio of 1.08, higher than the Sharpe ratio of 0.82 generated by the first method. Higher cross-asset dispersion also makes risk-adjustments in the Momentum signal more effective, as discussed in the section 'Risk Adjusted Momentum' on page 66.

[25] There are some exceptions to this similarity which explains why the CSM and TSM strategies are not perfectly correlated. For instance, we find that while a mid Liquidity regime leads to underperformance of 6-month and 12-month *TSM* Commodity strategies, the same regime actually favored 6-month and 12-month *CSM* Commodity strategies.
[26] When the normalizing trend signal is asset average return, it is equivalent to ranking assets according to their past Sharpe ratios.
[27] Risk adjustment in trend signals leads to exactly the same prototype Absolute Momentum strategies as in the previous section. On the other hand, it would make a difference in Absolute Momentum strategies based on 'Trend Following Channels', which will be introduced in the next Chapter on page 73.

Correlation of Momentum Strategies

One of the main benefits of Risk Factor investing is the low and stable factor correlation.[28] In our primer on Cross Asset Systematic Strategies, we investigated the correlation of Momentum strategies to other factor styles (Value, Volatility, Carry), and here we want to further analyze correlation between different Momentum strategies as well as their correlation to traditional asset classes.

Table 12 shows these correlations calculated over the 1992-2014 time period (below the matrix diagonal are correlations over the full sample period, and above the diagonal are correlations calculated during major market crises). Specifically, we calculate correlation between Absolute Momentum Strategies (12, 6, and 3 month signals), Relative Momentum Strategies (12, and 6M signals) as well as traditional asset classes (Equities, Bonds, Currencies and Commodities).

Momentum strategies within an asset class are positively correlated across signal time horizons and between Absolute and Relative Momentum models. For instance, during the full sample period from 1992 to 2014, the correlation between 12-month TSM models and 6-month TSM models was +77%, +74%, +73% and +67% respectively for Equity, Bond, Currency and Commodity asset classes; the correlation between 12-month TSM models and 12-month CSM models was +52%, +58%, +80% and +66% respectively for Equity, Bond, Currency and Commodity asset classes. This suggests the benefit of 'signal horizon diversification' could be relatively limited for a Trend-Following strategy within a single asset class. Moreover this 'within-asset class' strategy correlation tends to increase during market crises.

On the other hand, **correlations between Momentum strategies in different asset classes are generally low, leading to substantial cross-asset diversification benefits**. For instance, the correlation between 12-month TSM strategies for Bonds and 6-month strategies for Equity, Currency and Commodity asset classes were statistically insignificant at +8%, +7% and +5% respectively. We find similar conclusions for other signal horizons as well. This cross-asset diversification effect is consistent with the improved Sharpe ratios of diversified multi-asset Momentum strategies shown e.g. in Table 3 on page 21, in our analysis of prototype multi-asset Momentum strategies.

Momentum strategies are generally positively correlated with traditional asset classes. This is true for Bonds and Commodities, and to a lesser extent Equities and Currencies. This may come as no surprise as prolonged periods of asset appreciation (e.g. the bond rally over the last 20 years) will cause Momentum strategies to acquire long exposure in traditional assets. This finding is true for both Absolute and Relative Momentum strategies.

A nice feature of the Momentum correlation matrix is that **correlation with risky asset classes weakens or completely reverses during market crises** when risky assets sell off. For instance, on average positive levels of correlation between Equities and Equity Momentum becomes negative during market crises. Similar is true for Commodities, while the correlation of Bonds to Bond Momentum stays positive. This attractive feature is likely due to the fact that Equity and Commodity Momentum strategies have managed to capture declines in risk asset prices during the crises (by shorting these assets), while they remained invested in Bonds that generally did well during volatile time periods.

Historically, this has enabled Momentum strategies to provide downside protection and risk reduction to a portfolio of traditional risky assets. As shown in Table 12, during three major crisis periods during the past two decades, including the 1997-1998 Asian Financial Crisis, 2000-2001 Tech Bubble and 2007-2008 Global Financial Crisis, the correlation between MSCI World and 12-month Equity, Bond, Currency and Commodity prototype TSM Strategies were -21%, -24%, -23% and -15% respectively.

[28] See our primer on Cross Asset Systematic Strategies and the Investor Survey from our Risk Premia Conference.

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Table 12: Sample correlation between Cross Asset time series and Relative Momentum strategies during 1992-2014 (based on weekly data)

Color Scheme	Less than -50%	-50% to -20%	-20% to +20%	+20% to +50%	Greater than +50%

		Traditional				TSM - 12 Month				TSM - 6 Month				TSM - 3 Month				CSM - 12 Month				CSM - 6 Month			
		Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Traditional	Equity		1	33	37	-21	-24	-23	-15	-37	-13	-26	-33	-48	-16	-28	-36	27	-15	-14	2	36	-23	-13	-2
	Gov Bond	-5		19	-7	-7	53	-13	0	-4	45	-4	4	-2	38	-1	3	-4	61	-14	-3	1	44	-7	0
	Currency	28	15		26	-19	-4	-31	2	-21	5	-37	-14	-24	2	-38	-21	-8	-8	-27	-7	2	4	-30	-3
	Commodity	30	-4	25		-16	-8	-1	14	-12	-4	-7	-3	-23	-14	-17	-20	10	-12	-3	29	22	-8	-6	25
TSM - 12M	Equity	11	1	-4	1		11	34	2	88	12	32	19	73	2	24	18	28	3	39	6	30	2	36	1
	Gov Bond	-22	53	4	-4	4		9	13	18	76	14	26	19	48	19	24	-2	57	5	7	4	58	12	11
	Currency	-1	4	11	7	23	7		43	32	8	83	41	24	1	61	30	16	1	85	21	8	3	72	11
	Commodity	-2	3	8	26	15	5	29		7	15	36	70	5	3	26	60	13	6	34	60	9	2	28	58
TSM - 6M	Equity	-1	2	-5	4	77	8	18	12		22	30	23	83	8	23	22	22	6	32	11	29	10	30	7
	Gov Bond	-17	38	7	0	1	74	7	3	11		12	21	20	68	16	19	5	53	5	7	12	59	11	8
	Currency	-4	4	3	4	18	11	73	21	21	15		43	22	7	77	37	18	7	78	20	8	2	86	10
	Commodity	-8	0	-1	20	15	5	24	67	22	6	30		21	11	42	81	9	14	31	50	10	20	33	61
TSM - 3M	Equity	-10	2	-5	3	56	12	13	5	79	14	14	17		18	27	26	24	11	27	8	32	15	27	5
	Gov Bond	-14	25	6	-1	2	52	2	0	10	68	12	2	17		24	15	-4	64	6	0	0	70	10	-7
	Currency	-5	2	2	4	13	11	50	15	17	14	69	26	22	19		38	23	21	67	16	7	17	78	8
	Commodity	-11	-3	-1	10	12	3	17	52	19	5	23	69	18	5	26		12	14	21	44	10	16	26	54
CSM - 12M	Equity	38	-4	0	17	52	-2	12	12	49	0	12	13	51	2	15	12		0	23	11	73	-8	26	7
	Gov Bond	-17	54	9	-4	3	58	6	2	5	56	9	-2	8	66	9	-1	-1		2	-2	1	76	10	-2
	Currency	1	2	12	7	28	7	80	23	25	7	70	22	21	7	60	17	17	8		21	13	-1	84	7
	Commodity	3	0	2	32	12	2	13	66	14	2	16	58	9	3	14	57	11	2	15		17	0	21	80
CSM - 6M	Equity	35	-3	2	19	50	0	7	9	55	3	10	14	57	5	13	12	80	0	12	13		-4	12	14
	Gov Bond	-20	48	12	-2	1	57	7	3	7	61	10	3	10	69	12	3	-4	83	10	3	-1		2	2
	Currency	1	4	9	7	20	9	64	16	24	13	82	23	20	11	71	19	15	10	80	16	11	12		9
	Commodity	1	-2	1	28	10	1	12	55	16	2	13	68	11	-1	10	64	11	-2	11	78	14	0	11	
Ann. Excess Return (%)		5.0	2.5	0.2	2.2	11.0	9.9	6.0	6.8	10.8	4.1	5.4	4.8	7.7	3.7	4.3	4.9	8.6	5.8	8.5	10.1	5.7	3.6	7.8	7.5
Sharpe Ratio		0.31	0.64	0.02	0.11	0.78	0.70	0.58	0.63	0.80	0.29	0.53	0.45	0.59	0.25	0.43	0.47	0.62	0.35	0.39	0.53	0.41	0.22	0.35	0.38
Max DrawDown (%)		-59.1	-9.3	-40.2	-71.3	-31.4	-27.1	-22.2	-27.9	-27.5	-43.9	-22.3	-28.8	-21.8	-42.8	-27.1	-30.4	-36.3	-41.4	-63.4	-32.0	-33.9	-43.6	-45.9	-45.8

Source: J.P. Morgan Quantitative and Derivatives Strategy. * We used MSCI World Total Return Index for 'Equity', Barclays US Aggregate Total Return Index for 'Bond', inverted DXY Index for 'Currency', S&P GSCI Commodities Total Return Index for 'Commodity'.
** Lower triangular statistics are the all-sample pair-wise correlation and upper triangular are the correlation statistics during crisis periods.
*** Crisis periods we include for the correlation calculations are Jul 1997 - Aug 1998 (Asian Financial Crisis, Russian Default and LTCM), Jan 2000 – Sep 2001 (Tech Bubble), and June 2007 - Feb 2009 (Global Financial Crisis or GFC).

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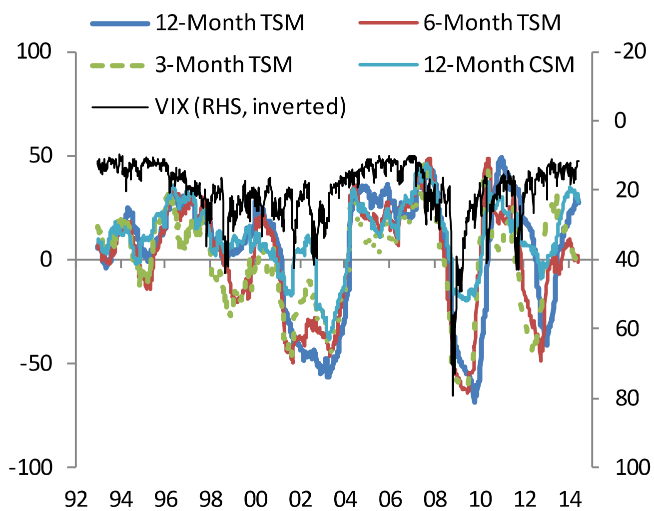
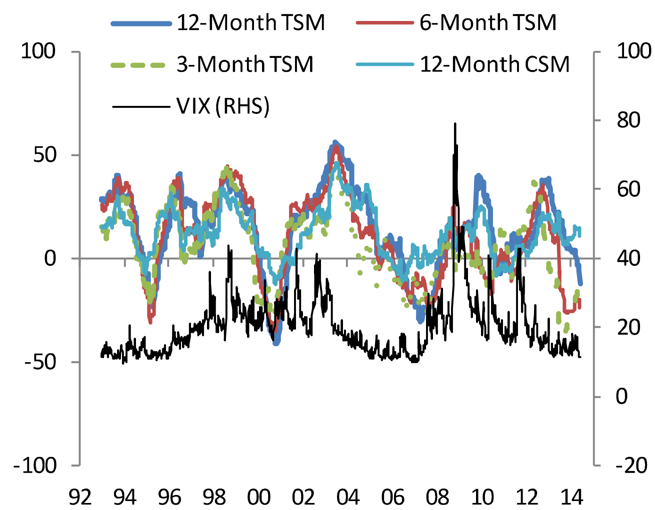
Figure 17-Figure 20 below show the average trailing 24-month correlations between traditional assets (Equity, Bond, Currency and Commodity) and prototype Momentum strategies of varying trend signal lengths[29]. These charts also show the average VIX levels, which illustrates the risk reducing impact of Momentum strategies when combined with a portfolio of traditional risky asset classes. For instance, the red solid line in Figure 17 shows the average trailing correlation between the MSCI World index and 6-month TSM strategies, and we identified a significant negative correlation during the high volatility tech bubble and global financial crisis periods. The correlation between Equities/Commodities with Momentum strategies was low or even negative during periods of market distress when volatility spiked. On the other hand, the positive correlation between Bonds and Momentum strategies during market sell-offs reflects their common ability to protect market downside.

Figure 17: Correlation of Momentum strategies with Equity (MSCI World), %



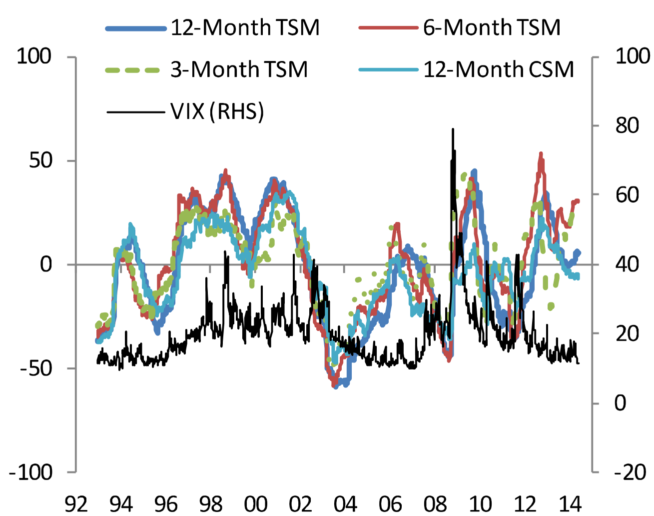
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 18: Correlation of Momentum strategies with Bonds (Barclays US Aggregate), %



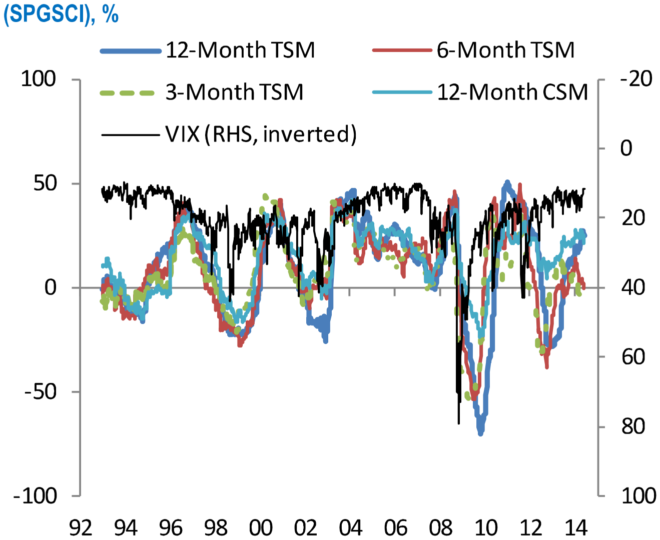
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 19: Correlation of Momentum strategies with DXY (%)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 20: Correlation of Momentum strategies with Commodity (SPGSCI), %



Source: J.P. Morgan Quantitative and Derivatives Strategy.

[29] We first calculate the correlation between a traditional asset with TSM/CSM strategies in Equity, Bond, Currency and Commodity asset classes. An equal average of the four correlation numbers is used to represent the diversification benefit of a multi-asset TSM/CSM portfolio.

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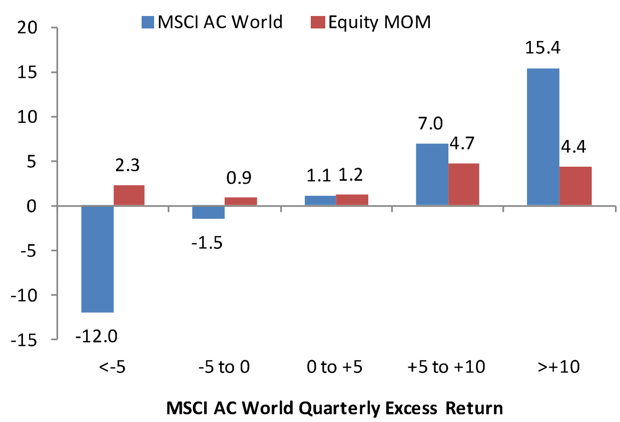
To further analyze the diversification properties of prototype Momentum factors and related asset-specific dynamics, we break down the excess returns of traditional assets including Equities (MSCI All-Country World), Bonds (Barclays US Aggregate) and Commodities (S&P GSCI) into historical return buckets. Average returns of prototype 12-month Absolute Momentum factors are calculated in each return bucket and compared to the traditional assets[30].

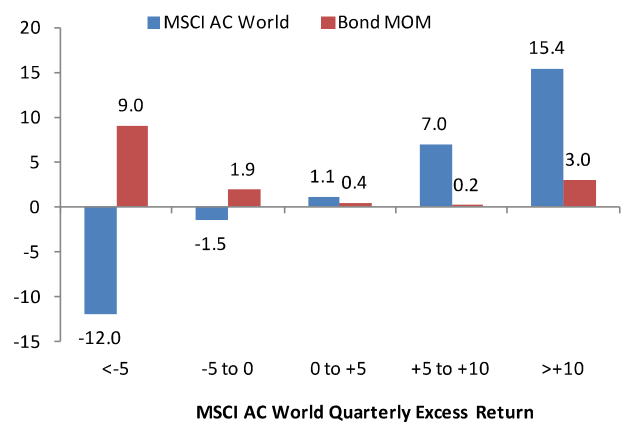
Figure 21-Figure 24 below show average quarterly returns of prototype cross asset 12-month Absolute Momentum strategies in different return buckets of the MSCI All-Country World index during 1992-2014. The prototype Equity Momentum factor almost always outperformed traditional equities during periods of low returns (<5% per quarter) and it provided positive returns on average during equity market downturns (as the Momentum strategy is shorting the market in general). On the other hand, during periods of strong equity market returns, the Momentum factor had positive performance but underperformed the equity benchmark. This convex payoff (Figure 21) is similar to the payoff of a 'long straddle' position.

Figure 21: Prototype 12M Equity Momentum Factor quarterly returns in ascending return buckets of Equities (%)



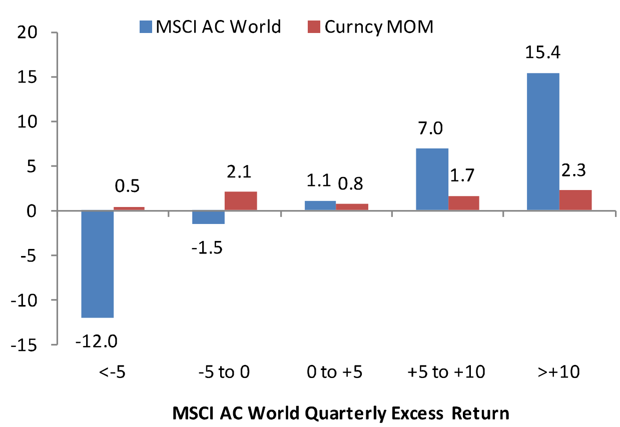
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 22: Prototype 12M Bond Momentum Factor quarterly returns in ascending return buckets of Equities (%)



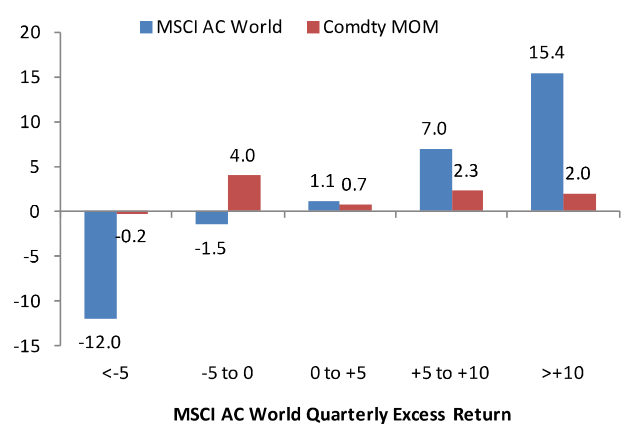
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 23: Prototype 12M Currency Momentum Factor quarterly returns in ascending return buckets of Equities (%)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 24: Prototype 12M Commodity Momentum Factor quarterly returns in ascending return buckets of Equities (%)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

30 12M Absolute Momentum factors are used to demonstrate main properties. Other prototype Momentum models show similar results.

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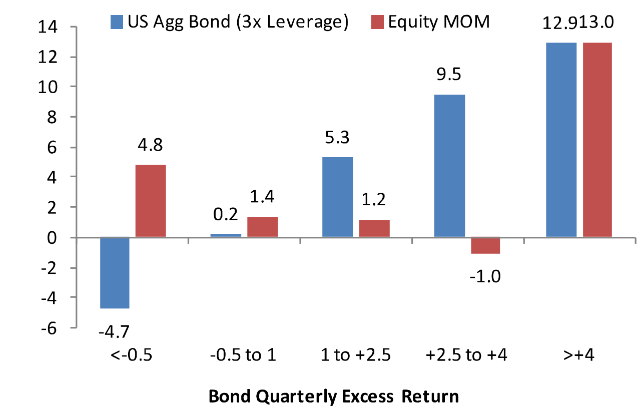
In addition, we find similar 'straddle'-like payoff patterns for prototype Bond 12-month Momentum (Figure 22), Currency and Commodity Momentum factors (Figure 23 and Figure 24). The above findings suggest **Momentum strategies across assets could provide effective diversification benefits to risky assets in general**.

We next examine prototype Momentum factors' relationship with Bonds. Figure 25-Figure 28 below show average quarterly returns of 12-month Absolute Momentum strategies in different return buckets of Barclays US Aggregate Bond index (3x leveraged for easier comparisons[31]). We note that Equity Momentum delivered similar return/risk to bonds when bonds performed well (>4% per quarter). On the other hand, during normal market periods when bonds returned less than 4%, the Equity Momentum factor was negatively correlated with bonds which suggests that Equity Momentum could provide effective diversification to a high-quality bond portfolio.

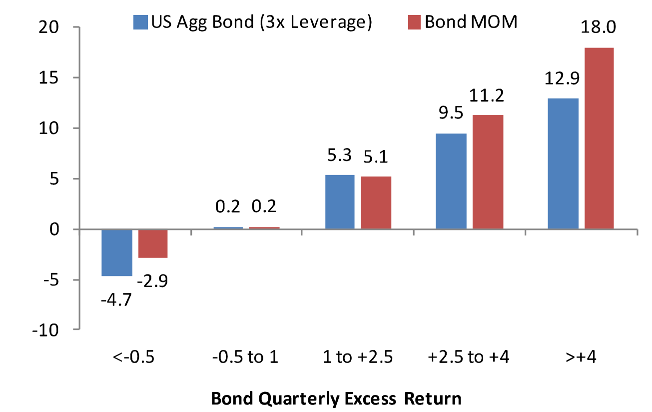
Figure 26 shows that the Bond Momentum factor delivered similar performance to bonds during bond rallies while helping to protect a certain degree of bond downside. According to our calculations, the downside return to risk ratio was -3 for bonds[32] and only -0.9 for Bond Momentum during bond downturns. Note that the backtest period 1992-2014 coincided with a structural bull market for bonds, and hence the Bond Momentum Factor had an overall long bond bias.

Figure 25: Prototype 12M Equity Momentum Factor quarterly returns in ascending return buckets of Bonds (%)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 26: Prototype 12M Bond Momentum Factor quarterly returns in ascending return buckets of Bonds (%)

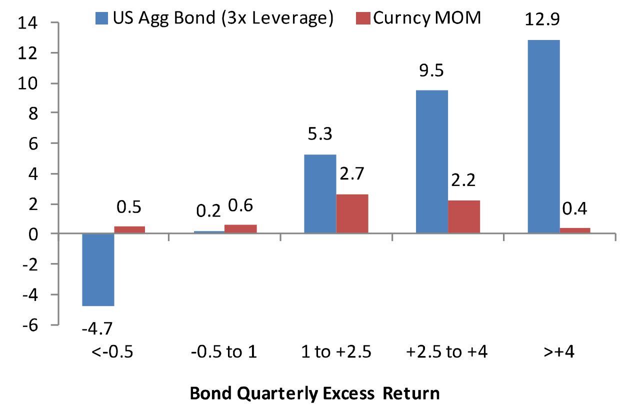


Source: J.P. Morgan Quantitative and Derivatives Strategy.

Similar to our findings in Equities, Currency and Commodity Momentum factors delivered positive returns in different return buckets of bonds (Figure 27 and Figure 28). The results are consistent with low correlations of Momentum to bonds during both normal and crisis periods.

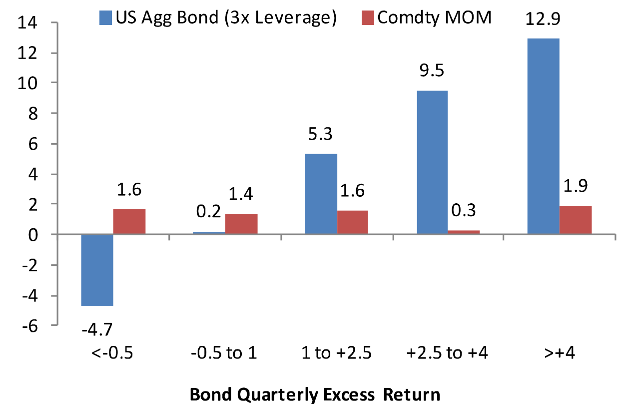
[31] Annualized Volatilty of Barclays US Aggregate Bond index was 3.6% during 1992-2014, roughly 1/3 of prototype Momentum models.
[32] 'Downside return to risk ratio' or return to risk ratio conditional on 'downside' is calculated by annualized return divided by annualized return volatility condition on periods when an asset showed negative returns.

Figure 27: Prototype 12M Currency Momentum Factor quarterly returns in ascending return buckets of Bonds (%)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

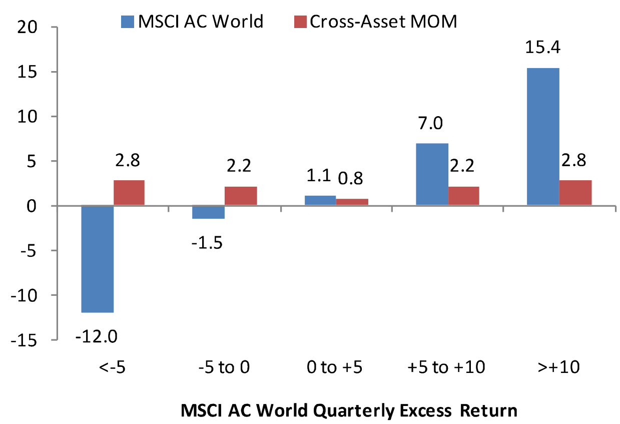
Figure 28: Prototype 12M Commodity Momentum Factor quarterly returns in ascending return buckets of Bonds (%)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

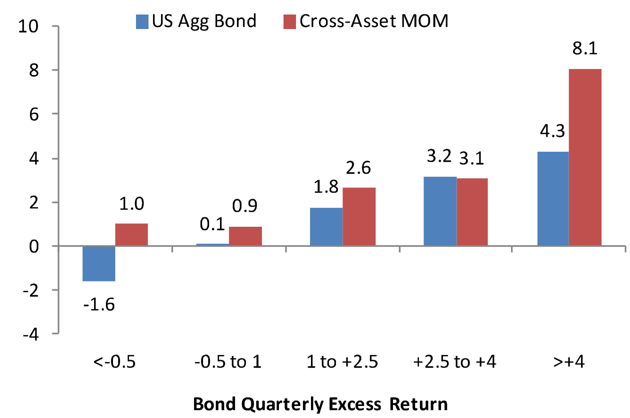
Combining momentum indices across assets, we also find that a multi-asset Momentum strategy delivered a convex payoff relative to major asset classes. Figure 29, illustrates the ‘straddle-like’ return profile of a cross-asset Momentum factor strategy relative to equities, and Figure 30 relative to bonds.[33] This ‘straddle-like' performance of cross asset Momentum strategies is consistent with the correlation structure between Momentum strategies and traditional assets shown in Table 12.

Figure 29: Convex payoff of prototype Cross Asset Momentum Factor with respect to Equities (quarter average returns in %)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 30: Convex payoff of prototype Cross Asset Momentum Factor with respect to Bonds (quarter average returns in %)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

33 The long-bond bias was due to structural bond bull market since the 1980s and we don’t expect the long-bond bias to persist in the future.

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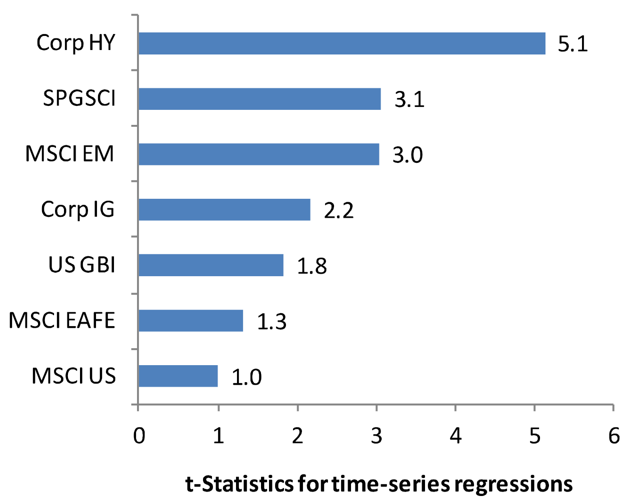
Selection of Trend Signal

Every Momentum strategy is based on a trading signal (or a set of signals) that attempts to identify the trends in asset prices. So far, we have examined simple trend signals such as 12-month or 6-month price return. The identification of a trend in a time series, also called 'Trend Filtering', is a mathematical discipline that can employ more complex methods than just observing recent time series returns.

The most basic trend indicator that we used – the past return – is based on the premise that **there are significant positive auto-correlations of asset returns,** and that past return is a predictive signal for the future return. This assumption was to some extent justified by a number of assets with statistically significant autocorrelation. For instance, Figure 31 below shows that past 1-month return was a significant forecaster of next-month returns for different asset classes.

Another simple trend indicator is the change relative to the '**Moving Average**' of an asset price. An advantage of using the moving average is that it is less sensitive to the choice of lookback window (as compared to simple price returns). A drawback of the simple arithmetic moving average is that it usually responds slowly to the development of trends. For this reason, one may use a weighted moving average to put more (or less) weight into more recent price observations. For example, Figure 32 shows a simple Trend-Following strategy on Copper futures <HG1 Comdty> based on an exponentially weighted moving average (EWMA) of the past 50-week excess return index. Specifically, a long (short) position is established when the last close price crosses above (below) the 50-week EWMA. We offer a more comprehensive overview of different choices of trend indicators and the related math in the **Appendix** on page 136 ('Mathematics of Trend Filtering Methods').

Figure 31: Previous months' returns predicts next month's returns across Asset Classes (1989-2014)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 32: A simple Trend-Following strategy on Copper futures based on Exponentially Weighted Moving Average

Source: J.P. Morgan Quantitative and Derivatives Strategy.

To assess the efficacy of various trend filters, we have tested and compared Momentum strategies derived based on various simple trend signals. The selection of signals includes indicators such as Moving Average (MA), Moving Average Convergence-Divergence (MACD) and Relative Strength Indicator (RSI). An explanation for each indicator we tested is given in the box below:

Definitions of Trend Indicators Tested

1) Ret(d_1): **Return** Trend Indicator that compares the price level now (one day before rebalance) with that d_1-days ago;

2) MA(d_1): **Moving Average** Trend Indicator that compares the price level now (one day before rebalance) with current d_1-day simple moving average;

3) X-Over(d_1, d_2): **Moving Average Cross Over** Trend Indicator that compares current d_1-day simple moving average; with current d_2-day simple moving average (where $d_2 > d_1$);

4) Up2Down(d_1): A Trend Indicator that measures the average positive daily return relative to average negative return over the past d_1-days; also known as **Gain to Pain indicator**;

5) MACD: **Moving Average Convergence-Divergence** (MACD). Let x be the difference between the 12-day Exponential Moving Average (EMA) and 26-day EMA. The commonly used MACD indicator compares x with its 9-day exponential moving average.

6) RSI: **Relative Strength Indicator** measures the velocity of a security's price movement. RSI is calculated from price returns over a certain time period as RSI = 100 - [100/(1 + [Avg Up return/Avg Down return])]

7) Ret2Vol(d_1): **Return to Volatility Ratio** Trend Indicator that divides the return of the past d_1 days by the volatility of returns;

8) InvVol(d_1): **Inverse Volatility** Indicator that divides 1 by the volatility of returns;

9) Regression: **Multi-Variate Panel Regression** based trend-filtering method introduced in the section 'Dynamically Rebalanced Signals' on page 46.

A complete set of performance backtests is shown in the Appendix 'Performance of Alternative Trend Signals' on page 150. [34] Table 13 (similar trend horizon) and Table 14 (different trend horizons) summarizes the backtests for several Absolute and Relative Momentum strategies based on different trend indicators. The last column shows its correlation with a 'default' Absolute Momentum strategy based on past 200-day or 1-year returns.

Similar to our findings in the analysis of factor correlation, Momentum strategies are positively correlated within asset classes and the correlation is most significant for strategies with similar trend signal horizons. For example, sample correlation between an equity Absolute Momentum strategy based on 200-day moving average has a +85% correlation with a similar strategy based on 200-day returns (Table 13); a bond Absolute Momentum strategy based on one-year returns has a +73% correlation with a similar strategy based on half-year returns (Table 14). Furthermore, we find that adding different trend signals could help improve risk-adjusted returns of a Momentum strategy based on a single trend indicator. We will discuss enhanced Momentum strategies with asset and trend signal diversification in the next Chapter on page 73.

Among these simple prototypes, the best performing strategy within each asset class tends to be based on simple trend indicators such as past 1-year return or 200-Day moving averages[35]. One possible explanation for this is a 'self-fulfilling' one: Since more people are familiar with the simple concept of 12-month Momentum or monitoring 200-day moving averages, these strategies would benefit more from investor familiarity. [36] On the other hand, more elaborated technical indicators such as MACD and RSI are usually used in conjunction to other trading systems such as Price Channels,

[34] We tested Absolute/Time Series Momentum (TSM) strategies for Equity, Bond, Currency and Commodity as well as Relative/Cross Sectional Momentum (CSM) strategies based on all the assets.

[35] There are a few exceptions. For instance, the 200-day Up to Down indicator worked better than past returns and moving average indicators in the bond asset class.

[36] More inflows into Momentum strategies could cause the Momentum effects to last longer and the performance of existing strategies to be stronger as long as trend signals don't reverse signs. On the other hand, more inflows into certain 'Relative Value' strategies could arbitrage away such value opportunities and make the strategy unprofitable.

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Ichimoku systems, etc. We discuss applications of Trend-Following Channels and related enhancements on prototype Momentum strategies on page 79.

Table 13: Performance of Momentum Strategies based on different Trend Indicators (based on the same signal horizon of 200 days)

Asset Class	Trend Signal	1992-2014 Return	1992-2014 Sharpe	1992-2014 MaxDD	1992-2014 Hit Rate	2011-2014 Return	2011-2014 Sharpe	2011-2014 MaxDD	2011-2014 Hit Rate	Corr/w Ret(200)
TSM - Equities	**MA(200)**	11.2	0.88	-24.7	54.1	8.9	0.67	-17.0	53.0	**84.6**
	Ret(200)	**11.8**	**0.90**	**-25.7**	**54.3**	**9.6**	**0.73**	**-17.8**	**53.8**	
	X-Over(5, 200)	11.1	0.86	-25.2	54.2	8.8	0.67	-15.4	54.5	**85.4**
	X-Over(10, 200)	10.3	0.79	-34.2	54.1	8.3	0.62	-18.6	53.7	85.6
	Up2Down(200)	6.6	0.58	-38.7	53.6	4.1	0.30	-26.5	53.6	57.6
	RSI(200)	6.6	0.75	-17.8	54.3	3.2	0.41	-10.1	54.6	83.0
TSM - Bonds	**MA(200)**	7.2	0.55	-36.3	52.3	0.4	0.04	-33.1	50.7	**83.3**
	Ret(200)	**7.7**	**0.59**	**-26.9**	**52.9**	**3.5**	**0.32**	**-21.3**	**51.7**	
	X-Over(5, 200)	7.2	0.56	-41.8	52.2	1.7	0.14	-31.9	50.0	**82.6**
	X-Over(10, 200)	7.0	0.53	-39.6	52.4	-0.9	-0.08	-34.3	49.8	84.0
	Up2Down(200)	8.6	0.67	-35.6	52.3	9.4	0.91	-15.2	53.0	**63.8**
	RSI(200)	4.8	0.54	-18.7	55.0	1.4	0.21	-8.7	53.4	**84.1**
TSM - Curncy	MA(200)	5.5	0.53	-29.2	53.2	-3.0	-0.30	-29.2	51.0	83.4
	Ret(200)	**7.0**	**0.68**	**-19.1**	**53.9**	**2.5**	**0.27**	**-11.5**	**52.4**	
	X-Over(5, 200)	5.6	0.54	-27.4	53.3	-0.6	-0.06	-27.4	51.7	83.9
	X-Over(10, 200)	6.4	0.62	-22.3	53.4	1.8	0.19	-22.3	51.5	85.5
	Up2Down(200)	1.8	0.21	-34.2	50.4	2.7	0.29	-11. 4	50.0	40.7
	RSI(200)	2.9	0.46	-18.0	52.4	-0.7	-0.15	-8.3	50.3	80.7
TSM - Comdty	**MA(200)**	5.0	0.47	-32.8	53.5	-6.7	-0.63	-32.8	50.6	**78.9**
	Ret(200)	**4.7**	**0.45**	**-33.6**	**53.5**	**-7.1**	**-0.68**	**-33.6**	**51.7**	
	X-Over(5, 200)	5.2	0.49	-25.3	53.3	-3.7	-0.35	-25.3	51.5	**79.9**
	X-Over(10, 200)	4.7	0.45	-28.4	52.9	-5.1	-0.48	-28.4	50.9	**80.7**
	Up2Down(200)	0.9	0.09	-45.8	52.2	-7.1	-0.76	-29.9	50.0	44.1
	RSI(200)	1.3	0.19	-18.2	52.8	-1.4	-0.23	-13.2	53.5	78.7
CSM - Cross Asset	**MA(200)**	7.4	0.86	-15.7	54.2	3.8	0.44	-14.4	52.6	**86.6**
	Ret(200)	**7.1**	**0.88**	**-15.7**	**54.0**	**2.6**	**0.34**	**-10.6**	**52.6**	
	X-Over(5, 200)	7.4	0.87	-15.2	54.0	5.2	0.61	-12.7	53.6	**87.1**
	X-Over(10, 200)	7.3	0.85	-14.5	54.2	5.5	0.63	-12.1	53.3	**87.2**
	Up2Down(200)	4.4	0.65	-17.6	53.2	1.6	0.26	-8.0	53.3	54.0
	RSI(200)	8.5	0.95	-14.4	54.5	2.9	0.36	-9.1	53.1	88.9
	Ret2Vol(200)	8.1	0.91	-14.1	54.7	1.9	0.24	-10.1	52.9	**89.5**
	InvVol(200)	5.1	0.65	-24.6	52.4	4.4	0.55	-13.7	52.9	**18.5**

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Table 14: Performance of Momentum Strategies based on different Trend Indicators (different signal horizons)

Asset Class	Trend Signal	1992-2014 Return	1992-2014 Sharpe	1992-2014 MaxDD	1992-2014 Hit Rate	2011-2014 Return	2011-2014 Sharpe	2011-2014 MaxDD	2011-2014 Hit Rate	Corr/w Ret(261)
TSM - Equities	**Ret(130)**	10.7	0.84	-28.0	53.6	9.1	0.69	-17.1	52.9	**75.5**
	Ret(261)	**10.9**	**0.82**	**-31.6**	**53.5**	**6.2**	**0.47**	**-24.9**	**52.1**	
	MA(200)	11.2	0.88	-24.7	54.1	8.9	0.67	-17.0	53.0	**76.9**
	X-Over(50, 200)	11.2	0.87	-28.1	53.8	7.3	0.54	-21.5	53.1	**80.4**
	Up2Down(130)	6.2	0.58	-30.2	53.3	4.9	0.42	-18.1	52.8	**44.0**
	MACD	0.0	0.00	-52.0	49.7	-2.7	-0.24	-25.4	50.3	-4.6
	RSI(14)	3.6	0.39	-28.6	52.6	1.6	0.18	-14.5	52.0	22.9
TSM - Bonds	Ret(130)	4.0	0.31	-43.9	51.9	-2.0	-0.17	-32.7	50.1	73.4
	Ret(261)	**9.8**	**0.75**	**-28.7**	**53.4**	**8.2**	**0.71**	**-16.2**	**53.8**	
	MA(200)	7.2	0.55	-36.3	52.3	0.4	0.04	-33.1	50.7	78.1
	X-Over(50, 200)	6.5	0.49	-39.8	52.3	2.1	0.17	-28.8	51.5	75.9
	Up2Down(130)	7.1	0.57	-44.6	52.2	7.9	0.75	-17.2	52.9	57.8
	MACD	-2.8	-0.22	-65.4	48.6	-12.0	-1.02	-35.9	46.7	-1.7
	RSI(14)	2.4	0.22	-44.4	51.9	-11.4	-1.16	-39.5	49.1	30.6
TSM - Curncy	**Ret(130)**	5.4	0.53	-22.5	53.1	0.3	0.03	-22.5	52.4	**73.2**
	Ret(261)	**6.0**	**0.58**	**-23.1**	**53.9**	**-1.3**	**-0.14**	**-16.9**	**53.0**	
	MA(200)	5.5	0.53	-29.2	53.2	-3.0	-0.30	-29.2	51.0	**73.4**
	X-Over(50, 200)	5.4	0.53	-19.3	52.8	0.4	0.05	-18.1	51.1	**75.9**
	Up2Down(130)	0.9	0.11	-26.4	49.8	-0.2	-0.03	-13.0	50.4	23.4
	MACD	-0.4	-0.05	-49.0	50.3	-3.9	-0.41	-22.6	49.9	-2.8
	RSI(14)	1.4	0.18	-33.8	51.3	-4.4	-0.55	-21.6	51.1	29.6
TSM - Comdty	Ret(130)	4.8	0.46	-29.1	53.2	-5.0	-0.48	-29.1	49.1	68.4
	Ret(261)	**6.8**	**0.63**	**-28.0**	**54.2**	**1.2**	**0.11**	**-23.9**	**52.4**	
	MA(200)	5.1	0.48	-32.8	53.5	-6.7	-0.63	-32.8	50.6	71.0
	X-Over(50, 200)	6.0	0.58	-29.1	53.2	-5.1	-0.51	-29.1	50.9	**69.9**
	Up2Down(130)	3.1	0.32	-30.1	52.9	-5.7	-0.62	-27.5	49.3	34.9
	MACD	1.0	0.10	-49.7	51.3	-7.7	-0.78	-29.8	50.1	10.7
	RSI(14)	1.2	0.15	-28.1	52.5	-4.5	-0.54	-21.1	51.5	38.8
CSM - Multi Asset	Ret(130)	6.6	0.78	-14.6	53.5	5.3	0.62	-10.6	52.4	78.9
	Ret(261)	**8.4**	**1.04**	**-17.4**	**54.7**	**5.9**	**0.78**	**-10.1**	**53.0**	
	MA(200)	7.4	0.86	-15.7	54.2	3.8	0.44	-14.4	52.6	80.4
	X-Over(50, 200)	6.7	0.80	-14.7	54.1	3.7	0.44	-12.8	52.4	82.9
	MACD	1.7	0.32	-18.7	51.2	2.0	0.41	-8.2	51.6	19.9
	RSI(14)	5.3	0.66	-16.8	52.6	0.2	0.03	-16.6	53.0	40.7
	Ret2Vol(130)	7.0	0.78	-15.1	53.5	5.5	0.62	-10.7	53.5	72.4
	InvVol(261)	5.2	0.65	-24.2	52.4	5.1	0.63	-12.7	53.3	**15.5**

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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For each Momentum strategy in Table 13 and Table 14, we also calculate its correlation with a 'default' strategy (based on past 200-day or 1-year return) in the last column to indicate the diversification benefit by pursuing alternative trend signals. According to mathematical box below, adding a trend signal (strategy) that has lower Sharpe ratio, but also lower correlation, can in some cases increase portfolio Sharpe ratio (by reducing the risk). The box below outlines how to calculate a correlation threshold that would justify adding a strategy into a portfolio (based on strategy Sharpe ratios).

Mathematical Box: Maximum Correlation Threshold

Assume that one is adding a strategy x (or more generally, a number of strategies $x_1, x_2, \ldots, x_N$ into an existing portfolio y with a goal of increasing Sharpe ratio (let's call the mixed portfolio the '**enhanced portfolio**'). What is the minimum average correlation between y and the x so that portfolio Sharpe ratio could be improved? Let's assume EMV weighting for the $(N+1)$ strategies (N strategies x and 1 strategy y) and strategies with a unit marginal volatility (return equals Sharpe ratio, after the weighting), then the portfolio return and variance could be written as (denote the Sharpe ratio of x_i by SR_i):

$$\text{Portfolio Return } = \mathrm{SR}_1 + \cdots + \mathrm{SR}_N + \mathrm{SR}_y$$

$$\text{Portfolio Variance } = 1 + N + 2N\bar{\rho}_{x,y} + N(N-1)\bar{\rho}_x$$

Here $\bar{\rho}_{x,y}$ is average correlation of strategies x with portfolio y, and $\bar{\rho}_x$ is the average pairwise correlation of strategies x. The enhanced portfolio could improve Sharpe ratio over the original strategy y if and only if:

$$\frac{\text{Portfolio Return}}{\text{Portfolio Volatility}} \geq \mathrm{SR}_y$$

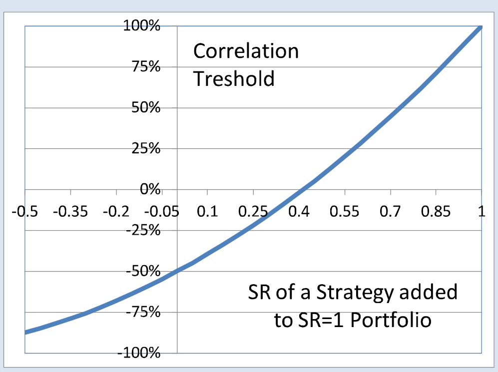
which is equivalent to:

$$\bar{\rho}_{x,y} \leq \frac{\left(\frac{\mathrm{SR}_1 + \cdots + \mathrm{SR}_N}{\mathrm{SR}_y} + 1\right)^2 - 1}{2N} - \frac{(N-1)\bar{\rho}_x}{2} - \frac{1}{2}$$

When we are adding 1 strategy ($N = 1$), this becomes

$$\bar{\rho}_{x,y} \leq \frac{1}{2}\left(\frac{\mathrm{SR}_x}{\mathrm{SR}_y} + 1\right)^2 - 1$$

which will be automatically satisfied when $\mathrm{SR}_x \geq \mathrm{SR}_y$. This suggests that when an alternative trend signal could generate a higher Sharpe ratio, adding that signal could enhance the portfolio Sharpe ratio. The Figure below illustrates the Correlation threshold as a function of SR (SR of portfolio y is equal to 1).

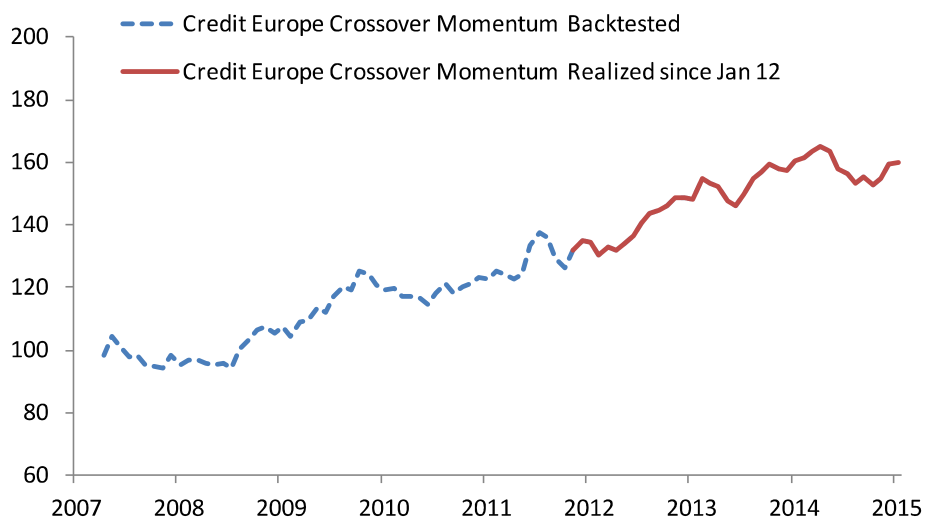


Source: J.P. Morgan

Investors may notice that the prototype models in Table 13 and Table 14 are monthly rebalanced within one day and then invested for the ensuing month. There are several potential drawbacks to this 'simplified' rebalancing scheme, including potential market impact from concentrated execution and uncertainties with regard to specific choices of rebalancing dates. Improvements could be done by introducing more frequent rebalances (i.e. weekly/daily rebalances rather than monthly rebalances) and smoothed turnover over a few trading days (rather than one-day rebalances).

For instance, the **J.P. Morgan Credit Europe Crossover Momentum Index** (**JCREMOXO** <Index> on Bloomberg) made use of moving average crossover trend signals on the Markit iTraxx Europe Crossover Index, which is rebalanced on every index business day and smoothes out daily strategy turnover to at most 25% of notional exposure. [37] While CDS indices could naturally position investors to cash in pure 'carry' opportunities in the credit space, it turns out that there is also significant Momentum premium capitalizing consistencies in default-adjusted credit spread returns. Since the Credit Europe Crossover Momentum Index was launched live in Jan 2012, it delivered out-of-sample annualized return and Sharpe ratio of +6.2% and 1.0 respectively, with moderate maximum drawdown -7.4% during Jan 2012-Mar 2015. The moving average crossover signal worked well during the Global Financial Crisis (GFC) in protecting strategy downside: the strategy delivered an annualized return and Sharpe ratio of +6.2% and 1.0 respectively during Aug 2007-Mar 2009. In comparison, the iTraxx Crossover 5Y on-the-run excess return index delivered an annualized return and Sharpe ratio of -8.8% and -0.8 respectively during the GFC.

Figure 33: J.P. Morgan Credit Europe Crossover Momentum Index



Source: J.P. Morgan Quantitative and Derivatives Strategy

Since the rebalancing schedule and turnover cost assumptions could have a significant impact on a Momentum strategy's after cost performance, we next examine our prototype Momentum models' sensitivities to alternative assumptions of rebalancing frequency, investment horizon as well as transaction costs.

[37] J. P. Morgan Credit Momentum Strategy Indices track trending behavior in the main credit default swap indices:

1) Strategy is harnessed using 5-day and 50-day moving averages on the Underlying Index ("Short Term Average" or "STA" and "Long Term Average" or "LTA" respectively)

2) On each Index Business Day:

If STA ≥ LTA: Strategy increases the long exposure (or decreases the short exposure) by 0.25x subject to a cap of 1x long

If STA < LTA: Strategy increases the short exposure in the Underlying Index by 0.25x subject to a cap of 1x short

3) Exposure is changed in steps of 0.25x

4) Strategy can start reacting quickly to a potential signal but limit the execution costs in case the signal is not persistent

Executions are assumed to be done at the closing level of the Underlying Index. For more information on the strategy design, please contact your J.P. Morgan salesperson or the Structuring Desk.

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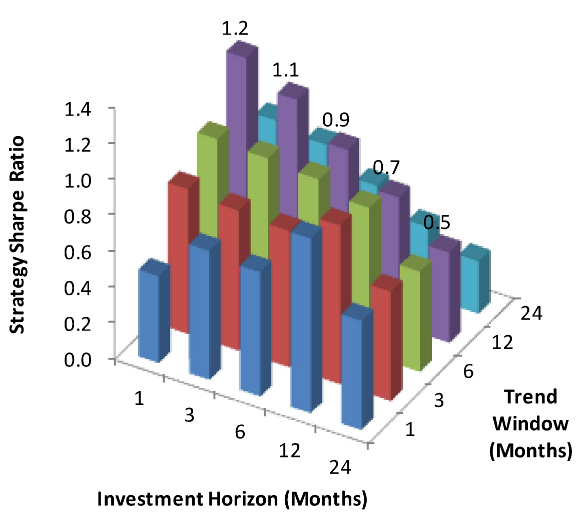
Investment Horizon, Rebalance Frequency and Transaction Costs

So far, we have focused on 'prototype' Momentum strategies based on various trend signals (e.g. past returns, moving averages) and examined different signal lookback windows (e.g. 3, 6, and 12 months). Our prototype strategies were rebalanced monthly and assets were held for one month. We have assumed a uniform 10 bps one-way turnover cost in all transactions. In this section, we examine alternative choices for rebalance methodology – rebalancing the portfolio at a different frequency (e.g. weekly, daily, quarterly) and choosing different asset holding period (e.g. holding assets longer than the rebalance frequency). We also discuss the impact of increasing the 'Transaction Cost' assumption on strategy performance.

Based on the same set of 40 assets, we ran tests of Absolute Momentum strategies of different signal lookback windows, but changed assets' holding period or investment horizon.[38] We also examined the performance of strategies with different rebalance frequency. For instance, while a monthly rebalanced strategy with 1 month investment horizon executes all long and short positions once a month (and holds them for a month), a daily rebalance strategy executes 1/21 of a position on each of the 21 business days in a month and also holds each of the positions for a month. In that regard, a higher rebalance frequency should lead to a similar level of the commission component of transaction costs and does not increase notional turnover of a strategy (unlike strategies with a short investment horizon).

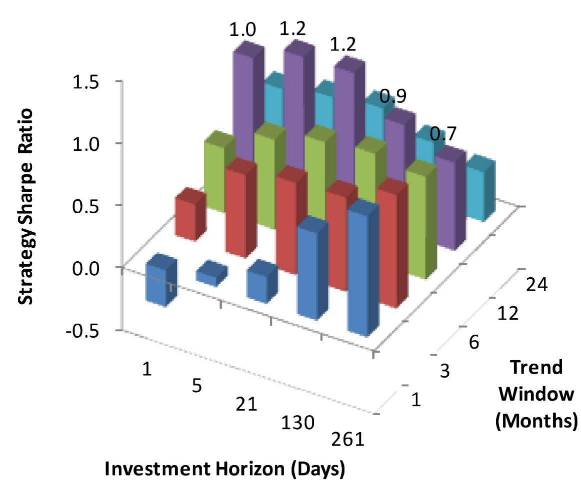
Figure 34 and Figure 35 shows the Sharpe ratios for multi-asset Absolute Momentum strategies based on different investment horizons (Figure 34 is for monthly rebalance and Figure 35 for daily rebalance). In both cases, a 'Trend Window' length of 12 months generates the best strategy Sharpe ratios. Generally, shorter investment horizons (e.g. 2 weeks to 3 months) perform better, indicating some time decay for the Momentum signal (e.g. Sharpe ratio was 1.2 for 1-month investment horizon and 0.7 for 1-year investment horizon).

Figure 34: Multi Asset TSM Strategy Sharpe ratio: monthly rebalance



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 35: Multi Asset TSM Strategy Sharpe ratio: daily rebalance



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 15 below shows compounded annual returns and Sharpe ratios of multi-asset Absolute Momentum strategies by Trend Window Size and Investment Horizon. We find that a trend-signal based on past 12-month return and 1-day to 1-month investment horizon could deliver high returns (ranging from +7.0% to +8.6% per annum) and Sharpe ratios (ranging from 1.01 to 1.21).

[38] To eliminate biases introduced from entering and exiting trades at different dates for the same investment horizon, we assumed positions were gradually built up during the course of portfolio rebalances. For example, for a monthly rebalance with a three-month investment horizon, we assume a rolling 1/3 of portfolio were rebalanced each month-end.

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Table 15: Annual Return and Sharpe ratios by Trend Window Size and Investment Horizon: Multi-Asset TSM

Trend Window (Months)	Invest Horizon (Months)					Invest Horizon (Weeks)					Invest Horizon (Days)				
	1	**3**	**6**	**12**	**24**	**1**	**4**	**13**	**26**	**52**	**1**	**5**	**21**	**130**	**261**
	Excess Return 1992-2014 (%)					Excess Return 1992-2014 (%)					Excess Return 1992-2014 (%)				
1	3.1	3.2	2.4	2.6	1.4	0.8	1.1	2.9	2.4	2.7	-2.3	0.3	1.1	2.3	2.7
3	5.6	4.7	3.7	3.7	2.2	4.6	4.9	4.7	3.7	3.8	1.9	4.5	4.9	3.7	3.8
6	6.4	5.8	5.3	4.4	2.6	4.9	5.7	5.4	5.1	4.4	3.4	4.9	5.6	5.2	4.4
12	8.6	7.3	5.8	4.3	2.7	8.3	8.1	7.0	5.7	4.2	7.0	8.0	8.1	5.7	4.2
24	4.9	4.6	3.5	2.5	1.7	4.1	4.4	4.2	3.3	2.5	3.6	4.0	4.4	3.4	2.5
	Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 1992-2014 (%)				
1	0.48	0.72	0.69	0.97	0.61	0.15	0.21	0.66	0.71	0.97	-0.29	0.08	0.22	0.70	0.97
3	0.81	0.78	0.76	0.88	0.61	0.66	0.74	0.79	0.75	0.91	0.30	0.67	0.74	0.75	0.91
6	0.92	0.91	0.89	0.82	0.56	0.72	0.84	0.84	0.87	0.83	0.52	0.72	0.83	0.88	0.82
12	**1.21**	**1.07**	0.89	0.72	0.50	**1.19**	**1.16**	**1.03**	0.87	0.70	**1.01**	**1.15**	**1.16**	0.87	0.71
24	0.70	0.66	0.53	0.39	0.29	0.60	0.64	0.61	0.49	0.39	0.53	0.60	0.64	0.50	0.40

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Detailed summaries of returns, Sharpe ratios, maximum drawdowns and other performance statistics are summarized in the Appendix 'Rebalancing and Investment Horizons' on page 140.

We also tested strategy performance for the impact of different choices of rebalance dates. For example, in monthly rebalanced strategies, we tested the performance when the strategy is rebalanced on the 1st to the 20th working day of the month instead of month-ends, and find that strategies have meaningful sensitivity to the specific choice of date. For example, Sharpe ratios range from 1.08 (16th working day rebalances) to 1.26 (19th working day rebalances) for a multi-asset Time Series strategy based on past 12-month returns. In comparison, month-end rebalance yields a Sharpe ratio of 1.21.

For weekly rebalance strategies, we tested non-standard rebalance dates (other than Fridays) as well. We found a similar level of performance divergence. With a turnover cost assumption of 10bps and assuming a four-week investment horizon, Friday rebalances produced a slightly worse Sharpe ratio (1.155) than similar strategies that rebalance on each Wednesday (1.170) or Thursday (1.169) during 1992-2014, as one or two-day ahead rebalance could take advantage of the price impact of the more widely pursued Friday rebalances.

We next analyzed the impact of alternative transaction cost assumptions. Portfolio turnover incurs transaction costs, which eat away strategy performance. With longer signal lookback windows (e.g. 12-month Momentum) and monthly investment horizons, transaction cost is generally not a concern for Momentum strategies in major global markets and during normal market environments. Shorter investment horizons and signal lookback windows will increase transaction costs.

Table 16 below shows various assumptions on one-way transaction cost and their impacts on the performance of daily-rebalanced prototype Time Series Momentum strategies with 12-, 3- and 1-Month trend signal window sizes. Consistent with our expectations, strategies with more stable trend signals and longer investment horizons are less sensitive to the transaction cost assumptions.

For instance, doubling our 10bps base case assumption of transaction cost for an Absolute Momentum (TSM) strategy based on 12-month return and 1-month investment horizon only decreases annual return by 0.4% per annum (from +8.1% to +7.7%). On the other hand, strategies with more volatile trend signals and shorter investment horizons are more susceptible to the performance drags from trading costs. For example, TSM based on 1-month return and 1-day investment horizon would have a significant Sharpe ratio of 0.71 without transaction costs. However, Sharpe ratio quickly eroded to -0.29 with a 10bps cost.

Table 16: Impact of Transaction Cost on Cross Asset Absolute Momentum Strategies: 1992-2014

Invest Horizon	One-Way Cost (bps)	Trend Signal: 12M Return			Trend Signal: 3M Return			Trend Signal: 1M Return		
		Return	Sharpe	Max DD	Return	Sharpe	Max DD	Return	Sharpe	Max DD
One Month	No Cost	8.6	1.22	-12.8	5.8	0.88	-14.5	2.9	0.52	-13.5
	5	8.4	1.19	-12.9	5.3	0.81	-16.5	2.0	0.37	-18.4
	10	**8.1**	**1.16**	**-13.0**	**4.8**	**0.74**	**-18.5**	**1.1**	**0.22**	**-23.5**
	20	7.7	1.10	-13.2	3.9	0.60	-22.4	-0.7	-0.09	-38.0
	50	6.3	0.91	-13.8	1.0	0.18	-32.8	-5.9	-1.01	-76.2
One Week	No Cost	8.9	1.27	-12.6	6.4	0.94	-13.7	3.7	0.57	-22.4
	5	8.5	1.21	-12.6	5.4	0.81	-18.6	2.0	0.33	-31.1
	10	**8.0**	**1.15**	**-12.7**	**4.4**	**0.67**	**-23.1**	**0.3**	**0.08**	**-38.8**
	20	7.2	1.03	-12.7	2.5	0.39	-31.5	-3.0	-0.42	-57.9
	50	4.6	0.68	-14.8	-3.2	-0.43	-59.6	-12.1	-1.89	-94.6
One Day	No Cost	8.9	1.26	-13.1	6.1	0.90	-14.8	4.8	0.71	-17.6
	5	7.9	1.14	-13.2	4.0	0.60	-24.7	1.2	0.21	-35.3
	10	**7.0**	**1.01**	**-13.3**	**1.9**	**0.30**	**-33.5**	**-2.3**	**-0.29**	**-51.3**
	20	5.1	0.76	-14.8	-2.4	-0.30	-52.5	-8.9	-1.28	-87.6
	50	-0.2	0.00	-36.2	-14.8	-2.00	-96.6	-26.2	-4.01	-99.9

Source: J.P. Morgan Quantitative and Derivatives Strategy.

In our approach to transaction costs we used bid-offer spread as a proxy for the full transaction cost. This neglects the market impact component that can be significant for less liquid assets or during time periods of low liquidity. In this approach, transaction costs are the same for strategies with the same signal and investment horizon, regardless of rebalancing frequency. For example, average turnover and transaction costs should stay the same, regardless of whether we rebalance 100% of notional in one day (e.g. end of month), 25% of notional each week over four weeks, or 1/21 of notional each day over 21 days. Table 17 below shows performance/risk statistics of multi-asset Absolute Momentum strategies based on past 12-month return, 1-month investment horizon and different assumptions of transaction costs.

Table 17: Transaction Costs impact investment horizon similarly regardless of rebalancing frequency (based on 12-month return signal)

Rebalance Freq	Invest Horizon	One-Way Cost (bps)	Ann. Return	Ann. Volatility	Max Drawdown	MaxDDur (in years)	Sharpe Ratio	Hit Rate	Return Skewness	Return Kurtosis
Monthly	*One Month*	No Cost	9.0	7.0	-12.4	2.1	1.27	55.8	-0.3	2.1
		5	8.8	7.0	-12.5	2.1	1.24	55.8	-0.3	2.1
		10	**8.6**	**7.0**	**-12.6**	**2.1**	**1.21**	**55.6**	**-0.3**	**2.1**
		20	8.1	7.0	-12.9	2.1	1.16	55.4	-0.3	2.1
		50	6.8	7.0	-13.6	2.7	0.98	54.9	-0.3	2.0
Weekly	*One Month*	No Cost	8.6	7.0	-12.7	2.0	1.22	55.8	-0.3	2.6
		5	8.4	7.0	-12.8	2.0	1.19	55.6	-0.3	2.6
		10	**8.1**	**7.0**	**-12.9**	**2.1**	**1.16**	**55.5**	**-0.3**	**2.6**
		20	7.7	7.0	-13.2	2.1	1.09	55.3	-0.3	2.6
		50	6.3	7.0	-13.8	2.8	0.91	54.5	-0.3	2.6
Daily	*One Month*	No Cost	8.6	7.0	-12.8	2.0	1.22	55.5	-0.4	2.6
		5	8.4	7.0	-12.9	2.0	1.19	55.4	-0.4	2.6
		10	**8.1**	**7.0**	**-13.0**	**2.0**	**1.16**	**55.3**	**-0.4**	**2.6**
		20	7.7	7.0	-13.2	2.2	1.10	55.1	-0.4	2.6
		50	6.3	7.0	-13.8	2.8	0.91	54.5	-0.4	2.6

Source: J.P. Morgan Quantitative and Derivatives Strategy.

The table above shows similar return/risk profiles under the same transaction cost assumption for strategies with different rebalancing frequency.

In practice, transaction costs should be lower for strategies with higher rebalance frequency due to lower market impact.[39] This may become particularly important during periods of poor liquidity when many investors may look to exit a certain strategy. Examples of these extreme liquidity events are the equity flash crash in May 2010, or more recently the one in fixed income in October 2014.

In addition, strategies with higher rebalance frequency should have more reliable performance estimations. In our test, we demonstrated that Sharpe ratio ranges from 1.08 (16th working day rebalances) to 1.26 (19th working day rebalances) for a multi-asset Absolute Momentum strategy based on past 12-month returns during 1992-2014. This ~20% performance dispersion from the random selection of a rebalance date increases the uncertainty of ex-post Sharpe ratios. [40] On the other hand, daily rebalanced strategies smoothed out notional exposure changes and are less sensitive to the specific choice of rebalance date; thus, their Sharpe ratio estimates are more reliable. For this reason, **we prefer a higher rebalance frequency for a Momentum strategy with the same trend signal and same investment horizon** (i.e. weekly/daily rebalances rather than monthly/quarterly rebalances).

More tests of transaction cost assumptions are summarized in the Appendix 'Transaction Cost Analysis' on page 146. For instance, we showed that most Absolute Momentum strategies based on past 1-day returns are not viable after incorporating reasonable transaction cost assumptions. For instance, a multi-asset TSM strategy based on past 1-day return with a 1-month investment horizon would deliver a Sharpe ratio of 0.49 with no transaction cost, while the Sharpe ratio rapidly deteriorate to -0.11 when a 5bps one-way cost is incorporated into the strategy.

In the next section on 'CTA Exposure to Prototype Momentum Factors', we attribute the performance of funds to various prototype Momentum Factors. We see that the more successful (larger) CTA funds are typically exposed to Trend Factors with longer lookback windows (6-12 Months). Besides aiming for more stable and consistent signals, this has reduced transaction costs and contributed to better fund performance.

[39] This is particularly important for a portfolio containing less liquid contracts. For instance, trading 100% of USD 1bn notional on some less liquid commodity contracts could have a huge market impact, rendering the Momentum strategy unprofitable. Table 16 and Table 17 make assumptions on the 'total cost' of turnover and didn't break down the cost into bid-ask, slippage, market impact, etc. One would reasonably assume higher average cost for strategies with less frequent rebalances due to higher market impact.
[40] There is some evidence of windfall gains of close-to-month-end rebalanced Momentum strategies related to CTA investor subscriptions of similar strategies. See the Appendix 'An Introduction to CTA' on page 127 for more details on CTA strategy seasonality.

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Dynamically Rebalanced Signals

In addition to selecting one or a combination of different momentum signals, a strategy can dynamically adjust the momentum signal selection based on recently observed price trends. Such a dynamic approach should have advantages over a fixed signal selection as assets' trending properties may change over time. For instance, an asset that previously experienced short term momentum may start exhibiting short term reversion due to a poor liquidity environment.

To design such a dynamically rebalanced signal, one would first need to decompose asset returns as being driven by various trend signals and examine which trend signal is most responsible for recent returns (e.g. is it a short term momentum, long term momentum, RSI, etc.). This can be done by solving the historical regressions of asset returns vs. various momentum signals which we denoted as $\widetilde{TS}$ in the formula below (one can use a 'panel regression' while possibly accounting for the time decay of information). [41]

$$R_{j,t} = \beta_{0,t} + \sum_i \beta_{i,t} \widetilde{TS}_{j,t-1}(LW_i) + \epsilon_{j,t} \quad \text{for all } j$$

where

$$\begin{aligned} R_{j,t} &= \text{Return of the } j\text{th asset,} \\ \widetilde{TS}_{j,t-1}(LW_i) &= \text{Trend signal } i \text{ with lookback window } LW_i, \\ \beta_{i,t} &= \text{Coefficents (or betas)for each of the trend signals } i. \end{aligned}$$

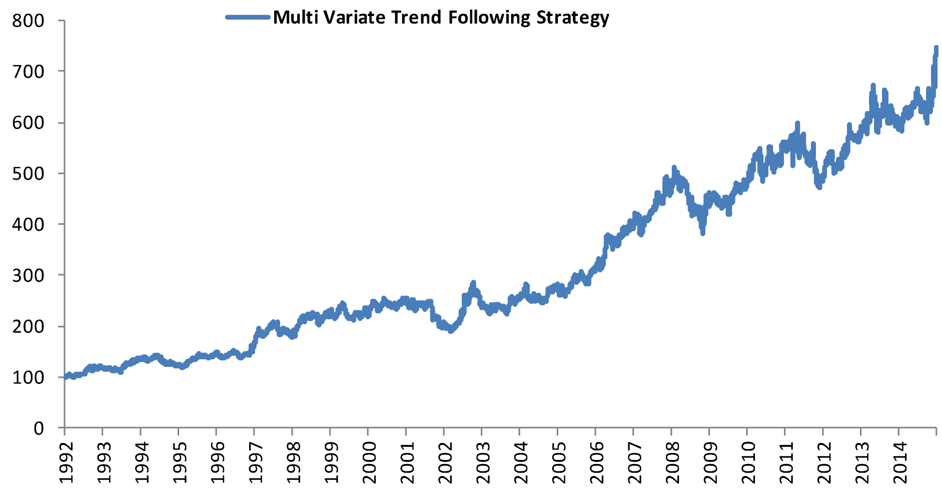
To illustrate this approach, we applied the dynamically rebalanced signal on the same universe of assets used in our prototype models and 3 different Momentum signals: ratio of 5-day, 21-day and 63-day moving averages to price levels a month ago. Specifically, at each month-end rebalancing date, we run regressions of past month asset returns versus the trend signals. [42] The regression is run repeatedly over the past three months to reduce estimation error. Then, trend signal coefficients $\beta_{i,t}$ are estimated as equal average of the regression betas over the past three month cross sectional regressions.

Finally, based on our estimation of trend signal betas and the current reading of 5-day, 21-day and 63-day moving average to price levels, we forecast the asset returns over the next month. Ranking the forecasted returns from high to low, the top 10 assets are selected in the long portfolio and bottom 10 assets are selected in the short portfolio. Assets in the long/short portfolio are rebalanced to target a 2% marginal volatility, and we assume a 10bps one-way turnover cost for the strategy.

Figure 36 below shows the cumulative performance of this dynamically rebalanced signal strategy that can capture short and medium term price trends. Over our backtest period from 1992 to 2014, the strategy delivered an annual return of 9.1% and Sharpe ratio of 0.70 respectively. Moreover, the strategy exhibited low correlation to our prototype Momentum strategies introduced in the previous section.

[41] The system of linear regressions could be regarded as a first order parametric approximation (penal data regression) of the generic 'predictive' relationship between past trends and future returns.
[42] We used the same set of currencies and cross asset futures as the underlying assets in this example. The return/trend signal information is based on price data one business day before each month-end rebalance date.

Figure 36: Cumulative performance of a dynamically rebalanced trend following signal (1992-2014)



Source: J.P. Morgan Quantitative and Derivatives Strategy

A similar model was proposed by Han, Zhou and Zhu (2015)[43], who solved the system of linear equations with 'averaged' historical betas by running a series of linear regressions on trend signals generated from a universe of U.S. listed stocks. They found that the resulting 'trend factor' on US stocks generated an average return of +1.63% per month from June 1930 to Dec 2013.

[43] Han, Yufeng and Zhou, Guofu and Zhu, Yingzi (2015), A Trend Factor: Any Economic Gains from Using Information over Investment Horizons? Available at SSRN: http://ssrn.com/abstract=2182667

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CTA Exposure to Prototype Momentum Factors

Having defined prototype Momentum Factors in each of the asset classes, we can attribute the performance of the CTA industry to these simple benchmarks. Specifically, we use 12, 6, 3, and 1 month Absolute Momentum indices in Equities, Bonds, Currencies and Commodities to evaluate the performance of broad CTA benchmarks such as BTOP50 or DJCS, as well as performance of several individual Managed Futures funds. Table 18 below shows the annualized Alpha, Beta (*t*-Statistics are reported below ex-post Alpha and Betas) and Adjusted R-squared for popular CTA benchmark indices[44] to eight selected Trend Factors[45] during the period from Jan 1992 to Dec 2014.

Table 18: Performance Attribution of CTA Benchmarks to Prototype Momentum Factors: 1994-2014

	After Fee CTA Benchmarks				Before Fee CTA Benchmarks			
	Barclay	**BTOP 50**	**DJCS**	**CISDM**	**Barclay**	**BTOP 50**	**DJCS**	**CISDM**
Ann. Alpha (%)	-1.66	-1.42	-3.35	0.07	1.46	1.95	-0.05	3.63
	(-1.37)	(-1.05)	(-1.76)	(0.05)	(1.21)	(1.44)	(-0.03)	(2.66)
Bond - 12 Month	0.05	0.09	0.16	0.07	0.05	0.09	0.16	0.07
	(1.61)	(2.58)	(3.21)	(2.09)	(1.59)	(2.56)	(3.21)	(2.10)
Curncy - 12 Month	0.10	0.12	0.19	0.14	0.10	0.12	0.19	0.14
	(2.90)	(2.90)	(3.30)	(3.49)	(2.94)	(2.96)	(3.34)	(3.51)
Equity - 6 Month	0.10	0.14	0.21	0.12	0.10	0.14	0.21	0.12
	(3.28)	(4.32)	(4.50)	(3.64)	(3.25)	(4.27)	(4.56)	(3.62)
Comdty - 6 Month	0.07	0.07	0.11	0.07	0.07	0.07	0.11	0.07
	(1.43)	(1.40)	(1.56)	(1.35)	(1.49)	(1.43)	(1.55)	(1.39)
Bond - 3 Month	0.18	0.22	0.23	0.20	0.18	0.22	0.23	0.20
	(5.74)	(6.12)	(4.58)	(5.49)	(5.75)	(6.11)	(4.62)	(5.50)
Comdty - 3 Month	0.07	0.06	0.11	0.12	0.07	0.06	0.11	0.12
	(1.55)	(1.19)	(1.53)	(2.20)	(1.56)	(1.21)	(1.54)	(2.23)
Equity - 1 Month	0.05	0.03	0.08	0.05	0.05	0.04	0.08	0.06
	(1.46)	(0.93)	(1.47)	(1.38)	(1.58)	(1.04)	(1.49)	(1.51)
Curncy - 1 Month	0.11	0.14	0.14	0.12	0.11	0.14	0.14	0.12
	(2.75)	(3.16)	(2.25)	(2.78)	(2.73)	(3.17)	(2.28)	(2.78)
Adjusted R^2 (%)	**43.33**	**48.35**	**46.59**	**46.79**	**43.66**	**48.53**	**46.99**	**47.22**
Loading By Assets (%)	After Fee CTA Benchmarks				Before Fee CTA Benchmarks			
	Barclay	**BTOP 50**	**DJCS**	**CISDM**	**Barclay**	**BTOP 50**	**DJCS**	**CISDM**
Equity	19.9	20.2	23.3	19.3	20.2	20.3	23.4	19.5
Bond	32.1	35.3	31.8	30.4	31.7	35.0	31.7	30.1
Currency	28.8	28.9	26.3	29.3	28.6	29.0	26.4	29.1
Commodity	19.2	15.6	18.6	21.1	19.5	15.7	18.5	21.3
Loading By Signal Horizons (%)								
12 Month	21.2	23.7	28.2	24.0	21.1	23.6	28.1	23.9
6 Month	22.4	24.7	26.4	21.5	22.5	24.4	26.4	21.4
3 Month	35.2	32.1	28.0	35.1	34.9	32.0	28.0	35.0
1 Month	21.2	19.5	17.4	19.3	21.5	20.0	17.5	19.6

Source: J.P. Morgan Quantitative and Derivatives Strategy.

[44] We approximate 'Before Fee' returns from a top-down approach. Specifically, we assume a 2% management fee and 20% performance fee (based on previous year's NAV change floored at 0% without applying High Water Mark), which are equally distributed each month.
[45] The eight trend factors are selected via running a forward 'Step-Wise' regression. Other model selection methods yield similar results. We assume an additional 15bps slippage cost per month for prototype Momentum indices to be more conservative on actual trading costs.

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One can make several observations from Table 18 above.

1) All regressions show statistically significant goodness of fit with an adjusted R-squared in the range of 45-50% (equivalent to an adjusted correlation of 67%-70% between the regression fitted and original CTA returns). All of the individual factor loadings are positive and most of them have significant *t*-statistics. This suggests that **our simple prototype Momentum Factors are indeed significant drivers of CTA industry returns**.

2) By looking at the aggregate weights in each asset class and signal time horizon, we find that **CTA benchmark indices are fairly diversified across different assets** (with a slight tilt towards Bond Momentum) **and across different signal time horizons** (with a slight tilt towards 3-Month horizon).

3) After-fee residuals (or 'Alphas') of broad CTA benchmarks are negative (except CISDM which had the best performance among the four CTA benchmarks) after controlling for the eight selected 'Trend Factors'. **Even on a before-fee basis, we find the CTA industry residuals were not significant after controlling for a set of in-sample best-fit Trend Factors (average before-fee alpha was +1.8% per annum)**.

We would like to comment on these findings. First, it is not surprising that the majority of CTA benchmark performance can be explained by prototype Momentum Factors. The negative residual of (after-fee) broad CTA benchmarks is also not surprising.[46] A broad benchmark of funds is bound to have a number of strong performing hedge funds but also a number of underperforming funds. Averaging performance of 'good' and 'bad' performers in a large sample, and applying uniform level of fees is likely to result in a benchmark that can be explained by set of Momentum Risk Factor indices and a negative residual.

Of course there are CTA funds that have ability to time various Risk Factors and deliver significantly positive alpha. Performance of those (high-percentile performing) funds can not be captured by prototype Momentum indices, as there is a positive alpha component that can not be replicated.

We have performed a similar performance attribution of CTA benchmarks to Fung and Hsieh's look-back straddle based cross-asset trend factors[47] in the **Appendix** 'CTA Exposure to Fung and Hsieh Factors' (page 139). Although significant, the overall explanatory power of Fung and Hsieh's factors was noticeably smaller, with an Adjusted R-squared ranging from 16% to 30%. In addition, CTA 'Alphas' become significant both before-fee and after-fee after controlling for Fung and Hsieh's factors, which suggests our Prototype Momentum Risk Factors can better capture CTA industry returns.[48] Additionally, our prototype Momentum Factors are (unlike lookback straddles) more easily tradable (e.g. via JPM investable indices[49]).

Furthermore, significant cross-asset and cross-trend signal horizon loadings suggest that **diversification** across a range of Momentum strategies and asset classes is indeed a big part of what CTAs do – the poor performance of CTAs from 2011-2013 was partly related to the high levels of cross asset correlations (see **'**Risks of Momentum Strategies' on page 12).

Based on the methodology in Table 18, one can approximately break down the CTA returns (before-fees) during the period 1994-2014. Specifically, there are two ways to break down CTA returns which we illustrate in Figure 37. From a return destination perspective, the gross total returns (after trading costs) earned by CTA funds are distributed as fees (including management fees and performance fees) to fund managers and net returns (including cash returns and net excess returns, before tax) to investors. Alternatively, the gross total return of CTA funds is equal to gross excess returns plus cash returns. From a return source perspective, gross excess returns of CTA funds comes from two sources: the **Manager-Specific Factor** (Alpha/Idiosyncratic Risk, before fees) is attributable to the CTA manager's selection and timing abilities of global market trends; the **Systematic Momentum Factor** results from exposures to systematic tradable Momentum factors in

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[46] The before-fee average performance of CTA funds (average of BarclayHedge, BTop50, DJCS and CISDM) delivered a positive Alpha of roughly 1.8% per annum with a t-statistic of 1.3.

[47] See, Fung, W. and D. A. Hsieh (2001), "The risk in hedge fund strategies: Theory and evidence from trend followers", Review of Financial Studies 14(2), 313-341.

[48] Specifically, a diversified multi-asset Trend Factor portfolio could be more relevant in analyzing CTA performances. In addition, we discussed the convex (or straddle/strangle like) payoff structure of multi-asset Trend Factors with respect to traditional assets in the section 'Correlation of Momentum Strategies' on page 35.

[49] See the Appendix on page 121 for a list of J.P. Morgan investable Momentum indices created by our global structuring desks.

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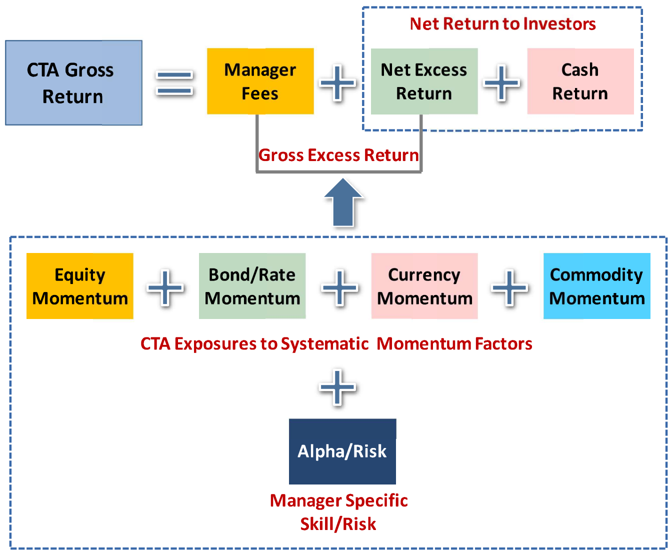
various asset classes. The Cash component of returns is basically the yield on collateral/unutilized cash, and has suffered over the past few years given the bond yield compression.

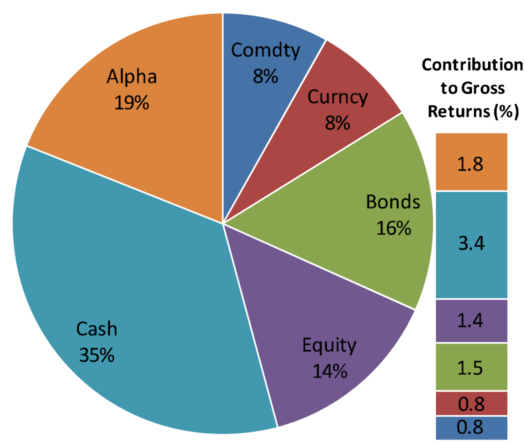
Figure 38 breaks down the return contribution according to 'Trend Factor' asset class exposures during the period 1994-2014. By asset class exposure, Equity (+1.4%) and Bonds (+1.5%) together contributed roughly 30% of total returns; Currency (+0.8%) and Commodity (+0.8%) each contributed 8%. The remaining +1.8% before-fee Alpha or 19% of the total return was statistically insignificant for broad CTA benchmarks. We also find that out of the +9.7% average total return of CTA benchmarks during 1994-2014, +6.2% (or 65% of total return) was before-fee excess return due to Momentum risk premia and Alpha (3.4% or about half of it was paid in fees). ~3.4% (or 35% of total return) was due to earning interest on position collateral and cash (e.g. treasuries).

Figure 37: Sources and destinations of CTA returns



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 38: CTA before-fee performance breakdown by asset class



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Besides analyzing the overall CTA industry, we also looked at five of the largest CTA funds with inception dates before 2000[50]. A similar study[51] of factor exposure (by asset and by signal horizon) is summarized in Table 19 below (we denote them as Fund 1-5). Similar to our study of the CTA fund industry, all regressions showed statistically significant explanatory powers for our 'Trend Factors' and high 'Adjusted R-squared'. The average Alpha for these relatively successful CTA funds was positive (+0.7% after fees and +4.2% before fees per annum) but not statistically significant for all funds[52]. Comparing the results with Table 18, we find these larger fund under our analysis delivered roughly 2.4% higher Alpha than the average CTA funds (-1.6% after fee and +1.8% before fee per annum).

[50] The analysis of fund performance is purely for the purpose of an objective academic study and we would prefer not to mention the fund names or selection methodologies to avoid conflicts of interest.
[51] We applied individual funds' stated management/performance fee structures to come up with before-fee NAVs (performance fee was applied after High-Water-Mark). Similar to our study of CTA benchmarks, for each fund, we included eight 'Trend Factors' by a Stepwise-Regression procedure. Factor loadings were then aggregated according to 'asset classes' or 'signal trend horizons'. We assumed an additional 15bps slippage cost per month for prototype Momentum indices to be conservative on actual trading costs.
[52] This finding is consistent with the claims that the larger and more successful CTA funds could deliver more Alpha to investors than the average CTA industry. In addition, while the larger funds performed better in absolute returns, we find their performances were partly due to systematic exposures to more successful asset-specific strategies (Equity/Bonds) and longer trend horizons (6-12 months).

Table 19: Performance attribution of individual CTA Funds to Cross Asset Trend Factors: 2000-2014

		Ann. Alpha		Adjusted	Factor Exposure By Asset (%)				Factor Exposure By Horizon (%)			
		(%)	*t*-Stat	R2 (%)	Equity	Bond	Curncy	Comdty	12M	6M	3M	1M
After Fee	**Fund 1**	3.46	(1.02)	41.8	14.0	37.5	8.8	39.7	38.6	41.9	3.4	16.1
	Fund 2	-0.71	(-0.25)	60.7	23.8	32.4	17.0	26.8	21.2	59.2	11.4	8.2
	Fund 3	0.36	(0.12)	55.6	28.4	29.6	24.3	17.6	36.3	27.1	15.6	21.0
	Fund 4	-1.20	(-0.42)	51.4	31.0	31.6	19.9	17.5	33.3	28.3	17.8	20.5
	Fund 5	1.31	(0.42)	24.4	-0.7	41.8	26.1	32.8	69.4	10.6	16.0	3.9
Before Fee	**Fund 1**	6.24	(1.84)	42.1	14.0	37.3	8.7	40.0	38.1	42.5	3.3	16.0
	Fund 2	1.80	(0.64)	61.8	21.8	29.6	21.6	27.0	32.3	46.8	10.0	10.8
	Fund 3	5.28	(1.73)	56.0	28.7	29.5	24.1	17.7	36.1	27.1	15.6	21.2
	Fund 4	3.17	(1.12)	51.8	25.5	31.5	22.9	20.2	35.9	22.2	26.2	15.7
	Fund 5	4.52	(1.43)	24.6	-0.4	40.9	26.3	33.3	62.0	18.3	14.9	4.8

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Compared with the broad CTA industry benchmarks, these five funds were more exposed to the relatively better performing Equity and Bond Trend Factors as well as the better performing 12-month and 6-month Trend Factor signals. These asset and signal 'tilts' of the larger CTA funds were similar to 'Value/Size tilts' practiced by many traditional Equity managers aiming to enhance risk-adjusted returns[53].

[53] The ability to tilt a multi-asset Trend-Following strategy is largely attributed to the 'skills' of quantitative CTA managers until one can identify systematic strategies to uncover these skills (essentially transforming Alpha into Systematic Betas).

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Chapter 3

Risk Management and Portfolio Construction

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Introduction

In the previous chapter we analyzed risk and returns of prototype Momentum Factors. There are a number of risks related to investing in individual Momentum Factors. For instance, we found that Momentum Factors have negative skewness and positive kurtosis and can suffer a sharp drawdown during market turning points.

In addition to tail risk, there are other risks related to Momentum investing. For instance, Momentum can underperform during prolonged periods of range-bound price action and signals used to identify Momentum can also become ineffective.

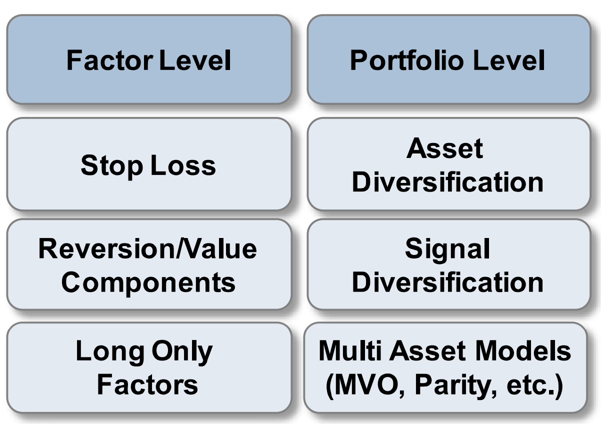
Investors can address these risks both at the individual Momentum factor level and at the portfolio level by combining various Momentum Factors. The figure below illustrates some of these risk-reduction methods that will be addressed in this chapter.

On a single factor/asset level, one can address the tail risk by introducing a ‘stop loss’ overlay. The rationale behind a stop loss overlay is to prevent large losses during market turning points at the expense of a performance drag during false signals. Adding a component of mean reversion or certain metric of Value style – when designing a Momentum Factor - can often achieve a similar effect of mitigating turning point risk. As we found that the short leg of a Momentum Factor is vulnerable to market turning points, one can simply design a 'long only' Momentum model.

On a portfolio level, investors should take advantage of cross-asset diversification. We have already shown that multi asset Momentum models outperformed single-asset Momentum Factors. In this section we will further investigate how to combine single-asset Momentum Factors into an effective multi-asset portfolio. For instance, one needs to select a certain methodology such as Markowitz MVO or Risk parity, and scale factors by asset volatility in a multi factor model. Diversification across asset classes cannot completely eliminate tail risk, but it can substantially dilute it as turning points do not occur in all markets simultaneously.

Momentum models should also look to diversify exposure (reduce leverage) to specific momentum signals. Effectiveness of signals over time may change, and certain signals may fail completely. Designing a model that relies on a combination of Momentum signals (e.g. a weighted average of medium and long term Momentum) may result in a more robust model, with less ‘signal-risk’. The set of risk methods we outline in Figure 39 can serve as a starting point in building a risk managed Trend-Following strategy.

Figure 39: Possible Methods to Manage Risks of a Momentum Strategy



Source: J.P. Morgan Quantitative and Derivatives Strategy

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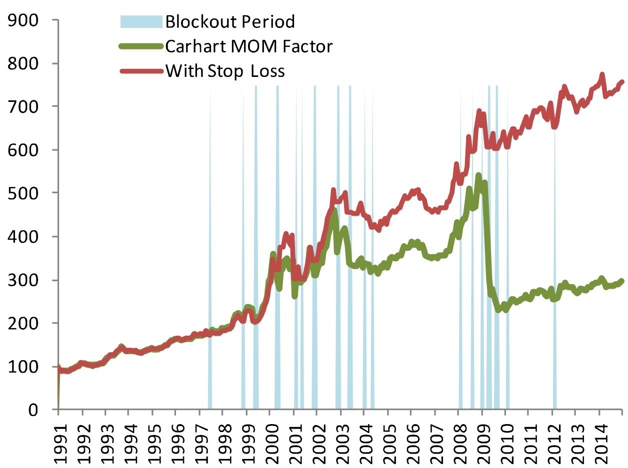
Stop-Loss and Volatility Signals

As introduced in Chapter 3 of our primer to Cross Asset Systematic Strategies, time-series portfolio risk management methods such as volatility-targeting, Constant Proportional Portfolio Insurance (CPPI), and others are frequently employed to reduce strategy risk.

Stop-loss is one of the most utilized risk management techniques amongst CTA managers[54]. The stop-loss approach can be used both on the level of individual assets and on a portfolio level. A stop loss strategy works as follows: The portfolio is fully invested, and instantaneously switches to the risk-free asset when the portfolio value reaches the stop-loss floor. This strategy is a special case of the broader Constant Proportional Portfolio Insurance (CPPI) approach. As we will show below, a stop loss applied to our prototype momentum strategies can in some cases improve the strategy's risk adjusted performance. However, these improvements are not dramatic – as one would expect, there is no simple cost-less solution that would entirely eliminate momentum tail risk.

To illustrate the use of a portfolio-level stop-loss enhancement on a Momentum strategy, we use Carhart's Momentum factor from Fama-French's website and apply a one-month block-out period (stay in cash) if a 5% stop-loss level is triggered. During the Momentum factor's out-of-sample period from 1991 to 2014 (a total of 288 months), stop-loss signals were triggered in 26 months (or 9% of the time). After applying these stop-loss block-out periods, the strategy return was roughly doubled from +4.6% per annum to +8.8%, and Sharpe ratio increased from 0.27 to 0.64. The stop loss risk control also reduced the strategy's tail risk: the maximum drawdown more than halved from -57.6% in the original strategy to -25.8%. In practice, a stop-loss control is usually applied on a daily basis and the block-out period is often dynamic to be more reactive to the changing market environment (e.g. can be expressed in terms of Z-scores).

Figure 40: Stop-Loss mechanism could enhance the risk/return profile of Momentum strategies



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 20: Performance of Stop-Loss when applied to Carhart's 12-month Momentum strategy (1991-2014)

	Carhart 12-Month Momentum Factor	*After Applying 5% Stop Loss and 1-Month Block-out*
Excess Return (%)	4.6	8.8
STDev (%)	17.2	13.7
MaxDD (%)	-57.6	-25.8
MaxDDur (yrs)	6.1	5.0
***t*-Statistic**	**1.7**	**3.4**
Sharpe Ratio	**0.27**	**0.64**
Hit Rate (%)	62.2	67.4
Skewness	-1.64	-0.45
Kurtosis	11.69	8.37

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Stop-loss can also be used at an individual asset level. The hybrid Momentum strategy we introduce in the section 'Long Only Momentum and Hybrid Strategies' effectively uses an Absolute Momentum signal to filter out assets with negative past performance. This is equivalent to setting up stop-loss triggers at the asset level.

[54] 'Cut your loss' and 'Let your profit run' (originally from David Ricardo) are among the most frequently cited adages in the managed futures industry.

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Stop-loss triggers are often applied on each rebalance date. However, more frequent stop-loss triggers could help avoid 'between-rebalance' tail risk. For instance, Han, Zhou and Zhu (2014)[55] used daily stop-loss triggers on Carhart's monthly rebalanced Momentum Strategy based on US stocks. Specifically, once a pre-specified stop-loss level (at 5%, 10% and 15% levels) is triggered on any day, the stock positions were closed until the end of the month (rebalance day). The authors show that this daily enforcement of stop-loss at a stock level could more than double the return and triple the Sharpe ratio of the original Momentum Strategy.

We test similar stop-loss mechanisms on prototype Absolute Momentum Strategies introduced in the last chapter. Specifically, at a certain pre-specified stop-loss thresholds x (x could be -3%, -5%, -7% and -10%) for the long assets, if the asset return exceeds this threshold (after leverage based on EMV), we then unwind the long position until the end of the next month. Similarly, at certain pre-specified stop-loss threshold y (y could be 3%, 5%, 7% and 10%) for the short assets, if the asset return rises above y, we then unwind the short position until the end of the next month[56] (i.e. at least a one-month block-out period).

The tables below show performance/risk characteristics for 12M Absolute Momentum strategies in different assets with stops losses on long and short positions. Table 21 shows performance of the original strategy and strategies with stop loss on the short position (no stop loss on long positions), Table 22 and Table 23 show the same but with 7%, and 3% stop loss on the long positions, respectively.

Implementing stop-losses usually decreases both strategy risk and returns as one expects less than 100% participation in the market. For instance, the after cost maximum drawdown of an Equity Absolute Momentum strategy was reduced from -31.6% to -23.9% when a 3% stop-loss is implemented on the short position (Table 21). Incorporating stop-loss triggers on the short side generally increased strategy Sharpe ratios and reduced drawdown of Equity Momentum strategies, while a stop-loss on the long-side often reduces strategy Sharpe ratio. Relatively inefficient stop-losses on the long side could relate to the short-term reversion tendencies of equity indices.

Table 21: Performance of Absolute Momentum Prototypes with Stop Loss of Short Positions and No Stop Loss on Long Positions

	3% Stop Loss on Short Positions				7% Stop Loss on Short Positions				No Stop Loss on Short Positions			
	Equity	**Bond**	**Curncy**	**Comdty**	**Equity**	**Bond**	**Curncy**	**Comdty**	**Equity**	**Bond**	**Curncy**	**Comdty**
Ann. Ex Ret (%)	11.5	9.1	5.2	6.6	10.9	9.7	5.7	7.1	10.9	9.8	6.0	6.7
CAGR (%)	11.2	8.7	4.9	6.3	10.6	9.3	5.4	6.8	10.6	9.3	5.6	6.3
STDev (%)	12.7	12.4	8.8	9.6	13.2	12.9	9.6	10.2	13.4	13.1	10.3	10.7
MaxDD (%)	-23.9	-34.7	-17.6	-22.5	-30.4	-27.2	-21.3	-24.1	-31.6	-28.7	-23.1	-28.0
MaxDDur (in yrs)	2.4	6.9	3.8	5.9	4.8	6.4	3.3	5.9	4.9	5.5	6.1	5.9
***t*-Statistic**	**4.3**	**3.5**	**2.8**	**3.2**	**3.9**	**3.6**	**2.8**	**3.3**	**3.9**	**3.5**	**2.7**	**3.0**
Sharpe Ratio	**0.90**	**0.73**	**0.59**	**0.69**	**0.83**	**0.75**	**0.59**	**0.69**	**0.82**	**0.75**	**0.58**	**0.63**
Hit Rate (%)	54.6	53.7	53.0	54.1	53.7	53.5	53.3	54.1	53.5	53.4	53.9	54.2
Skewness	-0.29	-0.24	-0.16	-0.38	-0.32	-0.24	-0.26	-0.29	-0.30	-0.24	-0.31	-0.28
Kurtosis	4.35	3.37	3.73	3.63	3.61	2.71	2.70	2.97	3.29	2.60	2.77	2.50

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Performance of Bond 12-month Absolute Momentum strategies was not improved with a simple stop loss on the short side (Table 21). On the other hand, a 10% stop-loss on the long side seems to benefit the Bond 12-month Absolute Momentum strategy. Currency and Commodity Momentum strategies appear to benefit from a 7% stop-loss on the long and a range of stop-losses on the short side.

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55 Han, Yufeng and Zhou, Guofu and Zhu, Yingzi (2014), "Taming Momentum Crashes: A Simple Stop-Loss Strategy". Available at SSRN: http://ssrn.com/abstract=2407199 .

56 We tested stop-loss mechanisms without one-month block-out requirement (i.e. new positions are established at the same month-end after intra-month stop-loss) and find weaker risk-adjusted strategy performances. The results are shown in the Appendix on page 164.

Similar to Equities Momentum, stop-losses tend to benefit Commodity Momentum strategies. For instance, the Sharpe ratio improved from 0.63 to 0.69 for the 12-month Commodity Absolute Momentum strategy while maximum drawdown is reduced from -28% to -18.4% (Table 22) when a 7% stop-loss is implemented on both long and short positions. More detailed summaries of performance/risk statistics under various stop-loss assumptions can be found in the Appendix 'Stop-Loss Trigger Sensitivities' on page 153.

Table 22: Performance of Absolute Momentum prototypes with Stop Loss of short positions and 7% Stop Loss on long positions

	3% Stop Loss on Short Positions				7% Stop Loss on Short Positions				No Stop Loss on Short Positions			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	7.8	7.9	5.0	5.8	7.3	8.5	5.6	6.5	7.1	8.6	6.0	6.1
CAGR (%)	7.5	7.6	4.8	5.6	6.9	8.1	5.3	6.2	6.7	8.2	5.7	5.8
STDev (%)	10.7	11.0	8.1	8.6	11.3	11.5	9.0	9.4	11.5	11.7	9.6	9.9
MaxDD (%)	-25.2	-33.4	-17.3	-15.5	-32.9	-25.8	-19.0	-18.4	-33.8	-25.0	-19.9	-20.3
MaxDDur (in yrs)	5.6	5.5	3.8	3.1	5.2	5.5	8.2	3.1	5.2	5.4	5.2	3.1
t-Statistic	3.5	3.4	2.9	3.2	3.0	3.5	2.9	3.3	2.9	3.5	2.9	2.9
Sharpe Ratio	0.73	0.72	0.62	0.67	0.64	0.73	0.62	0.69	0.62	0.73	0.62	0.62
Hit Rate (%)	54.5	53.6	53.0	54.1	53.6	53.3	53.5	54.1	53.5	53.3	53.7	54.0
Skewness	-0.30	-0.18	-0.09	-0.33	-0.34	-0.18	-0.26	-0.22	-0.31	-0.18	-0.29	-0.22
Kurtosis	5.64	3.88	5.48	3.84	4.85	3.03	3.72	3.29	4.42	3.01	3.75	2.82

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 23: Performance of Absolute Momentum prototypes with Stop Loss of short positions and 3% Stop Loss on long positions

	3% Stop Loss on Short Positions				7% Stop Loss on Short Positions				No Stop Loss on Short Positions			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	5.6	4.8	2.7	4.7	5.0	5.3	3.5	5.4	4.9	5.2	4.0	5.0
CAGR (%)	5.4	4.5	2.5	4.5	4.6	4.9	3.3	5.2	4.5	4.8	3.7	4.7
STDev (%)	8.9	9.0	6.6	7.3	9.7	9.8	7.7	8.2	10.0	10.0	8.3	8.7
MaxDD (%)	-20.2	-27.6	-21.8	-12.9	-26.0	-28.5	-28.4	-14.6	-26.9	-30.3	-25.0	-16.3
MaxDDur (in yrs)	3.4	7.5	9.5	2.6	5.2	8.2	9.5	2.5	5.2	5.2	8.1	2.7
t-Statistic	3.0	2.5	1.9	3.0	2.4	2.6	2.2	3.1	2.3	2.5	2.3	2.7
Sharpe Ratio	0.63	0.53	0.41	0.64	0.51	0.54	0.46	0.66	0.49	0.52	0.48	0.57
Hit Rate (%)	55.3	55.7	53.4	54.4	54.1	54.9	53.0	54.3	53.7	54.7	53.0	54.2
Skewness	-0.08	-0.04	-0.15	-0.25	-0.21	-0.06	-0.28	-0.14	-0.13	-0.09	-0.32	-0.13
Kurtosis	9.13	6.33	5.73	4.44	7.52	4.65	4.43	3.95	6.76	4.50	4.22	3.53

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 24 and Table 25 below summarize the sensitivities of Sharpe ratios and ratios of Return to Maximum drawdown to various stop-loss triggers on the long and short side. Consistent with our findings, the prototype 12M Absolute Momentum strategies prefer a wider stop-loss trigger on the long side (10+% for Equity/Bond and 7+% for Currency/Commodities), and a narrower stop-loss on the short side (e.g. 3%-7% for Equity, Currency, Commodity, with the exception of Bonds).

For a multi asset strategy, incorporating a 5% stop-loss on the short side (no stop-loss on the long), would have modestly improved the Sharpe ratio from 1.21 to 1.29 and reduced the strategy maximum drawdown from -12.6% to -10.6%. As 'Momentum Crash' risk is often realized during market rallies when a typical Momentum strategy still maintains short positions, a stop-loss applied on the short side seems to be more important than long position stop loss triggers.

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Table 24: Sharpe ratios for various Stop-Loss triggers (12M Absolute Momentum prototypes)

Equities

Stop Loss on Long Positions \ Stop Loss on Short Positions	3%	5%	7%	10%	None
3%	0.63	0.58	0.51	0.49	0.49
5%	0.72	0.68	0.61	0.58	0.58
7%	0.73	0.70	0.64	0.62	0.62
10%	0.83	0.80	0.75	0.73	0.73
None	0.90	0.87	0.83	0.80	0.82

Bonds

Stop Loss on Long Positions \ Stop Loss on Short Positions	3%	5%	7%	10%	None
3%	0.53	0.57	0.54	0.52	0.52
5%	0.66	0.68	0.67	0.66	0.66
7%	0.72	0.74	0.73	0.73	0.73
10%	0.74	0.76	0.77	0.75	0.76
None	0.73	0.75	0.75	0.74	0.75

Currencies

Stop Loss on Long Positions \ Stop Loss on Short Positions	3%	5%	7%	10%	Non
3%	0.41	0.49	0.46	0.46	0.48
5%	0.45	0.51	0.48	0.48	0.47
7%	0.62	0.66	0.62	0.62	0.62
10%	0.64	0.68	0.64	0.63	0.63
None	0.59	0.62	0.59	0.58	0.58

Commodities

Stop Loss on Long Positions \ Stop Loss on Short Positions	3%	5%	7%	10%	Non
3%	0.64	0.68	0.66	0.62	0.57
5%	0.55	0.61	0.59	0.57	0.52
7%	0.67	0.71	0.69	0.67	0.62
10%	0.66	0.70	0.68	0.65	0.60
None	0.69	0.72	0.69	0.67	0.63

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 25: Return to maximum drawdown ratios for various Stop-Loss triggers (12M Absolute Momentum prototypes)

Equities

Stop Loss on Long Positions \ Stop Loss on Short Positions	3%	5%	7%	10%	None
3%	0.28	0.27	0.19	0.18	0.18
5%	0.29	0.28	0.22	0.20	0.20
7%	0.31	0.28	0.22	0.21	0.21
10%	0.36	0.33	0.27	0.26	0.26
None	0.48	0.45	0.36	0.34	0.35

Bonds

Stop Loss on Long Positions \ Stop Loss on Short Positions	3%	5%	7%	10%	None
3%	0.18	0.20	0.18	0.17	0.17
5%	0.21	0.27	0.26	0.25	0.25
7%	0.24	0.29	0.33	0.34	0.34
10%	0.26	0.32	0.36	0.36	0.36
None	0.26	0.31	0.36	0.34	0.34

Currencies

Stop Loss on Long Positions \ Stop Loss on Short Positions	3%	5%	7%	10%	None
3%	0.12	0.13	0.12	0.13	0.16
5%	0.16	0.16	0.16	0.16	0.18
7%	0.29	0.33	0.29	0.27	0.30
10%	0.33	0.36	0.32	0.29	0.32
None	0.29	0.28	0.27	0.24	0.26

Commodities

Stop Loss on Long Positions \ Stop Loss on Short Positions	3%	5%	7%	10%	None
3%	0.36	0.38	0.37	0.31	0.31
5%	0.31	0.38	0.31	0.26	0.27
7%	0.37	0.42	0.35	0.30	0.30
10%	0.27	0.30	0.29	0.25	0.24
None	0.29	0.30	0.29	0.26	0.24

Source: J.P. Morgan Quantitative and Derivatives Strategy.

In a summary, improvements to Sharpe ratios from stop-loss signals have historically been modest. Stop-losses provide a more significant improvement to the ratio of return to maximum drawdown (e.g. with commodity, equity and currency stop loss). This is consistent with our view that signals can rarely eliminate the risks of a risk premia strategy. After the fact, one can easily design successful signals that would have eliminated tail risk from the backtest. However, fine tuned signals rely on a limited number of market episodes (in this case market turning points), and are often not statistically robust. Despite the limitations of stop-losses to eliminate tail risk, our tests have shown that including a stop-loss into a Momentum strategy can modestly improve the strategy's risk adjusted returns.

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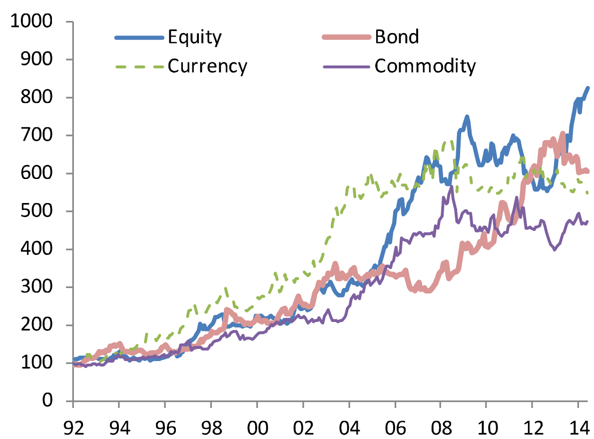
Besides Stop-Loss mechanisms, Volatility-targeting is another popular risk control method. In our implementation of prototype Trend Factors, we have targeted the same level of volatility for each underlier. This technique was implemented in the J.P. Morgan Mozaic strategy which will be introduced in the section ‘Long Only Momentum and Hybrid Strategies’.

Similar to Stop-Loss, Volatility-targeting can be applied at a portfolio level as well. For instance, we implemented a 12% annualized volatility[57] target risk control on prototype Trend factor portfolios for different assets during 1992-2014. Compared with the performance of prototype 12-month Absolute Momentum factors without volatility targeting (Table 3 on page 21), we didn’t find a noticeable difference in risk-adjusted performance. The reason is, unlike most traditional assets, one could not establish significant negative correlation between realized volatility of a strategy and its future return. [58]

Figure 41: Volatility Targeted prototype Trend Factors by asset class



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 26: Performance/risk stats for Vol-Targeted Trend Factors

	Equity	*Bond*	*Curncy*	*Comdty*	*Equal Weight*
Excess Ret (%)	9.9	8.4	7.9	7.2	8.9
STDev (%)	12.3	12.2	12.9	12.4	7.2
MaxDD (%)	-26.1	-19.9	-21.7	-29.6	-9.6
MaxDDur (yrs)	4.6	4.7	6.2	5.9	1.9
***t*-Statistic**	**3.9**	**3.4**	**3.1**	**3.0**	**5.8**
SR Vol-Tgt	**0.80**	**0.68**	**0.61**	**0.58**	**1.23**
SR No Vol-Tgt	0.82	0.75	0.58	0.63	1.21
Hit Rate (%)	61.7	62.5	59.9	61.0	63.9
Skewness	0.06	0.08	-0.02	-0.43	0.05
Kurtosis	0.55	1.33	1.54	1.58	-0.19

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Although portfolio-level volatility targeting turned out to be less effective than stop-loss mechanisms in controlling Momentum strategy risk, asset volatility as a regime signal did provide meaningful improvement for some Momentum strategies.

An example of such a regime-based risk control mechanism in Equities is illustrated below. The VIX index level is monitored at each month-end rebalancing date: when the VIX level is less than 25, 100% of notional is invested in the Carhart Momentum factor; when the VIX level is greater than 25, reduce notional exposure to the Momentum Factor to 50%. We test two versions of VIX signal enhanced Momentum factors. In the ‘long only’ version[59], we further reduce notional exposure to 0% when the observed VIX level is greater than 35; in the ‘long/short’ version, we go to short 50% notional exposure of the Momentum factor when the observed VIX level is greater than 35.

Historical performance of the original Carhart Momentum factor and the VIX signal risk control enhanced factors are shown below. During the backtest period from 1991 to 2014, the VIX signal based risk controlled mechanism significantly improved the Sharpe ratio of the original Momentum factor while reducing the strategy maximum drawdown by ~60%. In addition, the strategy displayed positive skewness in its return distributions compared with the negative skewness of the returns for the original Momentum factor.

[57] Ex-ante volatility is based on annualized standard deviations of past 24-month returns.
[58] See the section ‘Time Series Risk Allocation – Theory’ in Chapter 3 of our primer on Cross Asset Systematic Strategies for explanations on optimality conditions of volatility targeting and other risk management methods.
[59] Note that the ‘long-only’ here refers to long-only exposure to the Carhart Momentum factor which itself is a long/short stock strategy.

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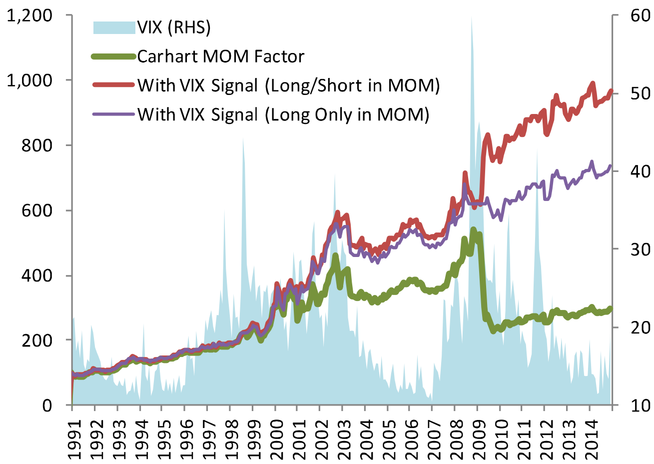
Figure 42: Enhanced Carhart Momentum strategy with VIX signal during 1991-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 27: Performance/risk for Enhanced Momentum strategy with VIX signal

	Carhart 12-Month Momentum Factor	*With VIX Control (Long/Short in MOM Factor)*	*With VIX Control (Long-Only in MOM Factor)*
Ex Return (%)	4.6	9.9	8.7
STDev (%)	17.2	13.1	12.4
MaxDD (%)	-57.6	-21.7	-21.7
MaxDDur (yrs)	6.1	5.0	5.0
***t*-Statistic**	**1.7**	**3.9**	**3.6**
Sharpe Ratio	**0.27**	**0.79**	**0.73**
Hit Rate (%)	62.2	63.9	65.3
Skewness	-1.64	0.74	0.60
Kurtosis	11.69	4.59	4.66

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Incorporating Value/Reversion Factors

In our previous studies of Cross Asset Systematic Strategies and Equity Risk Premia Strategies, we found that Value and Reversion based strategies tend to be negatively correlated with Momentum strategies. This creates the possibility that adding a Value/Reversion component to a Momentum factor could improve its risk adjusted performance.

Fama-French's High-Minus-Low (HML) Value factor and Carhart's 12-1 Momentum (MOM) factor[60] have both delivered positive returns over the past century, and the correlation between the two was -40% during 1927-2014. However, the MOM factor suffered steep drawdowns since 2000 (-31.5% during 2002-2004 and -57.6% during 2009-2010). Given their negative correlation, a portfolio allocating 50% to HML and 50% to MOM would have outperformed both factors with less risk. In fact, MOM drawdown was reduced to -18.5% during 2002-2004 and -32.9% during 2009-2010 after incorporating the HML factor.

Besides building a portfolio of Value and Momentum factors, one could directly incorporate these two styles into a multi-factor model. Below we test simple 2-factor models based on the MSCI World index universe. We ranked stocks according to single or composite factor scores at each month end, and go long an equally weighted basket of the top 10% of stocks while shorting an equal weighted basket of the bottom 10% of stocks ranked by the combined metric.

Results from our test are summarized in Figure 43 (distribution of monthly returns) and Table 28 (performance/risk analytics) where the factor definitions are described below:

1) **Model 1: 12MOM -** a simple Momentum Factor based on past 12-month USD total return;
2) **Model 2: 12-1MOM -** a Momentum Factor frequently used by academic studies based on past 12-month USD total return skipping the recent month;
3) **Model 3: 12MOM +1M Reversion -** a two-factor model based on the average of z-scores of the 12-month Momentum factor and 1-month reversion factor (negative 1-month Momentum);
4) **Model 4: 12MOM + Earnings Yield -** a two-factor model based on the average of z-scores of the 12-month Momentum factor and trailing 12-month earnings yield factor;
5) **Model 5: Enhanced MOM + Earnings Yield -** a two-factor model based on the average of z-scores of an enhanced Momentum factor and trailing 12-month earnings yield factor, where enhanced Momentum is defined as the past 12-month USD total return skipping the recent month divided by past 90-day volatility.

---

[60] The Fama/French benchmark portfolios are rebalanced quarterly using two independent sorts, on size (market equity, ME) and book-to-market (the ratio of book equity to market equity, BE/ME). The size breakpoint (which determines the buy range for the Small and Big portfolios) is the median NYSE market equity. The BE/ME breakpoints (which determine the buy range for the Growth, Neutral, and Value portfolios) are the 30th and 70th NYSE percentiles. The six portfolios used to construct MOM factor each month include NYSE, AMEX, and NASDAQ stocks with prior return data.

HML (High Minus Low) is the average return on two value portfolios minus the average return on two growth portfolios,
HML = 1/2 (Small Value + Big Value) - 1/2 (Small Growth + Big Growth).

Similar to HML, six value-weight portfolios are formed on size and prior (2-12) returns to construct the MOM factor. The portfolios, which are formed monthly, are the intersections of 2 portfolios formed on size (market equity, ME) and 3 portfolios formed on prior (2-12) return. The monthly size breakpoint is the median NYSE market equity. The monthly prior (2-12) return breakpoints are the 30th and 70th NYSE percentiles.

MOM is the average return on the two high prior return portfolios minus the average return on the two low prior return portfolios,
MOM = 1/2 (Small High + Big High) - 1/2(Small Low + Big Low).

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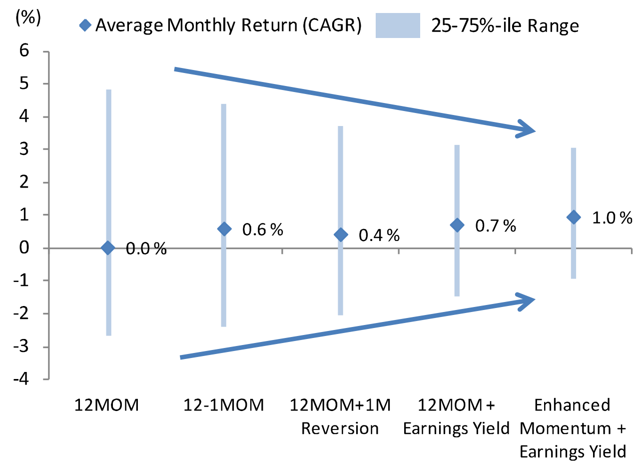
Figure 43: Monthly returns (average and 25%-75% percentile dispersion) for multi factor Momentum models during 1996-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy.

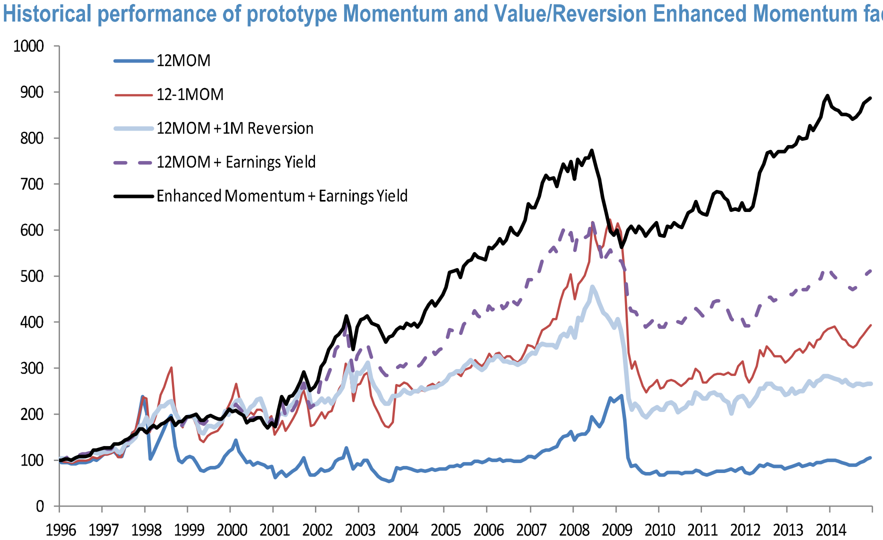
Table 28: Performance and risk statistics for prototype and Value/Reversion Enhanced Momentum risk factors (MXWO)

	12MOM Strategy	12-1 MOM Strategy	12MOM +1M Reversion	12MOM + Earnings Yield	Enhanced MOM + Earnings Yield
Excess Ret (%)	0.3	7.5	5.3	9.0	12.2
STDev (%)	33.7	28.9	19.8	16.4	13.5
MaxDD (%)	-76.5	-60.1	-59.4	-37.9	-27.5
MaxDDur (yrs)	11.1	6.1	6.5	6.5	4.5
***t*-Statistic**	**0.9**	**1.7**	**1.6**	**2.6**	**4.0**
Sharpe Ratio	**0.01**	**0.26**	**0.27**	**0.55**	**0.90**
Hit Rate (%)	61.8	60.1	57.9	61.0	63.2
Skewness	-1.01	-0.24	-0.97	-0.17	0.51
Kurtosis	6.55	5.58	5.19	2.96	3.89

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 43 shows that introducing a reversion/Value element into a Momentum model increases average monthly returns and reduces risk (dispersion of returns). Detailed performance statistics are shown in Table 28. While a prototype Momentum model would have generated a Sharpe ratio of ~0 during 1996-2014, the reversion/Value enhanced models had higher Sharpe ratios. For instance, incorporating 1-month reversion in the form of a single factor 12-1MOM model would have increased the return to 7.5% per annum and Sharpe ratio to 0.26. A two-factor model with 12-month Momentum and trailing 12-month earnings yield would have generated a return of +9.0% per annum and Sharpe ratio of 0.55. A model combining enhanced Momentum (volatility scaled 12-1MOM) and earnings yield further improves upon the result and generated an annualized return of +12.2% and Sharpe of 0.90. Figure 44 below plots the performance of the five examples described above.

Figure 44: Historical performance of prototype Momentum and Value/Reversion Enhanced Momentum factors



Source: J.P. Morgan Quantitative and Derivatives Strategy

Encouraged by the results of including reversion on stock-level equity Momentum indices, we tested the performance of prototype momentum factors when overlaid with short term reversion.

Specifically, we test the performance of Absolute Momentum factors modified to skip the recent past *N*-days' price data when determining asset trends. For instance, our prototype 12-month Absolute Momentum model assumes a positive trend if the price level one-year ago is higher than the price level one-day ago. A Momentum model that incorporates reversion assumes a positive trend if the price level one-year ago is higher than the price level one-month ago (i.e. by skipping price data during the past month).

Table 29 below shows the performance/risk statistics for 12-month and 6-month Absolute Momentum models which incorporate short-term reversals by skipping 5 and 21 days in the Momentum signal calculations. **Compared to the prototype models in the first four columns, we did not find a significant improvement that would work universally across all asset classes.**

While skipping the recent week in the trend calculation modestly improves return/risk profiles of 12-month Absolute Momentum strategies in Equities, Currencies and Commodities, it hurts 6-month Absolute Momentum strategies in Currencies and doesn't have material impact to 6-month Absolute Momentum strategies in the other asset classes. In addition, incorporating short-term reversion doesn't improve Bond Momentum strategies. Interestingly, incorporating a 21-day short-term reversal could help improve the Sharpe ratio of the 12-month Commodity Absolute Momentum strategy from 0.63 (without reversal) to 0.76. This is possibly related to the 'mean-reversion' of Commodity prices in recent years.

Table 29: Performance/risk statistics for prototype Absolute Momentum models incorporating near-term reversion

	12M Trend without Reversal				12M Trend Skipping 5-Days				12M Trend Skipping 21-Days			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	10.9	9.8	6.0	6.7	11.4	9.1	6.2	6.7	10.6	7.9	5.5	8.0
CAGR (%)	10.6	9.3	5.6	6.3	11.1	8.5	5.8	6.4	10.2	7.3	5.1	7.7
STDev (%)	13.4	13.1	10.3	10.7	13.5	13.1	10.3	10.7	13.5	13.1	10.2	10.5
MaxDD (%)	-31.6	-28.7	-23.1	-28.0	-32.6	-33.3	-27.4	-32.6	-34.8	-35.7	-31.4	-29.7
MaxDDur (in yrs)	4.9	5.5	6.1	5.9	4.9	7.0	6.1	5.9	5.2	7.0	6.1	5.9
t-Statistic	**3.9**	**3.5**	**2.7**	**3.0**	**4.0**	**3.3**	**2.9**	**3.0**	**3.7**	**2.9**	**2.6**	**3.6**
Sharpe Ratio	**0.82**	**0.75**	**0.58**	**0.62**	**0.85**	**0.69**	**0.60**	**0.63**	**0.79**	**0.61**	**0.54**	**0.76**
Hit Rate (%)	53.5	53.4	53.9	54.2	53.8	53.1	54.3	54.5	53.7	52.9	53.4	53.7
Skewness	-0.30	-0.24	-0.31	-0.28	-0.34	-0.23	-0.36	-0.27	-0.34	-0.26	-0.39	-0.25
Kurtosis	3.29	2.60	2.77	2.50	3.42	2.65	2.53	2.73	3.69	2.74	2.72	2.70

	6M Trend without Reversal				6M Trend Skipping 5-Days				6M Trend Skipping 21-Days			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	10.7	4.0	5.4	4.7	10.8	3.4	3.8	4.6	8.7	2.8	4.3	4.6
CAGR (%)	10.4	3.2	5.0	4.2	10.4	2.6	3.4	4.2	8.2	2.0	3.9	4.2
STDev (%)	12.8	13.1	10.1	10.4	13.0	12.9	9.9	10.4	12.8	13.3	10.0	10.2
MaxDD (%)	-28.0	-43.9	-22.5	-29.1	-29.4	-48.8	-20.7	-26.8	-30.5	-48.4	-21.5	-22.6
MaxDDur (in yrs)	3.1	11.0	2.8	3.1	3.2	11.0	4.0	3.1	3.5	11.0	5.0	3.1
t-Statistic	**4.0**	**1.4**	**2.5**	**2.1**	**3.9**	**1.3**	**1.8**	**2.1**	**3.2**	**1.0**	**2.1**	**2.1**
Sharpe Ratio	**0.84**	**0.31**	**0.53**	**0.45**	**0.83**	**0.27**	**0.38**	**0.44**	**0.68**	**0.21**	**0.43**	**0.45**
Hit Rate (%)	53.6	51.9	53.1	53.2	53.8	52.2	52.4	53.5	53.2	51.6	52.9	53.0
Skewness	-0.30	-0.18	-0.25	-0.23	-0.31	-0.21	-0.28	-0.28	-0.38	-0.19	-0.31	-0.22
Kurtosis	3.22	2.28	2.09	2.47	3.32	2.35	1.89	2.58	3.05	2.75	1.79	2.37

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 30 shows similar findings for Absolute Momentum strategies with different combinations of trend window size (from 3 to 24 months) and the short-term reversal window size (from 0 to 21 days). Across assets and Momentum signals, reversion did not consistently improve Sharpe ratios. We find that 10-21 day short-term reversals slightly improved Equity Momentum with long-term trend-window sizes (9-24 months). On the other hand, for short-term trend windows (< 6 months), Sharpe ratios were highest without any reversal signal.

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Bonds and Currencies don't appear to have significant reversal effects in our tests, and incorporating a 21-day reversal most often decreased the Sharpe ratios. The short-term reversal effect appears to improve 12-month Commodity momentum. More detailed results (performance, Sharpe ratio, risks, etc) on the short-term reversal effects in Absolute and Relative Momentum models can be found in the Appendix 'Short-Term Reversion Sensitivities' on page 153.

Table 30: Sharpe ratio of Momentum strategies with different look-back and term reversion (days skipped) Windows

Equities

Trend Signal (Month)	Days Skipped for Trend Signals: 0	5	10	15	21
24	0.62	0.61	0.62	0.60	**0.62**
12	0.82	0.85	**0.85**	0.83	0.79
9	0.89	0.88	**0.90**	0.86	0.80
6	**0.84**	0.83	0.77	0.77	0.68
3	**0.56**	0.52	0.52	0.52	0.51

Bonds

Trend Signal (Month)	Days Skipped for Trend Signals: 0	5	10	15	21
24	**0.64**	0.55	0.57	0.51	0.48
12	**0.75**	0.69	0.63	0.66	0.61
9	0.50	**0.56**	0.48	0.48	0.47
6	**0.31**	0.27	0.26	0.27	0.21
3	**0.42**	0.36	0.21	0.17	0.10

Currencies

Trend Signal (Month)	Days Skipped for Trend Signals: 0	5	10	15	21
24	**0.32**	0.26	0.22	0.20	0.18
12	0.58	0.60	0.56	**0.61**	0.54
9	0.62	**0.65**	0.62	0.50	0.38
6	**0.53**	0.38	0.48	0.46	0.43
3	0.45	**0.51**	0.37	0.39	0.24

Commodities

Trend Signal (Month)	Days Skipped for Trend Signals: 0	5	10	15	21
24	0.27	**0.31**	0.27	0.23	0.23
12	0.62	0.63	0.62	0.73	**0.76**
9	**0.35**	0.23	0.30	0.24	0.30
6	0.45	0.44	**0.46**	0.42	0.45
3	**0.50**	0.45	0.38	0.36	0.41

Source: J.P. Morgan Quantitative and Derivatives Strategy.

We also tested short-term reversal effects in Multi-Asset Relative Momentum strategies with various trend signal horizons. Incorporating short term reversion did not significantly increase Sharpe ratios, but it did reduce the maximal drawdown the strategy experienced. The benefit of short-term reversal effects seems to exist only at a 12-month trend signal horizon, whereas incorporating reversals in 24-month or 3-9 month horizons would decrease the strategy returns/Sharpe ratios (see the Appendix page 153). For instance, Table 31 below summarizes the performance/risk statistics for 12-month Relative Momentum models, and we find that the strategy's Sharpe ratio increases to 1.03 from 1.08 (with smaller max-drawdowns) when we incorporate a 10-day short-term reversal in the trend signal (maximal drawdown decreased from 17.4% to 13.1%).

Table 31: Performance/Risk Statistics for 12M Multi Asset Relative Momentum Models incorporating Near-Term Reversion

	12-Month Cross Asset Relative Momentum Strategy				
	No Reversion	**5-Day**	**10-Day**	**15-Day**	**21-Day**
Ann. Ex Ret (%)	8.4	8.7	8.6	8.6	8.1
CAGR (%)	8.4	8.8	8.7	8.6	8.1
STDev (%)	8.1	8.1	8.0	8.0	7.9
MaxDD (%)	-17.4	-14.8	-13.1	-13.4	-14.4
MaxDDur (in yrs)	4.2	4.1	4.2	3.9	4.8
***t*-Statistic**	**4.9**	**5.1**	**5.1**	**5.1**	**4.8**
Sharpe Ratio	**1.03**	**1.08**	**1.08**	**1.07**	**1.02**
Hit Rate (%)	54.7	55.0	55.1	55.3	55.2
Skewness	-0.35	-0.31	-0.35	-0.37	-0.36
Kurtosis	2.41	2.33	2.37	2.41	2.34

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Risk Adjusted Momentum

In the previous section, we saw that the Momentum/Value model that included 'volatility scaling' of the Momentum signal (Model 5) performed the best.[61] Table 32 below shows that incorporating volatility-scaling in a 12-1MOM strategy on the MSCI World index stock universe could also reduce strategy risk and increase strategy returns (annualized excess return increases from +7.5% to +10%).

Table 32: Performance/risk statistics for 12-1MOM and risk adjusted 12-1MOM strategies on the MSCI World index stock universe

	12-1MOM Strategy	12-1 MOM/Volatility Strategy
Excess Return (%)	7.5	10.0
Ann. Volatility (%)	28.9	19.2
Max Drawdown (%)	-60.1	-41.5
Max DD Duration (yrs)	6.1	6.5
***t*-Statistic**	**1.7**	**2.6**
Sharpe Ratio	**0.26**	**0.52**
Hit Rate (%)	60.1	64.5
Skewness	-0.24	-0.16
Excess Kurtosis	5.58	1.35

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Following this lead, we examined whether similar effects exist for Multi-Asset Relative Momentum Strategies. We define **Risk Adjusted Relative Momentum** factors by replacing the past 12-month return with the past 12-month return-to-volatility ratio in the prototype Relative Momentum factors (Figure 15):

Risk Adjusted Equity Relative Momentum Factor[62]: Long the three equity indices with the highest past 12 month return-to-volatility ratios and short the three indices with lowest past 12 month return-to-volatility ratios. Our index futures universe is: S&P/TSX 60 (Canada), CAC 40 (France), DAX (Germany), Hang Seng (HK), NIKKEI 225 (Japan), AEX (Netherlands), IBEX 35 (Spain), Swiss Market (Switzerland), FTSE 100 (UK), and S&P 500 (US).

Risk Adjusted Bond Relative Momentum Factor: Long the three bond futures with the highest past 12 month return-to-volatility ratios and short the three futures with the lowest past 12 month return-to-volatility ratios (monthly rebalanced); The universe was comprised of the following futures: Australia 10-year, Canada 10-Year, Germany 5-Year, Germany 10-Year, Japan 10-Year, US 2-Year, US 5-Year, US 10-Year, US 30-Year, and 3M Eurodollar.

Risk Adjusted Currency Relative Momentum Factor: Long the three G10 currencies with the highest past 12 month return-to-volatility ratios and short the three G10 currencies with the lowest past 12 month return-to-volatility ratios (monthly rebalanced).

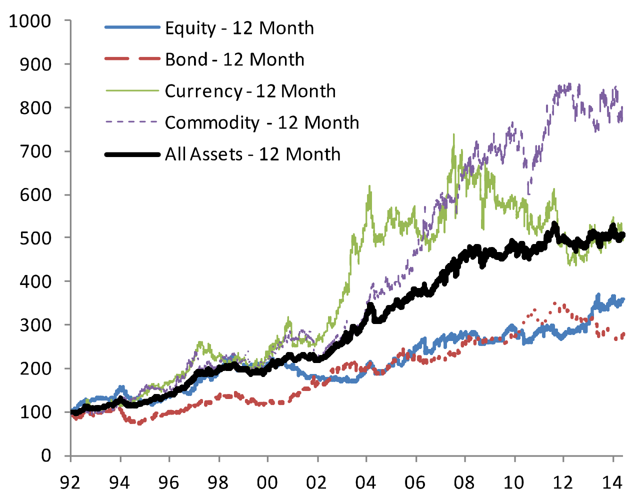
Risk Adjusted Commodity Relative Momentum Factor: Long the three commodity futures with the highest past 12 month return-to-volatility ratios and short the three commodity futures with the lowest past 12 month return-to-volatility ratios (monthly rebalanced); The commodity futures universe was: Wheat, WTI Crude Oil, Brent, ULSD, Gasoline, Aluminum, Copper, Gold, Silver, and Platinum.

Figure 45 and Table 33 below show the historical performance of risk-adjusted Relative Momentum factors defined above. Compared to the performance of factors without risk scaling (see also Figure 15 and Table 8 on page 27), we find that risk

[61] Similar signal scaling by asset volatility is popular in 'carry' strategies which rank assets according to their ex-ante yields divided by historical asset volatility (e.g. see Investment Strategies No. 12: JPM Carry to Risk Primer).
[62] Similar to our prototype Relative Momentum factors, each underlying asset is volatility targeted to have an annualized vol of 15%.

adjusted Relative Momentum signals **improved the risk/return profiles of Currency, Commodity, and Bond Momentum Risk Factors** significantly, while it didn't materially impact Equity Factors. In addition, the performance of a portfolio of asset-specific Relative Momentum strategies was significantly improved by adopting a volatility scaling approach (Sharpe ratio improves from 0.82 to 0.98).

Figure 45: Risk Adjusted Momentum Risk Factors by asset class



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 33: Performance/risk for Risk Adjusted Momentum Factors

	Equity	Bond	Curncy	Comdty	All-Asset
Ann. Ex Ret (%)	6.4	5.4	8.5	10.2	7.6
CAGR (%)	5.9	4.7	7.4	9.7	7.5
STDev (%)	11.2	12.6	16.4	14.1	7.7
MaxDD (%)	-28.1	-35.9	-41.1	-24.3	-13.3
MaxDDur (in yrs)	7.1	3.0	6.9	3.1	2.8
***t*-Statistic**	**2.7**	**2.0**	**2.5**	**3.4**	**4.6**
SR Vol Scaling	**0.57**	**0.43**	**0.52**	**0.73**	**0.98**
SR No Vol Scaling	**0.58**	**0.35**	**0.39**	**0.53**	**0.82**
Hit Rate (%)	53.0	52.6	52.7	54.5	54.3
Skewness	-0.39	-0.26	-0.33	-0.31	-0.36
Kurtosis	2.21	2.47	3.84	2.12	1.83

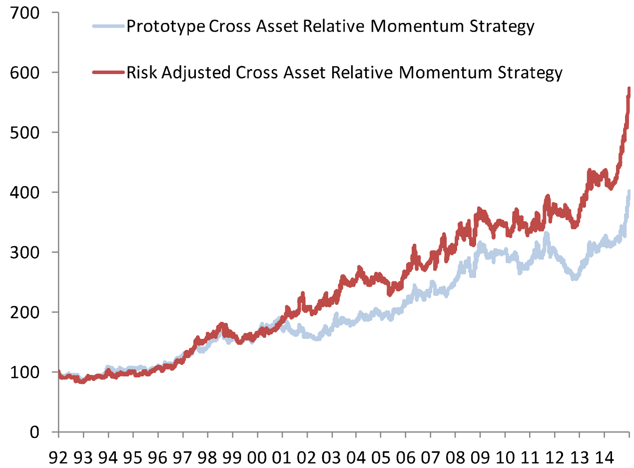
Source: J.P. Morgan Quantitative and Derivatives Strategy.

In Chapter 2 we showed that that the Relative Momentum effect is more significant when Momentum ranking is done across assets rather than within an asset class. For that reason, we next examine the impact of risk-adjusting our prototype cross-asset Momentum model. [63] Specifically, we rank the 40 assets in the prototype model according to their past 6-month return to volatility ratios (one business day before each month end). The top five ranked assets are selected in the long basket and bottom five ranked assets in the short basket. Each selected asset in the long/short basket is volatility targeted to have 10% marginal volatility and EMV weighted.

Figure 46 and Table 34 compare the historical performance/risk profiles of the cross-asset prototype Relative Momentum strategy and risk-adjusted Relative Momentum strategy described above. We find risk-scaling in the cross-asset Momentum ranking modestly increased returns/Sharpe ratio. In addition, the risk-adjusted strategy had a smaller maximum drawdown (-18.6%) compared with the prototype strategy (-23.5%) during 1992-2014.

[63] The pool of examined assets is the same as the set of futures/currency contracts we used for prototype Trend Factors. They include:
Equity Index Futures: S&P/TSX 60 (Canada), CAC 40 (France), DAX (Germany), HANG SENG (HK), NIKKEI 225 (Japan), AEX (Netherlands), IBEX 35 (Spain), Swiss Market (Switzerland), FTSE 100 (UK), and S&P 500 (US).
Fixed Income Futures: Australia 10-year, Canada 10-Year, Germany 5-Year, Germany 10-Year, Japan 10-Year, US 2-Year, US 5-Year, US 10-Year, US 30-Year, and 3M Eurodollar.
G10 Currency Pairs: AUDUSD, CADUSD, CHFUSD, EURUSD, JPYUSD, NZDUSD, SEKUSD, CHFEUR, JPYEUR, and NOKEUR.
Commodity Futures: Wheat, WTI Crude Oil, Brent, ULSD, Gasoline, Aluminum, Copper, Gold, Silver, and Platinum.

Figure 46: Impact of risk adjusting on a multi asset Relative Momentum strategy during 1992-2014: five assets



Source: J.P. Morgan Quantitative and Derivatives Strategy.
* Momentum signal is based on 6-month return/return to volatility ratios; 10bps one-way transaction cost is considered.

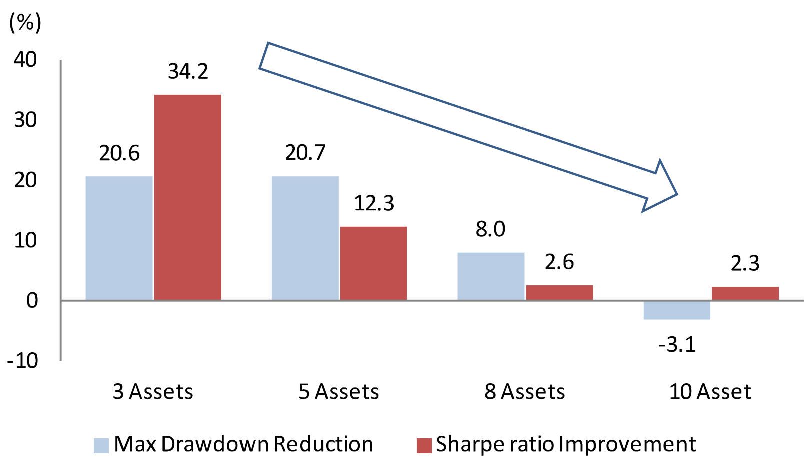
Table 34: Impact of risk adjusting on a multi asset Relative Momentum strategy during 1992-2014: five assets

	Prototype Cross Asset Relative Momentum Strategy	*Risk Adjusted Cross Asset Relative Momentum Strategy*
Excess Return (%)	6.2	7.9
STDev (%)	10.1	11.4
MaxDD (%)	-23.5	-18.6
MaxDDur (yrs)	3.0	2.7
***t*-Statistic**	**3.1**	**3.5**
Sharpe Ratio	**0.62**	**0.69**
Hit Rate (%)	53.0	53.6
Skewness	-0.20	-0.25
Kurtosis	1.81	2.12

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* Momentum signal is based on 6-month return/return to volatility ratios; 10bps one-way transaction cost is considered.

We also found that risk-adjustments in trend signals had a greater benefit for Relative Momentum strategies with a smaller number of assets. Figure 47 below shows that when the number of assets in the long/short baskets is less than 5, risk-adjustment in the Momentum signal significantly improves the risk/return profile of a cross-asset Relative Momentum strategy. Once the number of assets reaches 10, the performance difference between a prototype cross asset Relative Momentum strategy and a risk-adjusted cross asset Relative Momentum strategy becomes insignificant.

Figure 47: Benefit of Introducing Risk Adjustment in a Relative Momentum Strategy



Source: J.P. Morgan Quantitative and Derivatives Strategy

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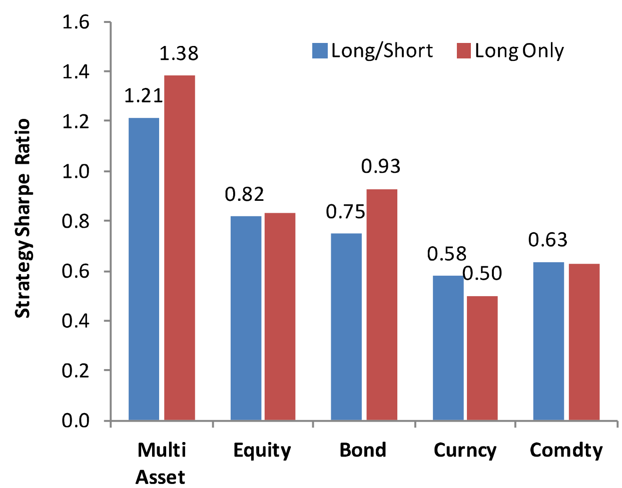
Long Only Momentum

A Momentum strategy can often be implemented as an 'active overlay' to a long-only traditional asset portfolio. Given the low or even negative correlation of momentum strategies to traditional assets, this often improves the risk/reward ratio of a traditional portfolio. If the weight of the Momentum factor is such that combined asset portfolio weights are positive, the overlay strategy could be regarded as an '**enhanced beta**' solution.[64]

A more direct way to implement a long only Momentum strategy is to eliminate the 'short' positions by construction. Specifically, a **Long-only Absolute Momentum** strategy goes long an asset when a positive trend is observed and stays in cash otherwise. **Long-only Relative Momentum** goes long a portfolio of assets with the largest relative strength of trend without shorting any assets.

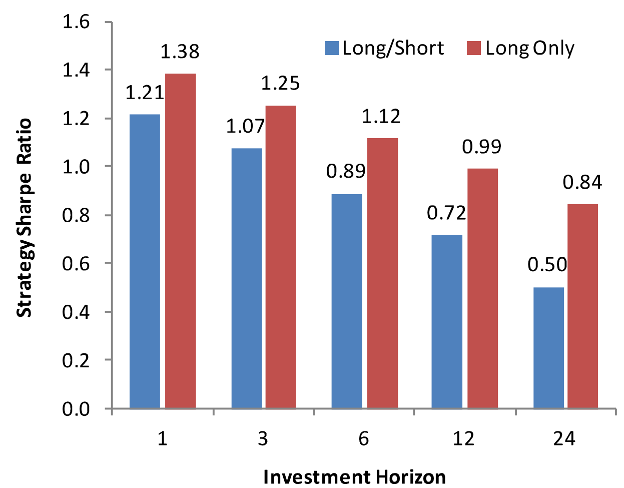
Below we demonstrate that 'long-only' Momentum strategies often outperform long/short strategies. For instance, Figure 48 below compares the Sharpe ratios of long-only and long/short Absolute Momentum strategies in different asset classes based on past 1-year return and one-month investment horizon. We find the long-only versions delivered better Sharpe ratios in Bond and Multi Asset levels. Figure 49, shows that long-only versions of multi-asset Absolute Momentum strategies improve Sharpe ratios at various investment horizons. This is similarly true for Relative Momentum strategies.

Figure 48: Sharpe ratios for long-only and long/short Absolute Momentum strategies based on past 12M returns



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 49: Sharpe ratios for long-only and long/short multi-asset Absolute Momentum strategies by investment horizon (# of months)



Source: J.P. Morgan Quantitative and Derivatives Strategy.

One can also combine Relative and Absolute Momentum into a single 'long-only' strategy. Instead of picking a fixed number of top-trending assets during each Relative ranking at portfolio rebalancing, Absolute Momentum could help determine the number of assets to go long. In a 'hybrid' long-only Momentum strategy, an asset is held long when both Relative and Absolute Momentum are confirmed.

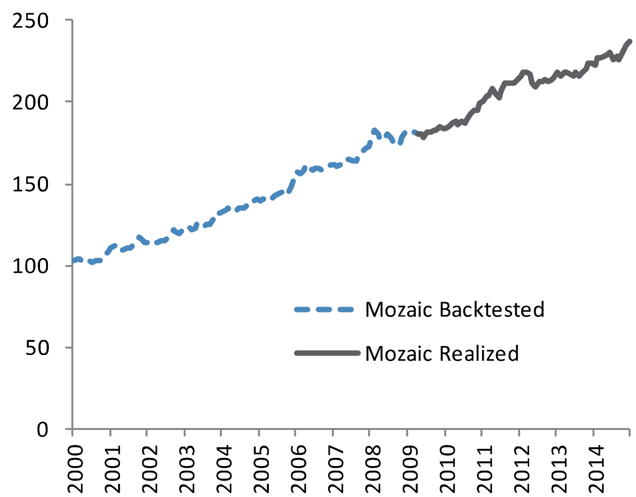
Our tests show that this type of 'hybrid Momentum' strategy can significantly reduce strategy drawdown without having a material impact on the average return. The reason is that absolute Momentum could help identify risky market drawdown periods. Overall, gains from drawdown reduction and missed upside cancel out, leading to similar returns but lower risk. The **J.P. Morgan Mozaic Index** (**JMOZUSD** <Index> on Bloomberg) is an example of a long-only 'hybrid Momentum'

[64] See page 13 on our guide to Cross Asset Systematic Strategies for a comprehensive review of strategy taxonomy including 'access beta', 'enhanced beta', 'alternative beta', 'alpha', etc. We also regard long-only Equity Risk Factors as enhanced beta strategies.

strategy that opportunistically holds up to 6 assets long (out of 12) based on past six month returns (Figure 50). The strategy invests in futures and baskets of futures. [65]

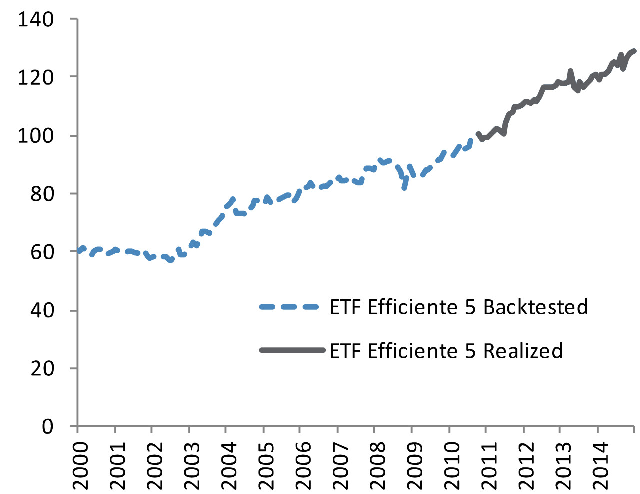
Another example of a long only momentum strategy is the **J.P. Morgan ETF Efficiente 5 Index** (**EEJPUS5E** <Index> on Bloomberg), which allocates between 12 ETFs in different asset classes and the J.P. Morgan US$ Cash Index based on past 6-month price Momentum (Figure 51). [66] The strategy employs an optimization technique to maximize the ex-ante portfolio Sharpe ratio and target a portfolio volatility of 5% per annum or less based on the co-variance structure during the past six months (by assuming persistence in covariance). Since October 2014, a variant of the Efficiente strategy is also tradable in the form of a US listed ETF (**EFFE** <Equity> on Bloomberg).

Figure 50: Performance of the J.P. Morgan Mozaic Strategy



Source: J.P. Morgan. Past Performance is not indicative of future returns.

Figure 51: Performance of the J.P. Morgan ETF Efficiente 5 Strategy



Source: J.P. Morgan. Past Performance is not indicative of future returns.

Given the J. P. Morgan Mozaic and J.P. Morgan ETF Efficiente strategies implement different risk management methodologies (Equal Marginal Volatility - EMV, and Mean Variance Optimization - MVO), we next compare these two strategies in more detail.

[65] These 12 futures are: Equity (S&P 500 Index Future, DAX Index Future, Nikkei Index Future), Fixed Income (10y US Treasury Future, 2y US Treasury Future, Bund Future, Schatz Future, JGB Future) and Commodity (S&P GSCI Agricultural ER Index, S&P GSCI Energy ER Index, S&P GSCI Industrial Metal ER Index, S&P GSCI Precious Metal ER Index)
[66] These 12 ETFs are (according to Asset Class): Equity (SPY, IWM, EFA, EEM), Fixed Income (TLT, LQD, HYG, EMB, TIP), and Commodities (GLD, GSG, IYR).

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Risk Methods: J.P. Morgan Mozaic and Efficiente

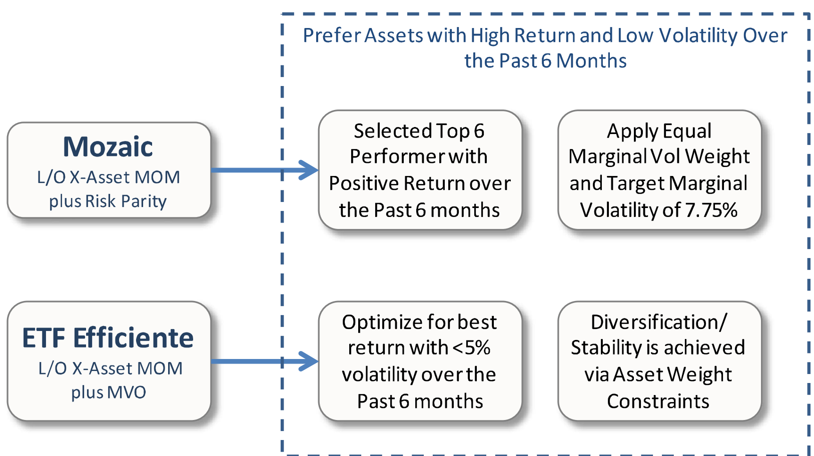
The J. P. Morgan **Mozaic** and J.P. Morgan **ETF Efficiente** strategies introduced in the previous section share many common features: both are designed to capture multi-asset (Equities, Bonds and Commodities) long-only Momentum risk premia.

A main difference between the two strategies is their employed **Risk Methodologies**[67]. The J.P. Morgan Mozaic strategy applies the concept of 'Risk Parity' to equalize the marginal volatility contributions of selected assets in its portfolio. After selecting top-performing assets, an Equal Marginal Volatility (EMV) mechanism is deployed to assign higher dollar weights to less volatile assets. In addition, downside risk is controlled via an Absolute Momentum signal: the strategy allocates risk weights to a top-performing asset only when it shows positive Momentum.

Instead of treating asset Momentum and risk management separately as done by J.P. Morgan Mozaic strategy, the J.P. Morgan ETF Efficiente strategy uses a Mean Variance Optimization (MVO) process to combine these two ingredients. Specifically, portfolio weights are the outputs from optimizing for the best return over the past 6 months with a portfolio volatility of 5%. Intuitively, this optimization process will lead to an overweight in assets with higher return, lower volatility as well as lower average correlation.[68] Portfolio-level risk management is achieved through the 5% overall strategy volatility targeting, and asset weight constraints. Specifically, asset weights are floored at 0% and capped at 20% for each of Bond, REIT, and Equity assets (with the exception of a 10% cap for Small cap equities), 10% for commodity assets, and 50% for TIPS and Cash.

The J.P. Morgan Mozaic and ETF Efficiente strategies were launched in 2009 and 2010, respectively, and both strategies delivered significantly positive (out of sample) performance. During the past five years (from Jan 2010 to Dec 2014), The J.P. Morgan Mozaic and ETF Efficiente strategies realized annualized excess returns of +5.2% and +6.8%, and Sharpe ratios of 1.3 and 1.2, respectively. Due to different composition and risk methods, their realized correlation was 62.3%, suggesting potential diversification benefits of holding both strategies. Indeed, an investment with equal allocation to these two strategies would have generated an annual excess return, max drawdown and Sharpe ratio of +6.2%, -3.2%, and 1.44 during the past five years. Consistent with our interpretation of Momentum risk premia, both strategies had negative skewness and positive excess kurtosis.

Figure 52: J.P. Morgan Mozaic and ETF Efficiente Strategies are designed to harvest cross-asset long-only Momentum Risk Premia



Source: J.P. Morgan Quantitative and Derivatives Strategy

[67] Interested readers could refer to Chapter 3 of our primer report on Cross Asset Risk Factors for more discussions on both theoretical and empirical aspects of different Risk Methodologies such as Mean Variance Optimization (MVO), Minimum Variance, Most Diversified Portfolio, Risk Parity, Black-Litterman etc. A brief summary of these methods is provided in the Appendix on page 148.
[68] Diversification ability of an asset in a portfolio is often measured by its average correlation with all other assets (or its correlation with an equal-weighted benchmark). Good diversification ability means that increasing the asset weight could reduce portfolio volatility.

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To summarize, Table 35 below compares the specifications and performance (after fees) of the J.P. Morgan Mozaic and J.P. Morgan ETF Efficiente Strategies.[69] Despite differences in regional focuses, traded instruments and risk methodologies, both strategies captured long-only Momentum risk premia across major asset classes.

Table 35: Comparisons of the J.P. Morgan Mozaic and J.P. Morgan ETF Efficiente strategies

Comparison of Strategy Details		
	J.P. Morgan Mozaic Strategy	**J.P. Morgan ETF Efficiente 5%**
Strategy Type	Enhanced Beta	Enhanced Beta
Asset Class	Multi Asset	Multi Asset
Regional Focus	Global Developed Markets	Global DM + EM
Risk Premia Style	Momentum	Momentum
Risk Method	**Equal Marginal Volatility**	**Mean Variance Optimization**
Underlying Instrument	Global Futures	US Listed ETFs
Apply Leverage	Yes	No
Asset Weight Constraint	No	Yes
Portfolio Risk Control	Stop Loss	Volatility Target

Comparison of Performance During 31 Dec 2009 - 31 Dec 2014		
	J.P. Morgan Mozaic Strategy	**J.P. Morgan ETF Efficiente 5%**
Excess Return (%)	5.2	6.8
Volatility (%)	4.1	5.8
Max Draw Down (%)	-5.1	-6.7
Max DD Duration (in yrs)	1.0	0.9
***t*-Statistic**	**2.8**	**2.6**
Sharpe Ratio	**1.3**	**1.2**
Hit Rate (%)	56.1	57.6
Return Skewness	-0.5	-0.6
Return Kurtosis	2.5	5.5

Source: J.P. Morgan Quantitative and Derivatives Strategy.

69 Both strategies could be further tailored (e.g. change underlying assets, change volatility target levels, change portfolio leverage etc) to satisfy different investment needs. For more information, please contact your J.P. Morgan salesperson or the Structuring Desk.

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Diversified Trend-Following Strategies

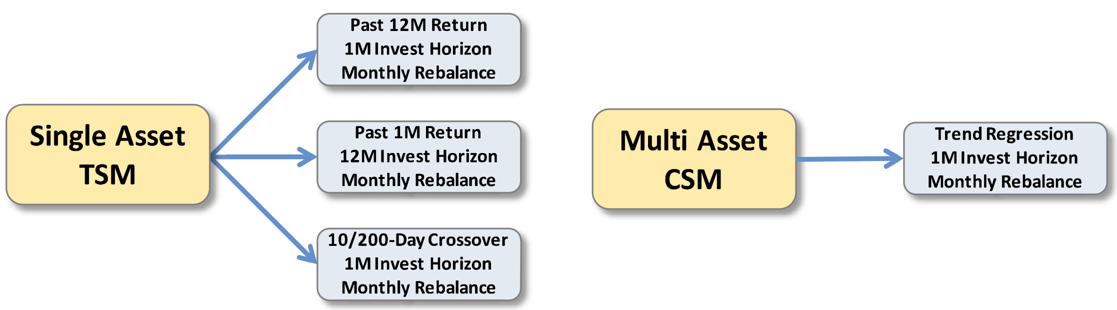
So far, we have considered risk reduction methods such as stop-loss, incorporating reversion, volatility scaling, combining strategies based on Risk Parity, etc. In this section, we explore perhaps the simplest risk reduction method – diversification of a Momentum strategy across asset classes and different momentum signals.

Diversification across asset classes was already discussed in our prototype models in Chapter 2. Diversification across various Momentum signals can be done in at least two different ways: 1) building a portfolio of Momentum strategies that each follow a different momentum signal, or 2) combining different Momentum signals to form a 'multi-signal' metric that is used to select the final portfolio. In this section we illustrate both approaches to build a Diversified Trend Following (DTF) strategy.

Portfolio of Momentum Indices Across Assets

To illustrate how a Diversified Trending Following strategy could be designed as a portfolio of Momentum strategies, we selected various trend signals and equally weighted the strategies following those signals. For example, as shown in Figure 53 below, three signals - past 1-month return, 10-day/200-day moving average crossovers and past 12-month returns (with 1-12 month investment horizon) - are used to represent short-to-medium-term trends for each of the asset classes. These three strategies are then equally weighted to form a 'Momentum Benchmark' for each of the asset classes. We chose Absolute Momentum (TSM) strategies for each asset class and a Relative Momentum (CSM) strategy (based on dynamically rebalanced signal introduced in the previous Chapter) to introduce asset and signal diversification[70]. While it is possible to further enhance performance by adding more elaborate trend signals (e.g. Kalman/Particle Filters), we focus on simple trend signals such as past returns and moving average crossovers.

Figure 53: An example of a long/short Diversified Trend Following (DTF) strategy with the same signals for each asset



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 36 below summarizes performance/risk metrics for our strategy (long/short version) across different asset classes based on the selection of trend signals in Figure 53. The last column is based on a strategy that puts equal weights in the five individual strategies with month-end rebalances.

[70] We used marginal asset volatility target of 30% for single-asset Absolute Momentum strategies and a marginal asset volatility target of 20% for the Multi Asset Relative Momentum strategy based on multi-variate regression.

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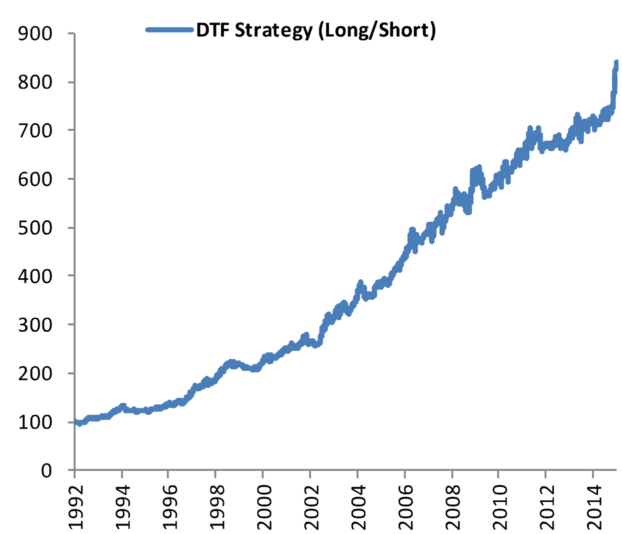
Table 36: Performance/risk analytics for long/short DTF strategy by asset class

	Equity	Bond	Curncy	Comdty	Multi Asset	DTF Long/Short
Ann. Ex Ret (%)	12.7	10.4	7.4	7.4	9.6	9.5
CAGR (%)	12.2	9.8	7.1	6.9	9.1	9.7
STDev (%)	15.2	14.4	11.2	11.5	13.7	7.5
MaxDD (%)	-26.6	-35.2	-21.0	-25.5	-25.3	-9.9
MaxDDur (in yrs)	4.2	7.0	3.4	3.7	2.6	1.9
***t*-Statistic**	**4.0**	**3.5**	**3.2**	**3.1**	**3.4**	**6.1**
Sharpe Ratio	**0.83**	**0.72**	**0.67**	**0.64**	**0.70**	**1.27**
Hit Rate (%)	53.6	53.4	54.4	53.9	53.1	55.7
Skewness	-0.37	-0.30	-0.38	-0.28	-0.11	-0.37
Kurtosis	4.18	3.34	3.32	3.80	2.37	3.01

Source: J.P. Morgan Quantitative and Derivatives Strategy. * Performances are based on 10bps one-way transaction cost assumption.

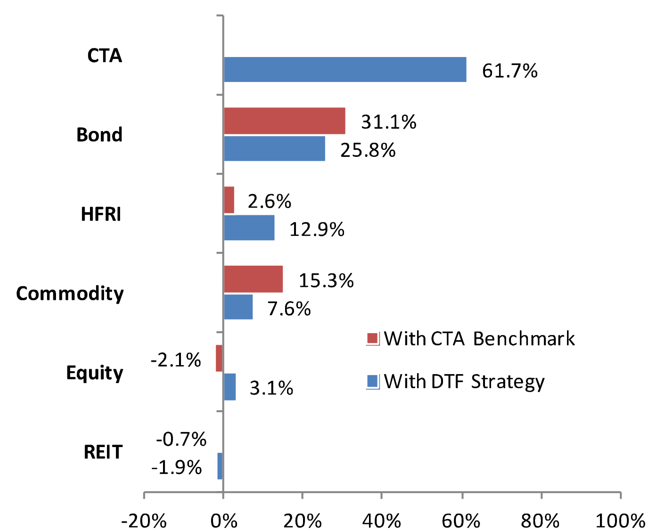
Compared with Table 3 in our discussion of 'prototype' Absolute Momentum strategies, the performance improvement over the prototype '12-month' TSM strategy is not dramatic: average return was enhanced by +1% per annum and Sharpe ratio was improved from 1.21 to 1.27. However, the illustrated DTF strategy above was performing much more consistently than the prototype 12-month Multi Asset Momentum strategy, which only delivered an average return of 3.5% and Sharpe ratio of 0.58 respectively during the 2011-2014 time period. In comparison, the average return of the DTF strategy is quite stable at +6.2% per annum during 2011-2014 with a Sharpe ratio of 0.91[71]. Additionally, the strategy only had a maximum drawdown of -9.9% compared with the prototype 12-month Momentum strategy's -12.6% drawdown. The persistent performance of the DTF (long/short) strategy can also be visualized in Figure 54.

Figure 54: DTF Strategy (Long/Short) Cumulative Performance



Source: J.P. Morgan. Past Performance is not indicative of future returns.

Figure 55: Cross Asset Correlation with DTF Strategy: 1992-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy.

[71] By comparison, the CTA industry (average of Barclay, BTOP50, DJCS and CISDM benchmarks) delivered an average excess return of only +2.9% and a Sharpe ratio of only 0.33 during 1992-2014 (+6.2% excess return and 0.72 Sharpe ratio before fees).

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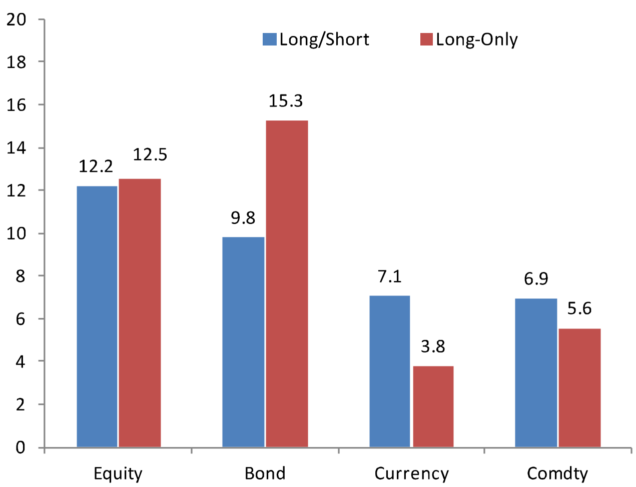
Figure 55 shows the DTF (long/short) strategy had a high correlation of +62% with the CTA benchmarks and similar level of correlations with major asset classes (compared to the respective assets' correlations with CTAs)[72].

In our DTF model, we used the same set of signals for all assets. This was done to maintain robustness of the backtest. Note that one does not have to use the same set of signals for each asset given that trending properties of assets are usually different (e.g. the potential presence of short term reversion, etc.). To illustrate such an approach, we have also tested the performance of a model that uses asset specific signals: Equity Momentum combines 1-month returns, 6-month returns and 200-day moving averages (monthly rebalance); Bond Momentum combines 12-month return and 12-month Up2Down signals[73] (monthly rebalance); Currency Momentum combines 12-month return (weekly rebalance) and 10-day/200-day moving averages (monthly rebalance); Commodity Momentum uses 12-month return and weekly rebalances. Such a strategy would have delivered a return of +10.6% and Sharpe ratio of 1.4 over the 1992-2014 time period.

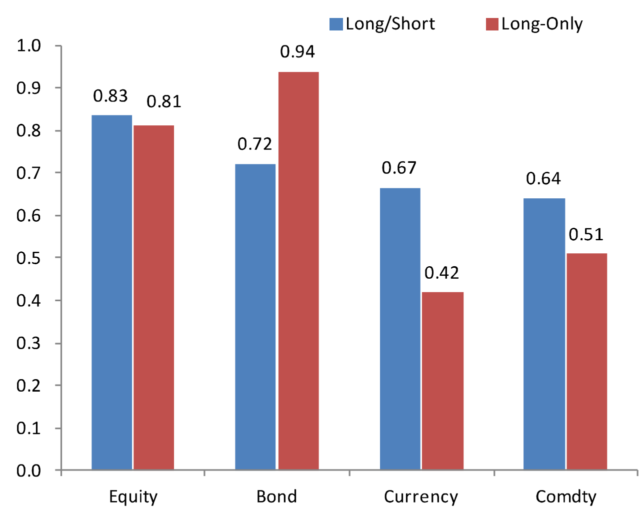
One can also implement a 'Long Only' version of DTF (by using the same trend signals and assets described in Figure 53). Figure 56 and Figure 57 below compare long/short and long only DTF strategies. Long-only DTF strategies delivered higher returns/Sharpe ratios in Bonds, similar returns/Sharpe ratios in Equities, and lower returns/Sharpe ratios in Currency and Commodity asset classes. These findings are consistent with our discussions in the section 'Long Only Momentum' on page 69.

Figure 56: Annual compounded returns of long/short vs. long-only DTF strategies during 1992-2014 (%)



Source: J.P. Morgan Quantitative and Derivatives Strategy
*Past Performance is not indicative of future returns.

Figure 57: Sharpe ratios of long/short vs. long-only DTF strategies during 1992-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy
*Past Performance is not indicative of future returns.

Momentum Scorecard Model for ETF Allocation

Another approach of diversifying across Momentum signals is a signal 'Scorecard' or 'Multi-factor' approach. Instead of pursuing a single trend signal each time and then equally weighting individual strategies that are based on those signals (as we did for the DTF strategy above), we use a '**Trend Scorecard**' method. The idea behind the 'Trend Scorecard' method is intuitive: although a single trend indicator may not work consistently, combining the scores from multiple trend indicators could improve the signal. This implementation of 'trend signal diversification' also relates to multi factor models and

[72] We used MSCI World Net Total Return Index for 'Equity', J.P. Morgan Global Aggregate Bond Total Return Index for 'Bond', S&P GSCI Commodities Total Return Index for 'Commodities', Dow Jones REIT Total Return Index for 'REIT' and HFRI Weighted Composite Index for 'Hedge Fund'.
[73] See definitions of signals in the section 'Selection of Trend Signal' on page 37.

concept of 'Model Averaging'.[74] Based on this approach, we designed a Momentum based asset allocation process applied to ETFs (for an overview of the ETF market see our 2014 J.P. Morgan Global ETF Handbook).

We have chosen a universe of 19 ETFs (6 Equity Markets, 6 Bond Markets and 5 Alternatives) to build our systematic Trend-Scorecard strategy (Table 37). Eight commonly used trend signals were included in forming the 'Momentum Scorecard' (6-month return, 12-month return, 3-month return scaled by volatility, 12-month return scaled by volatility, 200-day moving average, 5-day/100-day crossover, 10-day/200-day crossover, and 6-month return minus recent 2-week return). The model portfolio goes long the top six assets according to the aggregate Momentum score (average of individual trend-signal ranks), calculated a day before rebalance. Each asset in the long portfolio is targeted to have 10% marginal volatility and the maximum overall portfolio leverage is set at 150%.[75] We assumed 10bps one-way turnover cost for all the underlying ETFs. [76]

Table 37: Cross-asset ETFs for Tactical Asset Allocation

Asset Class	Country/Sector	Ticker	Name	Total Asset (US$mn)	6M ADTV (US$mn)	Ann. Return	Sharpe Ratio	Max Drawdown
Equity	Equities - US Large Cap	SPY	SPDR S&P 500 ETF Trust	179,297	26,110	5.9	0.40	-63.1
	Equities - US Mid Cap	IJH	iShares Core S&P Mid-Cap	26,137	195	8.9	0.53	-58.4
	Equities - US Small Cap	IWM	iShares Russell 2000 ETF	30,971	4,214	5.7	0.37	-61.9
	Equities - Int'l DM	EFA	iShares MSCI EAFE ETF	59,376	1,237	0.5	0.12	-63.1
	Equities - Emerging Mkts	EEM	iShares MSCI EM	31,509	2,218	5.8	0.35	-68.4
	Equities - Asia	AAXJ	iShares MSCI Asia ex Japan	4,336	68	3.6	0.27	-75.1
Fixed Income	Bonds - Short-Term UST	SHY	iShares 1-3 Year Treasury Bond	7,823	124	0.7	0.46	-5.5
	Bonds - Long-Term UST	TLT	iShares 20+ Year Treasury Bond	6,426	1,065	4.3	0.43	-27.4
	Bonds - TIPS	TIP	iShares TIPS Bond	13,044	70	2.9	0.52	-16.7
	Bonds - Investment Grade	LQD	iShares iBoxx Investment Grade	22,476	284	2.7	0.39	-26.5
	Bonds - High Yield	HYG	iShares iBoxx High Yield	17,456	640	2.2	0.26	-37.6
	Bonds - Emerging Markets	EMB	iShares JP Morgan EM Bond	4,795	101	6.1	0.58	-37.0
Alternatives	Comdty - Precious Metal	GLD	SPDR Gold Shares	28,260	834	0.3	0.10	-70.3
	Comdty - Energy	USO	United States Oil Fund	2,757	499	5.9	0.34	-81.0
	Comdty - Overall	DBC	PowerShares DB Comdty Fund	3,022	53	2.4	0.22	-61.3
	Real Estate - United States	VNQ	Vanguard US REIT	28,835	356	7.0	0.40	-75.5
	Real Estate - International	RWX	SPDR Dow Jones Int'l REIT	5,223	24	6.3	0.41	-75.7

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg.

Figure 58 below shows the performance of our 'Momentum Scorecard' ETF allocation strategy. The annual return was 8.6% and Sharpe ratio 1.32 (under 10bps transaction cost assumption) over the 1992-2014 time period.

For a comparison, an equally weighted portfolio of ETFs (with month-end re-balances) delivered a compounded annual return of +6.3% and a Sharpe ratio of 0.59 over the same time period, and the portfolio suffered a -43% draw-down during the 2008-2009 crisis.

[74] A similar idea was used to construct Multi-Factor scores for quantitative stock picking (e.g. J.P. Morgan Q-Score Model and Global 5-Factor Model introduced in our guide to Equity Risk Premia Strategies).
For explanation of model averaging see: Hoeting, J. A., Madigan, D., Raftery, A. E., and Volinsky, C. T. (1999), "Bayesian Model Averaging: A Tutorial," Statistical Science 14 (4), 382-417; Raftery, A.E., Madigan, D. and Hoeting, J.A. (1997), " Bayesian model averaging for regression models," Journal of the American Statistical Association 92, 179-191.
[75] Since the 10% marginal volatility target is less than the volatilities of Equities/Commodities/REITs, the maximum leverage limit is often effective during risky asset drawdowns, when there were elevated allocations to US Treasuries and Investment Grade Corporate bonds (essentially borrowing cash to invest in 'safer-haven' assets).
[76] The average bid-ask spread ranges from less-than 1bps of mid-prices for more liquid ETFs (such as SPY, TLT, GLD) to roughly 5-6 bps of mid prices for less liquid ETFs such as SLV and RWX. We used a higher cost to incorporate trading slippages and market impacts.

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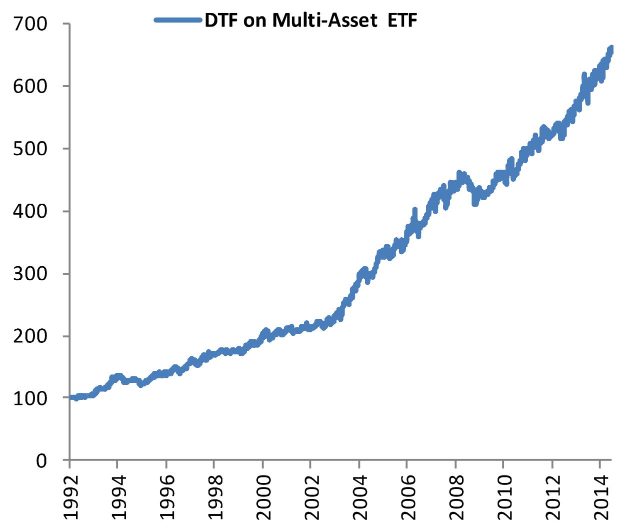
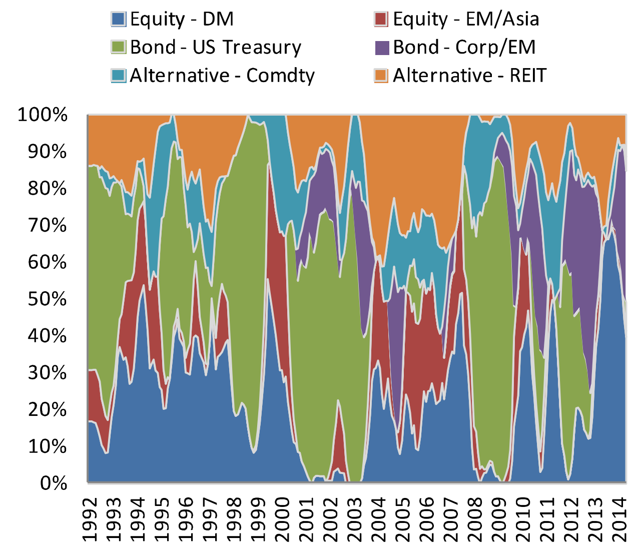
Figure 58: ETF Momentum Scorecard strategy



Source: J.P. Morgan Quantitative and Derivatives Strategy.
* Past Performance is not indicative of future returns.

Figure 59: Asset allocation weights for the ETF Scorecard Strategy



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 38 below shows the performance/risk statistics for the same strategy under different transaction cost assumptions. Without cost, the strategy delivered +9.1% annualized returns during 1992-2014 and a Sharpe ratio of 1.37; even under a 50bps one-way cost assumption for each portfolio turnover, the strategy still generates a statistically significant annualized excess return and Sharpe ratio of +7.5% and 1.14 respectively.

Table 38: Performance/Risk Analytics for Momentum Scorecard Strategy on Multi Asset ETF under Different Transaction Cost Assumptions

	One-Way Transaction Cost Assumption			
	No Cost	**10bps**	**20bps**	**50bps**
Ann. Ex Ret (%)	8.9	8.6	8.3	7.5
CAGR (%)	9.1	8.8	8.5	7.5
STDev (%)	6.5	6.5	6.5	6.5
MaxDD (%)	-11.6	-11.8	-11.9	-12.3
MaxDDur (in yrs)	1.6	1.6	1.8	2.0
***t*-Statistic**	**6.5**	**6.3**	**6.1**	**5.4**
Sharpe Ratio	**1.37**	**1.32**	**1.28**	**1.14**
Hit Rate (%)	54.9	54.9	54.8	54.5
Skewness	-0.50	-0.49	-0.49	-0.49
Kurtosis	3.30	3.30	3.29	3.26

Source: J.P. Morgan Quantitative and Derivatives Strategy.

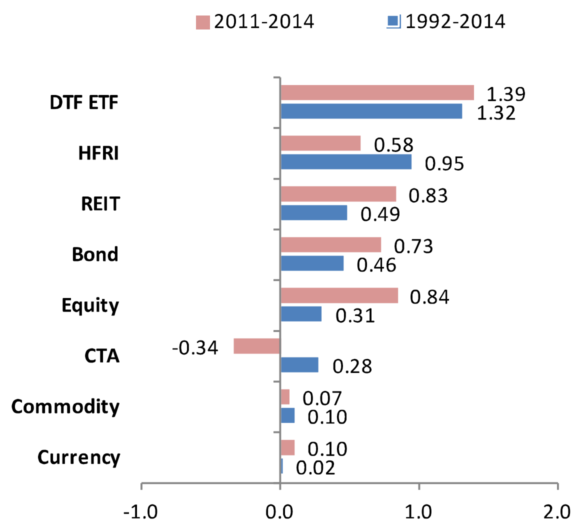
We next compare our '**Trend Scorecard**' tactical allocation strategy with major risky asset classes: Equities, Bonds, Commodities, REITs, Hedge Funds and CTAs[77].

[77] Similar to the exercises in DTF long/short and long-only strategies on currencies/futures, we used MSCI World Net Total Return Index for 'Equity', J.P. Morgan Global Aggregate Bond Total Return Index for 'Bond', S&P GSCI Commodities Total Return Index for 'Commodities', Dow Jones REIT Total Return Index for 'REIT', HFRI Weighted Composite Index for 'Hedge Fund' and the average of Barclay, BTop50, DJCS and CISDM CTA Indices for 'CTA'.

Figure 60 compares the Sharpe ratios of our ETF Momentum Scorecard strategy with these asset classes during Jan 1992 - June 2014 (full sample period) and during Jan 2011 - June 2014. Among the assets considered, Hedge Funds delivered a high Sharpe ratio of 0.95 (after fee) during the full sample period, while showing significant reduction of performance since 2011 (similar to CTAs).

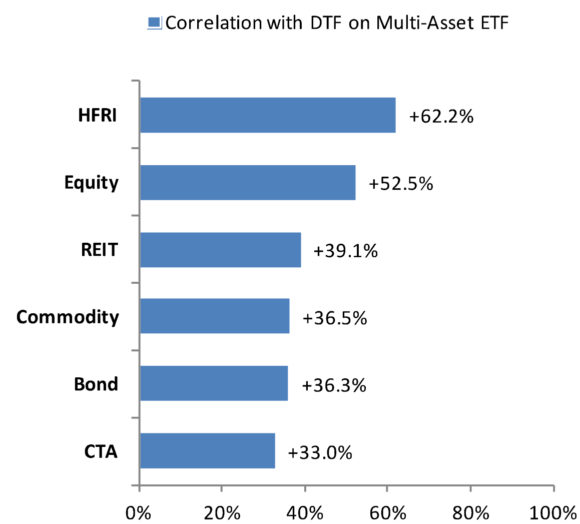
In comparison, our DTF ETF strategy based on the 'Momentum Scorecard' had a Sharpe ratio of 1.32 during the full sample period and 1.39 since 2011. Furthermore, the strategy was positively correlated with all risky assets (Figure 61), a reflection of its ‘long-only’ nature. In particular, it had a very high correlation (+62%) with hedge funds, suggesting following this simple Trend-Following strategy on cross-asset ETFs could enjoy the benefits of gaining significant exposures to Hedge Fund Risk Factors.

Figure 60: DTF ETF Strategy’s Sharpe ratio compared with major assets during 1992-2014 and during 2011-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 61: DTF ETF Strategy’s historical correlation with major assets during 1992-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy.

The strong performance of the strategy can be attributed to the following features (each discussed in the current Chapter): (1) long-only exposures to risky assets, (2) combining Absolute and Relative Momentum, (3) diversification across asset classes, and (4) diversification across momentum signals.

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Other Potential Enhancements

In this section we want to mention other methods that can be used to improve the risk-reward profile of Momentum strategies. In particular, we discuss several strategies based on price channels, and provide an outline of a regime based approach. The goal of these approaches is to identify **price trending and price reversion environments**. In that sense, they are related to strategies that combine Momentum with reversion in an attempt to mitigate Momentum risk.

Price Channels

Price channels refer to tools often used by technical analysts in assessing asset price trends. Examples include Donchian Channels, Pitchfork Channels, Percentile Channels, Keltner Channels, Bollinger's Bands and other variations. The main goal of price channels is to identify price trends and reversal points.

Some potential reasons why price channels could work are behavioral biases such as anchoring and extrapolation. Price Channels based on historical high/low prices (such as Donchian Channels and Pitchfork Channels[78]) try to capture these biases. Another reason for the potential importance of Price Channels is the market structure. For instance, limit orders, option strikes, or knock-out barriers are usually set at certain round price levels, or are determined by historical price distributions (e.g. 90% of the previous low price). These could provide important resistance or break-away levels to financial assets. A modification of the high/low price based channel tool is the so-called 'Percentile Channels' that use historical percentiles to validate a long/short trade signal (e.g. instead of requiring a price breaking up (or down) past its 100-day high (or low) to execute a long (or short) position, one could use 90th and 10th Percentile Channel as trigger levels.

Similar to high/low Channels and Percentile Channels, one can use **statistical confidence bands** around the estimation of a trend[79] and trade only when the trend is statistically significant: a positive trend is confirmed only when the price breaks above the higher band of the Price Channel and a negative trend is confirmed only when the price breaks below the lower band of the Price Channel.

Figure 62 shows an example of a systematic Trend-Following Channel strategy based on WTI crude oil futures and statistical confidence bands around the 30-day exponential moving average[80]. Specifically, a long position is entered when the close price crosses above 0.5 standard deviations above the past 30-day exponential moving average, and the long trade is unwound when the close price crosses below the 30-day exponential moving average. Similarly, a short position is entered when the close price crosses below 0.5 standard deviations under the past 30-day exponential moving average and the short trade is unwound when the close price crosses above 30-day exponential moving average.

---

[78] Donchian Channels is a Trend-following Channel breakout system developed by Richard Donchian. It plots the highest high and lowest low over past time intervals, and signals derived from this system are based on the following basic rules: when the price closes above the Donchian Channel, buy long and cover short positions; when the price closes below the Donchian Channel, sell short and liquidate long positions.
Pitchfork Channels is a Trend-Following Channel breakout system developed by Alan Andrews. The system contains three lines: the median trend line in the center with two parallel equidistant trend lines on either side. These lines are drawn by selecting three points, usually based on reaction to highs or lows during a particular historical time horizon.
[79] Methods for point estimation of trends can be found in the Appendix 'Mathematics of Trend Filtering'.
[80] In this example, the decay parameter lambda is set to be 0.5 and long/short band width is equal to 50% of past 30-day historical price volatility.

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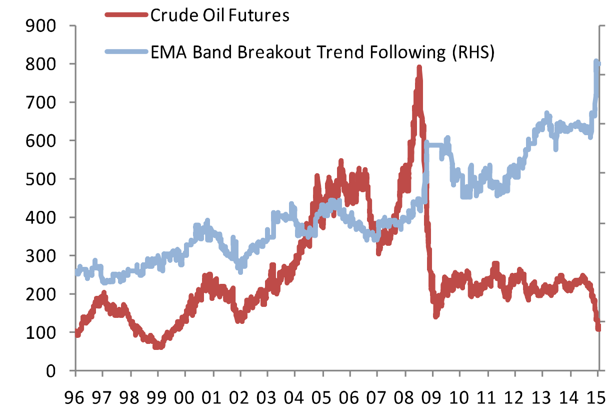
Figure 62: Exponential Moving Average (EMA) confidence band based Trend-Following strategy on crude oil (WTI) futures



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 63: P/L of JPY 100k notional investment in short-term reversion strategy on the Nikkei

Source: J.P. Morgan Quantitative and Derivatives Strategy.

A second use of statistical channels is to identify **short-term reversion,** which is a key risk-reducing component of Momentum strategies. For instance, **Bollinger's Bands** make use of moving averages and standard deviations of the past price information to derive overbought/oversold situations of a particular asset/security. [81] The rationale is based on the assumption of a normal distribution of price returns.

In a simple trading strategy on the Nikkei index based on standard Bollinger Bands, a buy signal is triggered when the index price crosses 2 standard deviations below the past 20-day moving average and a sell signal is triggered when the index price crosses 2 standard deviations above the past 20-day moving average. There were five long signals and four short signals triggered during 1 Jan 2014 - 31 Jan 2015, with a hit rate of 100%. Figure 63 shows the cumulative profit/loss (P/L) of such a strategy in 2014: a 45% return. Note that short-term reversion strategies generally work well in a range-bound market and could suffer in a strongly trending market. For instance, the same strategy based on standard Bollinger Band trading rules on the Nikkei index could have led to a -22% return in 2013. As a result, an assessment of general market conditions ('trending' or 'range-bound') is quite important.

An example of a market-adaptive Trend-Following strategy that uses high/low Trend Channels is the J.P. Morgan Continuum family of strategies.[82]. For example, the **J.P. Morgan Pure Continuum Basket of 16 Index (JMAB053E** <Index> on Bloomberg) allocates equal weights to 16 commodity futures based on the strategy's assessment of market conditions and trends. The strategy delivered an annualized return of 10% and Sharpe ratio of 1.1 during the past 10 years

[81] Bollinger's Bands is a contrarian Channel trading system developed by John Bollinger. In its standard setting, it consists of an N-period simple moving average (the mid-Band) and Upper/Lower bands based on two-standard deviations of past N-period price levels. $N = 20$ days in a Standard Bollinger Band. If the security price follows a normal distribution over a short-period of time, then the probably that the price will break above/below 2-standard deviations relative to its historical mean will be very small (roughly 4.55%).

[82] Continuum takes an equally weighted basket of S&P GSCI constituents using the Fast Continuum Methodology for each Commodity. Continuum strategy seeks to adjust its allocation approach to different market regimes; it employs rolling semi-annual Calibration Periods followed by monthly (FAST) Implementation Periods:

- Continuum determines the optimal pair of moving averages based on historical patterns during the respective Calibration Period and defines the nature of the regime which can be either Trending or Range bound
- During the Implementation Period, allocation signals are generated when the leading moving average (MA1) crosses the lagging moving average (MA2)
- The strategy monitors the market daily by means of Adaptive Regime Monitoring (ARM) to determine if sub-regimes are present. Three different ARM lookback periods are used, generating diversification across different time frames

For more information on the strategy design, please contact your J.P. Morgan salesperson or the Structuring Desk.

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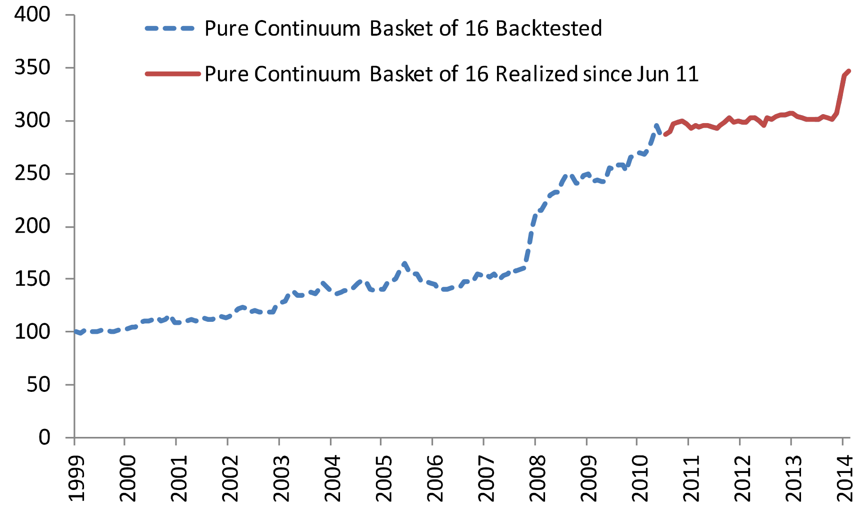
(Jan 2005 – Jan 2015). During the global financial crisis, the strategy returned 30% annualized and a Sharpe ratio of 2.1 (Aug 2007 – Mar 2009, Figure 64). The success of the Continuum strategy could be attributed to its use of moving averages and trend channels in detecting market conditions. Specifically, the market condition ('trending' or 'range-bound') is monitored on a daily basis for each individual commodity by observing the Adaptive Regime Monitor indicator.[83]

Figure 64: J.P. Morgan Pure Continuum Basket of 16 Commodities



Source: J.P. Morgan Quantitative and Derivatives Strategy

Regime-based Momentum Strategies

Another approach to identifying trending and reversion regimes is based on modeling macro regimes. For instance, we have reported performance of Momentum and reversion strategies in various macro regimes such as: Growth, Inflation, Volatility and Liquidity. During a 'bearish' macro regime, the observation horizon for asset trends typically becomes shorter and assets experience more reversion and price volatility. The opposite is true during 'bullish' macro regimes. A regime based Momentum strategy would first try to identify the macro regime and then adjust trending signals and leverage accordingly.

The **J.P. Morgan Asia ex-Japan Sector Rotator** (**CIJPAESR** <Index> on Bloomberg) is an example of a long-only macro-regime based Momentum strategy that opportunistically goes long up to 6 (out of 10) GICS sectors of the MSCI Asia ex-Japan stock universe. The performance of this strategy is shown in Figure 65. The strategy works as follows: a macro cycle indicator is observed on a monthly basis (the indicator is based on the OECD G7 lead indicator and US ISM Manufacturing PMI indices). Sector trends are defined as the past 3-month returns during macro Down cycles and 12-month returns during macro Up cycles.[84]

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[83] Adaptive Regime Monitor Indicator is defined as:

$$ARM_{\text{Raw}} = \frac{\dfrac{S_t - S_{t-L}}{S_{t-L}}}{\dfrac{S_{\max} - S_{\min}}{S_{\min}}}$$

where S_t is the security price, L is the lookback window size, $S_{\max}$ and $S_{\min}$ are the trend channel max and min during the lookback window similar to Donchian Channels.

[84] For more information on the strategy design, please contact your J.P. Morgan salesperson or the Structuring Desk.

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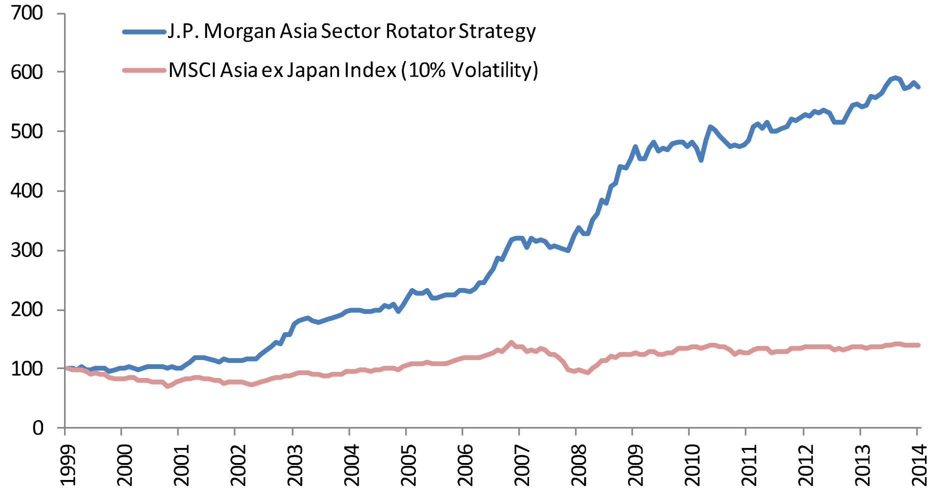
Figure 65: Historical performance of the J.P. Morgan Asia ex-Japan Sector Rotator



Source: J.P. Morgan Quantitative and Derivatives Strategy.
* MSCI Asia ex-Japan index is scaled to have ex-post volatility of 10% per annum, roughly equal to the realized volatility of the J.P. Morgan Asia ex-Japan Sector Rotator strategy.

Regime-based Trend-Following is a very broad field of research that can analyze not just broad macro regimes but also the impact of various **macro catalysts** (such as central bank announcements, releases of OECD/PMI, etc) and **market indicators** such as implied volatility, credit spreads, volumes, etc;

More recently, there is increased use of various scientific (Machine Learning) methods to uncover trending and reversion price regimes. These methods include State Space Models, Neural Networks, Graphical Models, Genetic Algorithms, Support Vector Machines and others. Interested readers can refer to Hastie et al. (2008) and Bishop (2007) for the mathematics underlying these methods. [85]

[85] See, Hastie, T., R. Tibshirani, and J. Friedman (2008), Elements of Statistical Learning, Second Edition, Springer; and Bishop, Christopher M. (2007), Pattern Recognition and Machine Learning, Springer.

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Chapter 4

Seasonality

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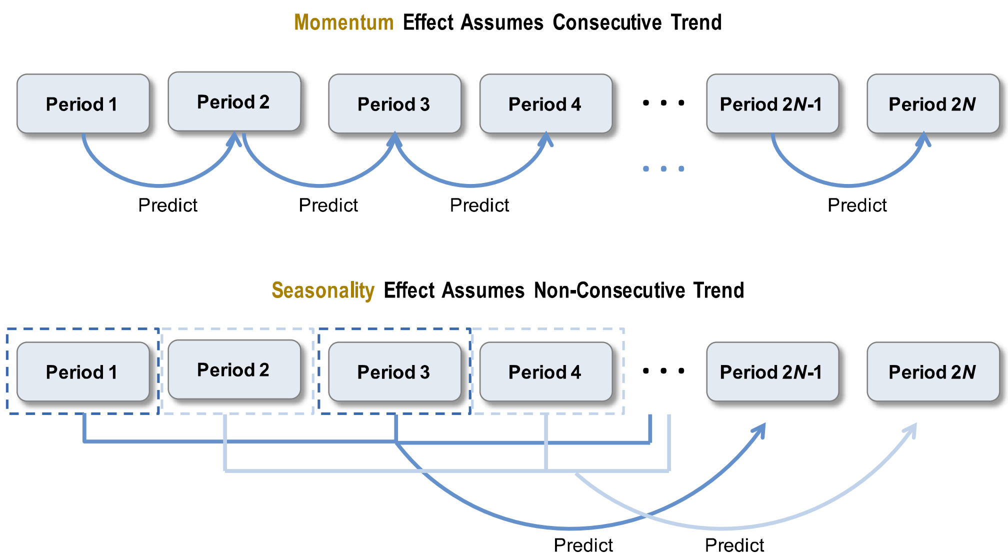
Introduction to Seasonality

Seasonal behavior of prices would suggest that assets show predictable behavior during certain months, days of the week, calendar seasons or other non-consecutive time periods. Similar to momentum, possible existence of seasonality patterns would contradict efficient market hypothesis. Theoretically, seasonality is closely related to momentum: while momentum can be defined by positive correlation between consecutive time periods, seasonality is defined by positive correlation of non-consecutive time periods.

To illustrate the difference - the Momentum factor assumes trending of an asset price in consecutive time periods (e.g. if performance was positive for the past 6 months, Momentum assumes it will be positive in the 7th month). Seasonality assumes trending of asset prices in non-consecutive time periods. For instance, if the performance was positive in March, June, September and December, the asset is expected to keep on delivering positive returns in those months. This is also illustrated by an example in Figure 66 below.

Figure 66: A Stylized Example of Consecutive Trend (Momentum) and Non-Consecutive Trend (Seasonality)



Source: J.P. Morgan Quantitative and Derivatives Strategy

Similar to Momentum, Seasonality effects could exist in both Absolute and Relative terms. **Absolute Seasonality strategies explore the continuations of non-consecutive time-series trend patterns** such as the 'option expiry week' effect we discussed in Price Patterns of Weekly Momentum that indicates US equities tend to outperform during the option expiry week (third Friday). **Relative Seasonality strategies try to identify seasonal patterns in relative performance**. For example, small cap stocks tend to outperform large cap stocks in January.

Examples of Seasonality effects include:

Month of the Year Effect: The 'Month of the Year' Seasonality effect refers to the underlying asset's tendency of showing out/under performance in certain months of a year. For example, the 'Sell in May effect' suggests that risky assets generally display good performance during Nov-Apr and bad performance during May-Oct in a year.

Week of the Month Effect: The 'Week of the Month' Seasonality effect refers to the underlying asset's tendency of showing out/under performance in certain weeks of a month. For example, the 'Option expiry' effect in the US suggests that US large cap stocks with significant option activities generally display good performance during the third-Friday week of a month, and bad performance during the fourth-Friday week of a month.

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Day of the Month Effect: 'Day of the Month' Seasonality effect refers to the underlying asset's tendency of showing out/under performance in certain business days of a month. For example, the 'month-end' effect suggests that certain assets could perform better during 1-5 business days around the month end. The 'month-end' effect could be related to 'window dressing' activities of long-only fund managers, monthly asset rebalances, or reversion of option expiry effect.

Day of the Week Effect: The 'Day of the Week' Seasonality effect refers to the underlying asset's tendency of showing out/under performance in certain days of a week. For example, the 'Friday' effect suggests that certain assets could perform better on Fridays than on other days of a week. A possible explanation for this effect is the weekly seasonality of investor psychology.

Asset-specific seasonal effects: For example, seasonality in some commodities relates to the supply/demand cycles of the underlying asset such as demand for power/energy during cold winter months, demand for gold during the Indian holiday season, etc. Equity sectors can also exhibit seasonality based on consumer spending seasonality, holidays schedule, election cycles, etc.

There are a number of drivers of seasonal price patterns, and they are generally specific to an asset or a market. A number of asset specific seasonality effects are documented in academic and sell side research.

Equity seasonality effects are well documented. For instance, Wachtel (1942), Rozeff and Kinney (1976), French (1980), Ariel (1987), Lakonishok and Smidt (1988), Brown et al. (1983), etc have identified the 'January effect' or 'Turn of the Year effect' in the US and international equity markets. In addition, Bouman and Jacobsen (2002) validated the 'Halloween effect' in 36 of the 37 countries in their study. [86] Another example is the annual pattern of US equity market performance during stages of a Presidential Election Cycle (Wong and MacAleer (2008))[87]. An and Park (2012) found a significant relationship between stock market and election cycles in international markets.

In our research report on Price Patterns of Weekly Momentum, we documented seasonality patterns related to option expiry cycles. In particular, delta hedging of option overwriting strategies usually leads to development of price momentum in the third week of a month, and subsequent reversion during the fourth week. Based on our finding, our structuring desk created the J.P. Morgan Kronos Strategy (Bloomberg ticker: JPMZKRNS<Index>) to track the effect. [88] After our report was published, academics reported on the same effect in the work of Stivers and Sun (2013).[89] Authors find that weekly returns of S&P 100 stocks tend to be high during the option expiry week relative to returns of other stocks with less option activity.

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[86] The Halloween effect, or Sell-in-May effect, is based on the old market wisdom of "Sell-in-May and go away" which dates back more than a century. The effect says that equity markets tend to return higher in winter months (November through April) than in summer months (May through October).

[87] Stock prices tended to fall during the first half of a Presidency, reached a trough in the second year, rose during the second half of a Presidency, and reached a peak in the third or fourth year.

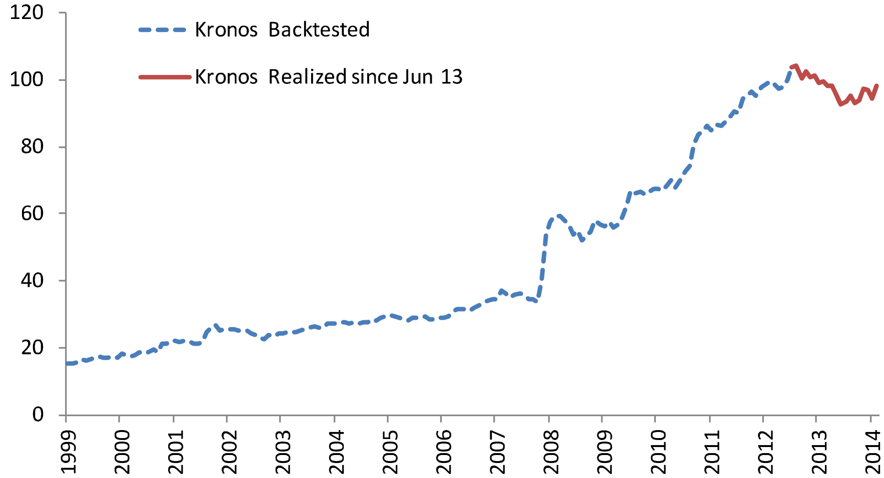
[88] The J.P. Morgan Kronos Strategy provides exposure to the S&P 500 end-of-month mean reversion strategy and the S&P 500 options expiry Momentum strategy using E-mini S&P 500 Futures:

1. One week before the end of month, if the front month E-mini S&P 500 Futures contract (Bloomberg: ES1 <Index>) is:
   Below the front month contract's level on the last day of the previous month, then go long the futures contract
   Above the front month contract's level on the last day of the previous month, then go short the futures contract
The index is fully invested for the next 5 business days.

2. Three business days before S&P 500 options expiry, if the front month E-mini S&P 500 Futures contract is:
   Above the front month contract's level on the previous expiry, then go long the futures contract
   Below the front month contract's level on the previous expiry, then go short the futures contract
The index is fully invested for the next 3 business days.
For more information on the strategy design, please contact your J.P. Morgan salesperson or the Structuring Desk.

[89] Stivers, Chris T. and Sun, Licheng, Returns and Option Activity over the Option-Expiration Week for S&P 100 Stocks (July 16, 2013). Journal of Banking and Finance, Vol. Forthcoming. Available at SSRN: http://ssrn.com/abstract=1571786.

Figure 67: Historical Performance of J.P. Morgan Kronos Strategy (1999-2014)



Source: J.P. Morgan Quantitative and Derivatives Strategy

Seasonality is known to exist in **government and corporate bond markets** as well. For instance, Chang and Huang (1990), and Wilson and Jones (1990) demonstrated the presence of a 'Turn of the year effect' in the US corporate bond market. In addition, Jordan and Jordan (1991) find evidence of a week-of-the-month effect for the corporate bond market. Athanassakos (2008) found that Canadian government bonds perform better in the May to October period than in the November to April period, opposite to the 'Halloween effect' observed in the equity market; Fridson (2000) documents seasonality in the spread between high-yield corporate and Treasury bonds; Smith (2001) finds 'January effect' for international bond markets in Germany, France and United Kingdom for both local currency and U.S. dollar returns.

In the **currency markets**, McFarland et al. (1982) showed that on average, US dollar-denominated returns are higher on Mondays and Wednesdays, and lower on Thursdays and Fridays, and this 'Friday-to-Monday effect' is due to an increase in the demand for non-US currencies prior to weekends. Copeland and Wang (1994) found that currencies generally exhibit greater volatility when there is an upcoming holiday, which could be caused by an increase in trading when these longer holiday effects occur. Li, Liu, Bianchi and Su (2011) found that there are five currencies (AUD, EUR, CHF, SEK and GBP) showing a significantly higher return in December than in other months, and the higher returns in these currencies are reversed in the month of January.

Seasonality effects in commodities were well observed for energy, livestock and agricultural products, which relate to seasonal supply and demand dynamics. For instance, Sørensen (2000) analyzed the seasonality in agricultural commodity prices[90], and provides empirical evidence on the theory of storage that predicts a negative relationship between stocks of inventory and convenience yields. Similarly, Lucia and Schwartz (2002), and Manoliu and Tompaidis (2002) consider seasonality in electricity and natural gas futures markets, respectively. Seasonality also exists in relative terms in the commodity markets, and the relative seasonality effects are often based on some economic relationship of commodity products. For instance, corn/ethanol crush spread usually displays seasonal variations.

There are various explanations for asset seasonality, and they tend to be different for different asset classes. For instance Ogden (2003) relates equity return patterns to the seasonality of macroeconomic variables while Keloharju and Linnainmaa (2014) attribute asset seasonality to seasonal variations in more generic Risk Factors that drive asset returns. Beyond macroeconomic and Risk Factor based explanations, Kamstra et.al (2003) links stock return seasonality to investor behavior changes due to the amount of daylight through the fall and winter with varying significance by latitudes. In the Treasury bond market, Kamstra, Kramer and Levi (2014) find that the seasonal pattern in Treasury returns is significantly correlated

[90] It is well documented that the Chicago Wheat, Corn, and Soybean futures exhibit strong seasonal tendencies for open interest to increase as the U.S. harvests approach.

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with a proxy for variation in investor risk aversion across the seasons[91]. Kamstra et al. (2014) analyzed the flow of money between mutual fund categories, and revealed investor preference for "safe" mutual funds in the autumn and risky funds in the spring. These Mutual Fund Flows, they argue, could be the reason behind seasonal asset allocations and the observed seasonality effects related to different asset classes.

Given the typically small statistical samples, there is also no general agreement on significance of various seasonal effects. For instance, based on three hundred years of UK stock market data, Zhang and Jacobsen (2012) suggest that the well-known 'January effect' is sample specific i.e. not significant in the full sample. However, the 'Halloween effect' or 'Sell in May effect' has been persistently significant during long-samples of economic/market regimes. In the currency market, Joseph and Hewins (1992) and Ke et al. (2007) found that the 'Friday-to-Monday effect' is subject to significant variations based on their studies of UK and Taiwan FX markets.

[91] Instead of traditional reasons for stock market seasonality, the authors conclude that "Seasonal Treasury return pattern does not arise due to macroeconomic Seasonalities, seasonal variation in risk, the weather, cross-hedging between equity and Treasury markets, conventional measures of investor sentiment, Seasonalities in the Treasury market auction schedule, Seasonalities in the Treasury debt supply, Seasonalities in the FOMC cycle, or peculiarities of the sample period considered".

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Quantifying Seasonality Across Assets

In this section, we analyze several Seasonality effects based on the same dataset used for our prototype Momentum Factors in Chapter 2-3. While there are various ways to analyze Seasonality effects, we focus on historical returns and test whether the returns in a particular day, week and month are above/below historical averages, and show statistically significant deviations.

Table 39 below shows the average 'Week-of-the-Month' (1st, 2nd, 3rd, and 4th week) returns during 1990-2014 along with *t*-statistics showing whether the returns in a particular week is statistically different from other weeks. We find that the first week (notably in UK/US) and the third week (notably in US/Japan) were generally positive for global equities, while the second (notably in France/Japan) and the fourth Friday weeks (notably in the US) were generally negative for global equities.

There are also some interesting 'Week-of-the-Month' seasonality effects in other asset classes. For instance, 5/10-year Germany Bunds tend to perform strongly during 1st-2nd Friday weeks, and relatively weak during 3rd-4th Friday weeks; CADUSD tends to be strong in 1st Friday weeks and weak in 3rd Friday weeks; JPYUSD tends to be strong in 2nd Friday weeks and weak in 1st Friday weeks; Silver tends to be weak during 3rd Friday weeks, while Platinum tends to be strong during 2nd Friday weeks.

Table 39: Average Week-of-the-Month Returns during 1990-2014 in basis points

Asset	1st Week	2nd Week	3rd Week	4th Week	Asset	1st Week	2nd Week	3rd Week	4th Week
Equity - Canada	+23.0 (1.1)	-5.7 (-1.3)	+15.5 (0.5)	-0.4 (-0.9)	Curncy - AUDUSD	+19.2 (1.6)	+8.8 (0.3)	+1.0 (-0.6)	-6.8 (-1.6)
Equity - France	+37.2 (1.9)	-21.1 (-2.0)	+11.2 (0.2)	-0.2 (-0.6)	Curncy - CADUSD	+13.8 (2.3)	+1.6 (0.0)	-11.6 (-2.5)	+1.6 (0.0)
Equity - Germany	+35.4 (1.5)	-4.8 (-1.0)	+6.4 (-0.3)	-0.1 (-0.7)	Curncy - CHFUSD	-0.7 (-0.4)	-7.6 (-1.3)	+10.7 (1.0)	+11.1 (1.1)
Equity - HK	+34.4 (0.6)	+5.5 (-1.0)	+18.1 (-0.3)	+22.3 (-0.1)	Curncy - DKKUSD	+2.8 (-0.1)	-2.8 (-0.8)	+6.5 (0.5)	+9.4 (0.9)
Equity - Japan	+21.7 (1.5)	-49.4 (-3.0)	+19.4 (1.3)	-16.4 (-0.9)	Curncy - EURUSD	+4.0 (0.4)	-5.4 (-0.9)	+4.1 (0.4)	+6.5 (0.7)
Equity - Netherlands	+36.0 (1.4)	-9.5 (-1.6)	+27.2 (0.9)	-2.6 (-1.2)	Curncy - GBPUSD	+5.3 (0.2)	-12.4 (-2.4)	+10.3 (1.0)	+5.5 (0.3)
Equity - Spain	+24.2 (0.7)	+0.5 (-0.8)	+27.7 (0.9)	-6.4 (-1.2)	Curncy - JPYUSD	-20.1 (-2.3)	+15.9 (2.2)	+0.4 (0.2)	+2.9 (0.6)
Equity - Switzerland	+34.9 (1.6)	+2.0 (-1.0)	+15.1 (0.1)	-2.6 (-1.3)	Curncy - NOKUSD	+13.6 (1.3)	-0.3 (-0.5)	-4.6 (-1.0)	+6.9 (0.4)
Equity - UK	+35.1 (2.2)	-9.2 (-1.5)	+13.3 (0.4)	-5.7 (-1.2)	Curncy - NZDUSD	+18.8 (1.2)	+21.3 (1.5)	+4.8 (-0.5)	-1.9 (-1.3)
Equity - US	+38.1 (2.1)	-4.6 (-1.5)	+28.2 (1.2)	-10.8 (-2.1)	Curncy - SEKUSD	+10.3 (1.0)	-1.5 (-0.4)	-3.5 (-0.7)	+11.5 (1.1)
Bond - Australia 10-year	+5.7 (-0.5)	+14.6 (1.2)	+6.6 (-0.3)	+3.5 (-0.9)	Comdty - Wheat	-32.3 (-1.0)	-12.3 (0.0)	-15.4 (-0.2)	+1.9 (0.7)
Bond - Canada 10-Year	+10.8 (0.7)	+4.4 (-0.8)	+4.2 (-0.8)	+7.8 (0.0)	Comdty - Crude Oil	+15.0 (0.1)	-0.1 (-0.6)	-9.5 (-1.0)	+54.9 (1.8)
Bond - Germany 5-Year	+7.1 (1.0)	+7.5 (1.2)	+0.2 (-1.9)	+4.2 (-0.2)	Comdty - Brent	+31.1 (0.3)	+19.9 (-0.2)	-12.7 (-1.6)	+57.4 (1.5)
Bond - Germany 10-Year	+10.1 (0.4)	+12.7 (1.1)	+4.2 (-1.1)	+7.6 (-0.2)	Comdty - ULSD	-0.6 (-0.6)	+21.6 (0.4)	-10.3 (-1.0)	+40.4 (1.2)
Bond - Japan 10-Year	+3.4 (-1.1)	+7.2 (0.3)	+8.6 (0.8)	+7.6 (0.4)	Comdty - Gasoline	+31.7 (0.4)	+5.0 (-0.8)	-9.7 (-1.4)	+60.6 (1.6)
Bond - US 2-Year	+5.2 (1.9)	+2.3 (-0.7)	+2.7 (-0.3)	+1.9 (-0.9)	Comdty - Aluminum	-18.7 (-0.9)	-4.3 (0.1)	+0.1 (0.4)	-4.6 (0.1)
Bond - US 5-Year	+9.2 (1.2)	+5.2 (-0.2)	+5.8 (0.0)	+2.4 (-1.2)	Comdty - Copper	-0.7 (-1.0)	+10.6 (-0.4)	+6.0 (-0.6)	+43.2 (1.5)
Bond - US 10-Year	+8.9 (0.2)	+7.8 (-0.1)	+8.9 (0.2)	+5.0 (-0.7)	Comdty - Gold	-5.3 (-0.9)	+22.3 (1.5)	-8.4 (-1.1)	+11.3 (0.6)
Bond - US 30-Year	+7.4 (-0.4)	+5.6 (-0.7)	+14.1 (0.6)	+10.2 (0.0)	Comdty - Silver	+26.2 (0.8)	+19.5 (0.5)	-31.7 (-2.1)	+14.5 (0.2)
Rates - 3M Eurodollar	+3.4 (1.5)	+2.4 (0.5)	+1.8 (-0.3)	+0.7 (-1.5)	Comdty - Platinum	+18.5 (0.5)	+48.3 (2.5)	-10.9 (-1.6)	-2.1 (-1.0)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* The t-statistic in the bracket is from a two-sample test of returns within a particular week and outside that week.
** Below-average returns are color-coded red and above-average returns are color coded green.

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Table 40: Day-of-Month Return Seasonality from 1990-2014 (in basis point)

Asset	-10d	-9d	-8d	-7d	-6d	-5d	-4d	-3d	-2d	-1d	Month End	+1d	+2d	+3d	+4d	+5d	+6d	+7d	+8d	+9d	+10d
Equity - Canada	+3.3 (0.2)	+8.5 (1.1)	+0.8 (-0.2)	-6.4 (-1.4)	-10.1 (-2.0)	+0.2 (-0.3)	-2.3 (-0.7)	+4.4 (0.4)	+0.6 (-0.2)	+4.7 (0.4)	+15.8 (2.3)	+8.9 (1.1)	+7.4 (0.9)	+11.3 (1.5)	-0.5 (-0.4)	-10.3 (-2.0)	+3.4 (0.2)	-8.7 (-1.8)	-10.0 (-2.0)	+2.4 (0.1)	+4.8 (0.5)
Equity - France	+6.7 (0.6)	-3.2 (-0.6)	-0.5 (-0.3)	-18.9 (-2.6)	-15.3 (-2.2)	+1.4 (-0.1)	+4.5 (0.3)	+14.8 (1.6)	+17.4 (2.0)	+9.5 (1.0)	+9.9 (1.0)	+11.1 (1.2)	+8.3 (0.8)	+11.1 (1.2)	-1.0 (-0.4)	-4.8 (-0.8)	-6.0 (-1.0)	-2.6 (-0.6)	-22.7 (-3.1)	+9.3 (0.9)	+5.9 (0.5)
Equity - Germany	-1.9 (-0.5)	+8.5 (0.8)	+6.3 (0.5)	-20.5 (-2.8)	-13.1 (-1.9)	-7.2 (-1.2)	+10.4 (1.0)	+11.1 (1.1)	+12.1 (1.2)	+2.1 (0.0)	+7.3 (0.6)	+11.7 (1.2)	+13.0 (1.3)	+12.1 (1.2)	-0.5 (-0.4)	-5.1 (-0.9)	+0.0 (-0.3)	-4.6 (-0.9)	-17.8 (-2.5)	+11.9 (1.2)	+8.3 (0.7)
Equity - HK	+18.0 (1.3)	-4.9 (-1.0)	-4.1 (-0.9)	+6.0 (0.1)	-7.4 (-1.3)	-7.0 (-1.2)	+13.7 (0.9)	+7.3 (0.2)	+20.0 (1.6)	+7.7 (0.3)	+27.2 (2.3)	+12.2 (0.7)	+26.8 (2.3)	-6.0 (-1.1)	+7.9 (0.3)	+8.2 (0.3)	+0.2 (-0.5)	-4.6 (-1.0)	-17.0 (-2.3)	-8.7 (-1.4)	+21.9 (1.8)
Equity - Japan	-0.7 (0.0)	-11.8 (-1.3)	+14.2 (1.7)	+0.4 (0.1)	-15.8 (-1.8)	+2.0 (0.3)	+5.0 (0.6)	+16.4 (1.9)	-1.3 (-0.1)	+4.2 (0.5)	-6.7 (-0.7)	+8.8 (1.1)	+21.0 (2.5)	-1.4 (-0.1)	+4.2 (0.5)	-3.1 (-0.3)	-17.9 (-2.0)	-6.1 (-0.7)	-14.6 (-1.7)	-19.7 (-2.3)	+16.5 (1.9)
Equity - Netherlands	+8.4 (0.7)	+11.9 (1.2)	+3.8 (0.1)	-9.7 (-1.6)	-9.2 (-1.6)	-8.3 (-1.5)	+5.8 (0.4)	+6.9 (0.5)	+12.9 (1.3)	+2.2 (-0.1)	+6.4 (0.5)	+17.1 (1.9)	+13.5 (1.4)	+9.2 (0.8)	+0.3 (-0.3)	-0.6 (-0.5)	-3.7 (-0.9)	-1.3 (-0.6)	-20.7 (-3.1)	+11.7 (1.1)	+7.5 (0.6)
Equity - Spain	+6.2 (0.4)	+5.7 (0.4)	+4.4 (0.2)	-16.7 (-2.4)	-8.7 (-1.4)	-4.5 (-0.9)	-2.8 (-0.7)	+8.0 (0.7)	+9.3 (0.8)	+2.1 (-0.1)	+9.2 (0.8)	+13.2 (1.3)	+15.2 (1.5)	+13.8 (1.4)	-4.2 (-0.8)	+0.1 (-0.3)	+6.4 (0.5)	+1.4 (-0.1)	-24.5 (-3.3)	+15.1 (1.5)	+7.8 (0.6)
Equity - Switzerland	+4.6 (0.3)	+1.2 (-0.3)	-0.0 (-0.4)	-6.0 (-1.4)	-9.8 (-1.9)	-4.3 (-1.1)	+2.0 (-0.1)	+6.4 (0.5)	+9.2 (1.0)	+8.2 (0.8)	+8.9 (0.9)	+12.6 (1.5)	+18.0 (2.3)	+9.5 (1.0)	+4.3 (0.2)	+0.5 (-0.4)	-3.0 (-0.9)	-4.9 (-1.2)	-19.0 (-3.4)	+11.5 (1.3)	+11.6 (1.3)
Equity - UK	+7.3 (0.8)	+5.4 (0.5)	-0.2 (-0.3)	-13.2 (-2.3)	-8.8 (-1.7)	-5.1 (-1.1)	+0.6 (-0.2)	+8.3 (1.0)	+12.9 (1.7)	-0.4 (-0.4)	+4.1 (0.4)	+20.1 (2.8)	+14.0 (1.9)	+2.5 (0.1)	+3.4 (0.2)	-0.3 (-0.3)	-0.8 (-0.4)	-1.7 (-0.5)	-18.6 (-3.2)	+6.1 (0.7)	+3.0 (0.2)
Equity - US	+3.1 (0.1)	+10.9 (1.3)	-1.3 (-0.6)	-14.0 (-2.6)	-10.1 (-2.0)	-2.7 (-0.9)	+0.6 (-0.3)	+12.5 (1.5)	+9.2 (1.0)	+2.6 (0.0)	-2.1 (-0.8)	+22.3 (3.0)	+4.2 (0.2)	+12.1 (1.4)	-4.7 (-1.2)	-6.9 (-1.5)	+7.4 (0.7)	-14.8 (-2.7)	-4.5 (-1.1)	+16.2 (2.1)	+8.5 (0.9)
Bond - Australia 10-year	+2.0 (0.1)	+3.0 (0.5)	-0.8 (-0.8)	-0.2 (-0.6)	-4.9 (-2.3)	+2.4 (0.2)	+2.4 (0.2)	+1.6 (0.0)	+1.4 (-0.1)	+2.8 (0.4)	+7.9 (2.2)	+5.0 (1.1)	-1.2 (-1.0)	+2.3 (0.2)	-1.9 (-1.2)	-0.0 (-0.6)	+4.5 (1.0)	-2.3 (-1.4)	+5.1 (1.2)	-2.4 (-1.4)	+3.4 (0.6)
Bond - Canada 10-Year	+4.7 (1.4)	+2.2 (0.3)	-1.5 (-1.4)	-3.3 (-2.2)	-1.0 (-1.2)	+2.7 (0.5)	+3.6 (1.0)	+3.0 (0.7)	+0.4 (-0.5)	+4.2 (1.2)	+10.6 (4.2)	+2.2 (0.3)	+1.8 (0.1)	-1.0 (-1.2)	+3.4 (0.8)	-2.7 (-2.0)	+1.0 (-0.2)	-0.9 (-1.1)	-1.2 (-1.3)	-0.6 (-1.0)	+4.8 (1.5)
Bond - Germany 5-Year	+1.0 (0.1)	+0.9 (0.0)	-2.3 (-2.6)	-1.5 (-1.9)	+1.3 (0.3)	+1.1 (0.2)	+0.3 (-0.5)	+0.7 (-0.1)	+1.1 (0.1)	+1.5 (0.5)	+4.3 (2.7)	+0.9 (0.0)	+0.0 (-0.7)	+0.3 (-0.5)	+2.7 (1.5)	+0.6 (-0.2)	+2.3 (1.1)	+1.0 (0.1)	+1.3 (0.3)	+0.3 (-0.5)	+0.1 (-0.6)
Bond - Germany 10-Year	+2.4 (0.4)	+2.3 (0.3)	-2.6 (-2.2)	-0.6 (-1.2)	+1.7 (0.0)	+1.0 (-0.3)	+0.8 (-0.4)	+2.0 (0.2)	+1.4 (-0.1)	+2.1 (0.2)	+7.9 (3.2)	+1.5 (-0.1)	-0.1 (-0.9)	-1.4 (-1.6)	+3.7 (1.1)	+2.4 (0.4)	+3.5 (1.0)	+2.2 (0.3)	+2.2 (0.3)	-0.5 (-1.1)	+3.3 (0.8)
Bond - Japan 10-Year	+4.1 (1.9)	+0.8 (-0.3)	+1.4 (0.1)	+1.7 (0.3)	+1.7 (0.3)	+1.2 (-0.1)	+3.8 (1.6)	+0.6 (-0.4)	-2.8 (-2.6)	+2.6 (0.9)	+1.7 (0.3)	+1.2 (0.0)	-1.1 (-1.5)	-0.1 (-0.9)	+2.5 (0.8)	-0.0 (-0.9)	+0.4 (-0.6)	+0.3 (-0.6)	+3.9 (1.8)	+3.3 (1.3)	-0.7 (-1.3)
Bond - US 2-Year	+0.3 (-0.5)	+0.8 (0.3)	+0.3 (-0.5)	-1.1 (-2.9)	-0.5 (-1.9)	-0.0 (-1.1)	+0.5 (-0.1)	+0.8 (0.3)	+0.6 (0.0)	+2.2 (2.8)	+2.8 (3.8)	+0.6 (0.0)	+1.2 (1.1)	+0.5 (-0.1)	+1.0 (0.7)	-0.5 (-1.9)	-0.4 (-1.7)	+0.5 (-0.2)	+0.6 (-0.1)	+0.5 (-0.2)	+1.6 (1.7)
Bond - US 5-Year	+1.7 (0.3)	+1.1 (-0.1)	+0.6 (-0.4)	-2.4 (-2.5)	-2.0 (-2.3)	-0.5 (-1.1)	+1.1 (0.0)	+2.2 (0.7)	-0.2 (-1.0)	+4.5 (2.3)	+7.0 (4.1)	+1.2 (0.0)	+2.0 (0.6)	-0.2 (-1.0)	+3.0 (1.3)	-1.7 (-2.0)	-0.3 (-1.0)	+1.2 (0.0)	+1.2 (0.0)	+1.0 (-0.1)	+3.6 (1.7)
Bond - US 10-Year	+3.1 (0.7)	+2.1 (0.2)	+1.1 (-0.2)	-2.8 (-2.1)	-3.8 (-2.5)	-0.1 (-0.8)	+1.8 (0.1)	+3.5 (0.9)	+0.1 (-0.7)	+6.3 (2.2)	+9.4 (3.6)	+1.0 (-0.3)	+1.5 (-0.1)	-1.5 (-1.5)	+4.5 (1.3)	-2.7 (-2.0)	+0.8 (-0.4)	+1.4 (-0.1)	+1.3 (-0.2)	+1.2 (-0.2)	+4.8 (1.5)
Bond - US 30-Year	+5.3 (1.0)	+0.9 (-0.3)	+3.3 (0.4)	-2.5 (-1.3)	-4.2 (-1.8)	+1.8 (-0.1)	+3.0 (0.3)	+3.6 (0.5)	+0.1 (-0.6)	+9.4 (2.2)	+14.8 (3.8)	+0.4 (-0.5)	+1.1 (-0.3)	-7.2 (-2.7)	+5.1 (0.9)	-4.0 (-1.8)	+1.6 (-0.1)	+0.5 (-0.5)	+0.7 (-0.4)	-0.5 (-0.7)	+8.5 (1.9)
Rates - 3M Eurodollar	+0.4 (-0.1)	+0.4 (0.1)	+0.3 (-0.3)	-0.6 (-2.4)	-0.6 (-2.3)	-0.4 (-1.8)	+0.2 (-0.4)	+0.5 (0.2)	+0.2 (-0.5)	+1.3 (2.2)	+1.5 (2.7)	+0.3 (-0.3)	+0.8 (0.9)	+0.5 (0.2)	+0.9 (1.3)	-0.1 (-1.1)	-0.0 (-1.1)	+0.3 (-0.3)	+0.6 (0.5)	+0.6 (0.4)	+1.0 (1.3)
Curncy - AUDUSD	-2.1 (-0.8)	-1.5 (-0.7)	+2.2 (0.2)	-1.1 (-0.5)	-1.9 (-0.8)	-6.4 (-1.8)	+2.4 (0.3)	+8.8 (1.8)	-2.8 (-1.0)	+1.8 (0.1)	+7.1 (1.4)	+4.3 (0.7)	+5.2 (1.0)	-3.1 (-1.0)	+2.9 (0.4)	+6.8 (1.3)	-0.9 (-0.5)	+1.2 (0.0)	-3.0 (-1.0)	+14.2 (3.1)	-4.2 (-1.3)
Curncy - CADUSD	-2.6 (-1.1)	-3.2 (-1.3)	+0.1 (-0.1)	-3.9 (-1.6)	+1.2 (0.3)	+3.4 (1.1)	+1.1 (0.3)	+2.4 (0.8)	+2.9 (0.9)	-0.9 (-0.5)	+4.3 (1.4)	+3.0 (1.0)	+4.4 (1.5)	+1.9 (0.6)	+0.8 (0.2)	+0.8 (0.1)	-0.8 (-0.4)	-0.7 (-0.4)	-2.7 (-1.1)	+4.0 (1.3)	-6.1 (-2.4)
Curncy - CHFUSD	+2.3 (0.4)	+4.6 (1.0)	+1.6 (0.3)	+2.3 (0.4)	+1.5 (0.2)	-2.0 (-0.6)	+6.5 (1.5)	+3.6 (0.8)	-6.3 (-1.7)	+2.7 (0.6)	+5.5 (1.3)	-2.0 (-0.6)	+4.5 (1.0)	-0.8 (-0.3)	-3.5 (-1.0)	-2.7 (-0.8)	-4.7 (-1.3)	-0.9 (-0.4)	+1.3 (0.2)	+1.5 (0.3)	-0.4 (-0.2)
Curncy - DKKUSD	+0.7 (0.0)	+1.8 (0.3)	+1.4 (0.2)	+0.6 (0.0)	+0.0 (-0.2)	-1.0 (-0.5)	+5.7 (1.4)	+6.6 (1.6)	-4.3 (-1.4)	+0.1 (-0.1)	+5.0 (1.2)	-1.6 (-0.6)	+6.5 (1.6)	-2.3 (-0.8)	-2.1 (-0.7)	+0.0 (-0.2)	-3.6 (-1.2)	-2.9 (-1.0)	+1.0 (0.1)	+2.7 (0.6)	+1.9 (0.4)
Curncy - EURUSD	+1.0 (0.2)	-1.5 (-0.5)	+1.8 (0.4)	+1.4 (0.3)	-0.9 (-0.3)	-1.7 (-0.5)	+5.2 (1.4)	+5.1 (1.4)	-5.8 (-1.7)	+2.8 (0.7)	+2.6 (0.7)	+0.1 (0.0)	+5.4 (1.4)	-3.8 (-1.1)	-2.4 (-0.8)	+0.4 (0.1)	-3.4 (-1.0)	-3.4 (-1.0)	-0.2 (-0.1)	+1.7 (0.4)	+1.8 (0.4)
Curncy - GBPUSD	-1.0 (-0.5)	+3.6 (0.8)	+2.4 (0.5)	-1.8 (-0.8)	+1.4 (0.2)	-3.7 (-1.4)	+5.3 (1.4)	+6.8 (1.8)	+0.5 (-0.1)	+3.5 (0.8)	+7.8 (2.1)	+0.7 (0.0)	+2.4 (0.5)	+1.8 (0.3)	-5.9 (-2.0)	-0.3 (-0.3)	-5.7 (-2.0)	-7.1 (-2.4)	-0.9 (-0.5)	+4.6 (1.2)	+3.6 (0.9)
Curncy - JPYUSD	+7.9 (2.1)	+0.5 (0.2)	-2.0 (-0.4)	-8.8 (-2.2)	+5.4 (1.5)	-6.3 (-1.6)	+1.0 (0.3)	-0.5 (0.0)	-2.8 (-0.6)	+1.5 (0.5)	-0.4 (0.0)	-2.4 (-0.5)	-5.0 (-1.2)	-1.3 (-0.2)	-0.2 (0.0)	+3.0 (0.9)	-5.7 (-1.4)	+8.0 (2.2)	+2.0 (0.6)	-2.5 (-0.6)	+0.8 (0.3)
Curncy - NOKUSD	+2.3 (0.4)	+0.1 (-0.2)	+3.5 (0.7)	-3.0 (-0.9)	+5.0 (1.0)	-1.5 (-0.5)	+5.0 (1.0)	+4.9 (1.0)	-3.1 (-0.9)	+2.6 (0.4)	+9.0 (2.0)	+1.5 (0.2)	+5.9 (1.2)	+2.6 (0.4)	-2.5 (-0.8)	-2.3 (-0.7)	+0.3 (-0.1)	-2.1 (-0.7)	-6.9 (-1.8)	+3.7 (0.7)	-0.7 (-0.4)
Curncy - NZDUSD	-1.1 (-0.7)	-1.3 (-0.7)	+4.5 (0.7)	+0.3 (-0.4)	-2.7 (-1.1)	-2.1 (-0.9)	+0.0 (-0.4)	+3.7 (0.5)	-3.8 (-1.4)	-0.3 (-0.5)	+6.8 (1.2)	+6.5 (1.1)	+6.0 (1.0)	+0.2 (-0.4)	+1.7 (0.0)	+3.6 (0.4)	-0.1 (-0.5)	+6.8 (1.2)	+2.0 (0.0)	+10.8 (2.2)	-0.2 (-0.5)
Curncy - SEKUSD	+4.1 (0.9)	+4.4 (0.9)	+1.1 (0.2)	+1.1 (0.2)	+0.4 (0.0)	-5.7 (-1.5)	+8.6 (1.9)	+0.0 (-0.1)	-5.7 (-1.4)	+3.2 (0.6)	+5.2 (1.1)	-1.1 (-0.4)	+6.4 (1.4)	+0.3 (0.0)	-3.1 (-0.8)	+1.0 (0.1)	+0.1 (-0.1)	-5.5 (-1.4)	-1.3 (-0.4)	+5.2 (1.1)	-0.2 (-0.1)
Comdty - Wheat	-2.5 (0.0)	+11.6 (1.5)	-11.4 (-0.9)	-0.4 (0.2)	-2.3 (0.0)	-1.7 (0.1)	+8.7 (1.2)	+0.6 (0.3)	-6.0 (-0.4)	-32.4 (-3.1)	+5.5 (0.8)	+5.7 (0.8)	-4.2 (-0.2)	+2.8 (0.5)	-2.2 (0.0)	-12.7 (-1.1)	+8.1 (1.1)	-4.7 (-0.2)	-13.5 (-1.1)	+5.4 (0.8)	-9.3 (-0.7)
Comdty - Crude Oil	-10.1 (-1.1)	+2.3 (-0.1)	-5.8 (-0.7)	-18.6 (-1.8)	+16.3 (1.1)	+18.8 (1.3)	-1.9 (-0.4)	+11.9 (0.7)	+18.5 (1.3)	+5.6 (0.2)	+10.6 (0.6)	+13.6 (0.9)	+3.1 (0.0)	-1.6 (-0.4)	-2.6 (-0.5)	-19.4 (-1.8)	-10.2 (-1.1)	+17.2 (1.2)	-0.9 (-0.3)	+24.1 (1.8)	-4.0 (-0.6)
Comdty - Brent	-16.2 (-1.8)	-2.1 (-0.6)	-2.8 (-0.7)	-18.7 (-2.0)	+30.6 (2.2)	+20.0 (1.3)	+4.1 (-0.1)	+5.8 (0.1)	+20.5 (1.4)	+13.9 (0.8)	+14.8 (0.9)	+12.4 (0.6)	+0.9 (-0.3)	+6.2 (0.1)	+1.7 (-0.3)	-6.1 (-1.0)	-14.8 (-1.7)	+19.1 (1.2)	-3.5 (-0.7)	+29.3 (2.1)	-4.4 (-0.8)
Comdty - ULSD	-16.9 (-1.7)	-0.1 (-0.2)	-4.5 (-0.6)	-16.2 (-1.6)	+15.9 (1.2)	+5.3 (0.3)	-2.0 (-0.4)	+14.2 (1.0)	+16.5 (1.2)	+6.1 (0.3)	+2.9 (0.0)	+3.0 (0.1)	+3.9 (0.1)	-2.2 (-0.4)	-5.8 (-0.7)	-19.5 (-1.9)	-8.1 (-0.9)	+27.9 (2.2)	+2.7 (0.0)	+23.5 (1.8)	+2.5 (0.0)
Comdty - Gasoline	-8.7 (-1.1)	+2.8 (-0.2)	-1.7 (-0.5)	-20.6 (-2.1)	+13.7 (0.8)	+20.6 (1.3)	-1.8 (-0.5)	+14.8 (0.8)	+25.1 (1.7)	+18.7 (1.2)	+11.7 (0.6)	+20.1 (1.3)	+10.9 (0.5)	-4.1 (-0.7)	-10.5 (-1.3)	-24.8 (-2.5)	-8.6 (-1.1)	+26.6 (1.8)	-2.1 (-0.6)	+21.4 (1.4)	+1.9 (-0.2)
Comdty - Aluminum	+1.8 (0.4)	-8.1 (-1.0)	+9.6 (1.5)	-7.1 (-0.8)	-1.9 (-0.1)	+0.7 (0.3)	-4.6 (-0.5)	-0.3 (0.1)	+1.6 (0.4)	+5.7 (1.0)	+12.1 (1.9)	-7.2 (-0.8)	-4.2 (-0.4)	-8.7 (-1.0)	-6.1 (-0.7)	-1.3 (0.0)	-8.3 (-1.0)	+7.9 (1.3)	-2.9 (-0.2)	+0.4 (0.2)	-5.7 (-0.6)
Comdty - Copper	+5.1 (0.2)	-1.4 (-0.6)	+11.3 (0.9)	-7.4 (-1.2)	+3.8 (0.0)	+2.5 (-0.1)	+21.6 (2.1)	+6.4 (0.3)	+9.0 (0.6)	+2.5 (-0.1)	+22.7 (2.2)	-1.2 (-0.5)	+8.3 (0.5)	-7.6 (-1.3)	-1.8 (-0.6)	+5.4 (0.2)	-6.1 (-1.1)	+1.5 (-0.2)	-2.7 (-0.7)	+7.3 (0.4)	-3.6 (-0.8)
Comdty - Gold	+13.0 (2.1)	+7.0 (1.1)	+10.0 (1.6)	+2.5 (0.3)	-5.0 (-1.0)	+3.4 (0.4)	+4.3 (0.6)	+4.8 (0.7)	-4.5 (-0.9)	-1.8 (-0.5)	+9.7 (1.5)	-2.7 (-0.6)	-4.8 (-1.0)	-3.0 (-0.7)	+5.5 (0.8)	+0.6 (-0.1)	+2.6 (0.3)	+5.3 (0.7)	-1.7 (-0.5)	-3.6 (-0.8)	-4.6 (-1.0)
Comdty - Silver	+10.6 (0.9)	+8.2 (0.6)	+16.9 (1.5)	+0.9 (-0.1)	-7.9 (-1.0)	-2.5 (-0.4)	+10.7 (0.9)	+6.5 (0.5)	-7.6 (-0.9)	+7.8 (0.6)	+23.6 (2.1)	+9.4 (0.7)	-8.0 (-1.0)	+7.2 (0.5)	+18.2 (1.6)	-9.7 (-1.1)	-1.7 (-0.4)	+7.2 (0.5)	-9.5 (-1.1)	-4.5 (-0.6)	-6.1 (-0.8)
Comdty - Platinum	+10.6 (1.1)	-0.2 (-0.4)	+11.2 (1.2)	-10.8 (-1.8)	-5.9 (-1.1)	-8.7 (-1.5)	-3.0 (-0.7)	+0.9 (-0.2)	-12.4 (-2.0)	+2.5 (0.0)	+29.7 (3.7)	+7.8 (0.7)	+4.3 (0.3)	+0.4 (-0.3)	+5.0 (0.4)	-6.1 (-1.2)	+12.0 (1.3)	+8.0 (0.8)	+16.8 (2.0)	+5.1 (0.4)	+4.3 (0.3)

Source: J.P. Morgan Quantitative and Derivatives Strategy. * The t-statistic in the bracket is from a two-sample test of returns within a particular month-day and outside that month-day. ** Below (Above)-average returns are color-coded red (green).

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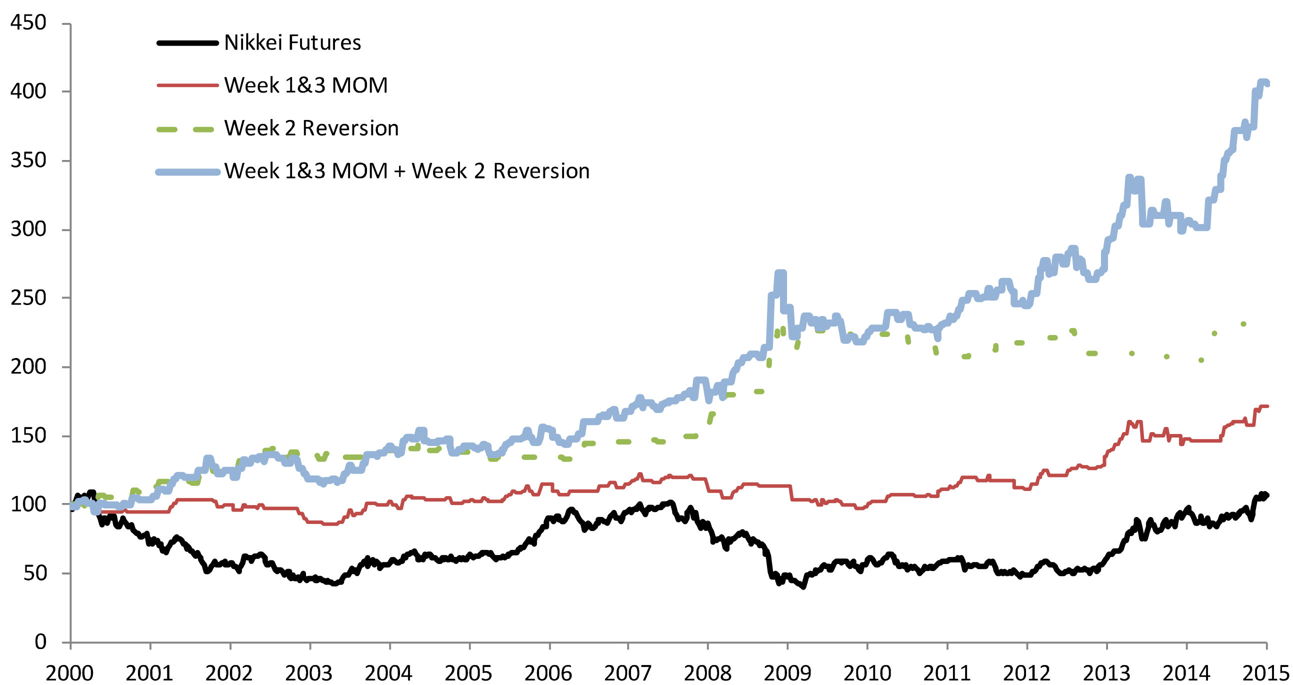
There are various explanations for this Week-of-Month effect in equities. For instance, the 3rd week seasonality may be partly attributed to investor behavior during expiry cycle of index option contracts, as we explained in our report on Price Patterns of Weekly Momentum.[92] The fourth week underperformance could be reversion of the 3rd week effect, and the first week/turn of the month seasonality could be due to the 'Turn-of-the-Month' effect. As shown in Table 40, global equity markets tend to be strong three business days prior to and after month-ends. This 'turn-of-the-month' Seasonality effect in equities[93] could be due to long-only fund inflows (subscriptions). Lastly, there is evidence of reversion during the second (notably in Japan market) and fourth (notably in the US market) Friday weeks following strong returns in the first and third weeks.

Figure 68 and Figure 69 show performance of 'Week-of-Month' and 'Day-of-Month' seasonality effects in S&P 500 futures and Nikkei futures. In particular, we constructed long only indices to capture:

(1) **1st and 3rd Week Momentum**: We enter a long position in the front month futures contract in the first and third Friday weeks if we observe positive price Momentum over the past four weeks;

(2) **2nd or 4th Week Reversion**: We enter a long position in the second (Nikkei) or fourth (S&P 500) Friday week if we observe negative price Momentum over the past four weeks.

Figure 68: Historical Performance of Week-of-the-Month Seasonality Strategies on Nikkei Futures (hedged into USD) during 1999-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy.

[92] Expiry dates for Asia-based index options are usually different. For instance, expiry date for Hang Seng Index option is the business day immediately preceding the last Business Day of the Contract Month; Expiry date for Nikkei Index option is the business day preceding the second Friday of each expiration month. Given earlier expiry of Nikkei index options, the investor behavior-based explanation could be the opposite to the other markets: given Japan was in a bear market during the past 20-years, investors likely enter expiry week with a reduction in 'long' stock hedge positions (of put options), resulting in negative market performance.
[93] We find similar 'turn-of-the-month' Seasonality effect in global government bond markets in the last two business days of a month.

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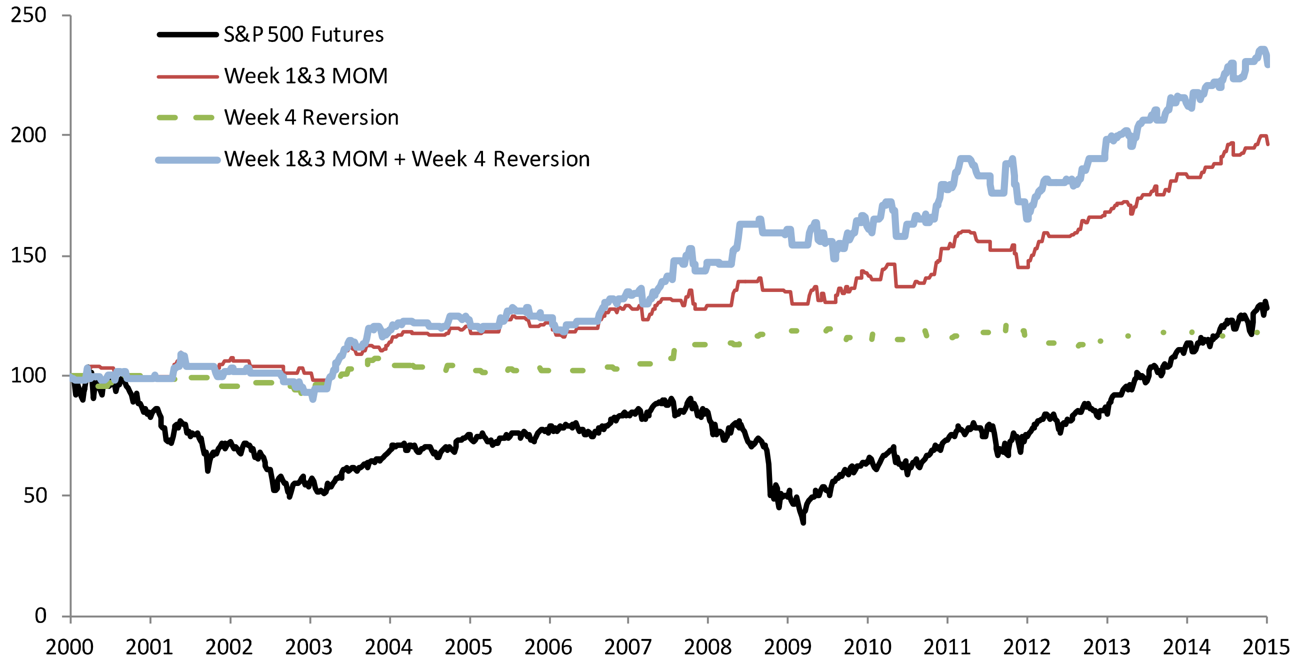
Figure 69: Historical Performance of Week-of-the-Month Seasonality Strategies on S&P 500 Futures during 1999-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy.

It is interesting to find that such a simple long-only Seasonality strategy would help avoid most of the equity drawdowns during the 2000-2001 tech bubble bust and the 2007-2008 Global Financial Crisis. Detailed performance/risk statistics are summarized in Table 41, where we also include an equally weighted Week-of-the-Month strategy combining S&P 500 and Nikkei strategies. Diversification between the two markets leads to a significant increase in return and Sharpe ratio during 2000-2014.

Table 41: Performance/Risk analysis of 'Week-of-the-Month' Seasonality Strategies for S&P 500 and Nikkei Index Futures during 2000-2014

	S&P 500 Futures				Nikkei Futures				Combined Strategy (Equal Weight)
	Long Only	Week 1&3 MOM	Week 4 Reversion	Week 1&3 MOM + Week 4 Reversion	Long Only	Week 1&3 MOM	Week 2 Reversion	Week 1&3 MOM + Week 2 Reversion	
Ann. Ex Ret (%)	1.7	4.6	1.0	5.7	0.0	3.6	6.0	9.7	7.9
STDev (%)	18.6	6.6	5.0	8.3	22.0	9.2	8.9	12.8	8.2
MaxDD (%)	-62.2	-10.2	-8.8	-17.0	-64.4	-21.3	-13.4	-19.2	-11.7
MaxDDur (in yrs)	13.3	2.0	3.7	2.0	14.8	5.1	5.8	3.2	2.1
***t*-Statistic**	**0.7**	**2.8**	**0.9**	**2.8**	**0.4**	**1.6**	**2.7**	**3.1**	**3.8**
Sharpe Ratio	**0.09**	**0.69**	**0.21**	**0.69**	**0.00**	**0.39**	**0.67**	**0.76**	**0.97**
Hit Rate (%)	54.2	90.2	93.1	83.3	54.0	90.2	95.8	86.0	76.2
Skewness	-0.60	-0.36	2.18	0.18	-0.38	-0.46	5.10	1.39	0.43
Kurtosis	6.78	11.04	32.26	7.28	2.37	11.61	77.78	19.80	8.93

Source: J.P. Morgan Quantitative and Derivatives Strategy.

One needs to keep in mind that the strategy performance was tested 'in-sample'. In other words we have identified the seasonal patterns (1st and 3rd week momentum, and 2nd and 4th week reversion) in the sample, and tested a hypothetical strategy that would have invested in these effects over the same sample time period. In that regard, the backtests are illustrative of the historical Seasonality effects, and do not imply continued performance in the future.

We next report 'Day-of-the-week' Seasonality effects by looking at average performance of various assets from Monday to Friday during 1990-2014 (Table 42). We find that almost all assets performed relatively weak on Mondays (weak performances are mostly statistically significant for currencies and commodities). In addition, equities rallied on average on Tuesdays and Fridays; G10 currencies rallied against the USD on Tuesdays and Thursdays and declined on Mondays; commodities performed relatively well during Wednesday-Friday periods. Historically "safe-haven" currencies (CHF, JPY, DKK, GBP) were weak on Fridays whereas commodity currencies (AUD, CAD, NZD) were relatively strong, which could be characterized as 'Friday risk-on' in the G10 currency market.

These patterns could be partly explained by investors' risk-taking behavior: more risk-taking on Thursdays-Fridays, and subsequent reversals on Mondays.

Table 42: Average Day-of-the-Week Returns during 1990-2014 in basis points

Asset	Mon	Tue	Wed	Thu	Fri	Asset	Mon	Tue	Wed	Thu	Fri
Equity - Canada	+0.9 (-0.4)	+3.8 (0.7)	-0.2 (-0.8)	+1.8 (-0.1)	+3.7 (0.6)	Curncy - AUDUSD	-4.1 (-2.9)	+3.0 (1.0)	+0.6 (-0.3)	+3.4 (1.2)	+3.3 (1.1)
Equity - France	-1.6 (-1.0)	+5.6 (1.1)	-0.0 (-0.5)	+3.4 (0.4)	+1.9 (0.0)	Curncy - CADUSD	-2.7 (-2.6)	+2.2 (1.6)	+0.8 (0.3)	+0.2 (-0.1)	+1.3 (0.8)
Equity - Germany	+7.0 (1.3)	+3.5 (0.3)	-1.9 (-1.2)	-0.9 (-0.9)	+4.3 (0.5)	Curncy - CHFUSD	-1.3 (-1.0)	+2.1 (0.9)	+0.7 (0.1)	+2.6 (1.2)	-1.4 (-1.1)
Equity - HK	+1.6 (-0.8)	+3.5 (-0.4)	+11.0 (1.4)	-3.9 (-2.1)	+13.0 (1.9)	Curncy - DKKUSD	-1.7 (-1.5)	+2.7 (1.3)	+0.5 (-0.1)	+3.4 (1.7)	-1.7 (-1.5)
Equity - Japan	-7.8 (-2.0)	+3.1 (0.9)	+0.7 (0.3)	+4.5 (1.3)	-2.1 (-0.5)	Curncy - EURUSD	-3.4 (-2.4)	+2.1 (1.2)	+0.6 (0.2)	+1.8 (1.0)	+0.3 (0.0)
Equity - Netherlands	+4.8 (0.6)	+4.7 (0.5)	-0.6 (-1.0)	+0.6 (-0.7)	+5.1 (0.7)	Curncy - GBPUSD	-2.0 (-1.9)	+2.2 (1.0)	+0.8 (0.0)	+4.7 (2.7)	-1.8 (-1.8)
Equity - Spain	-3.2 (-1.6)	+8.1 (1.5)	-3.1 (-1.6)	+4.0 (0.4)	+7.3 (1.3)	Curncy - JPYUSD	-0.2 (0.1)	+2.6 (1.7)	-2.6 (-1.4)	+2.5 (1.7)	-3.8 (-2.1)
Equity - Switzerland	-0.7 (-1.2)	+3.6 (0.3)	+3.5 (0.2)	+2.5 (-0.1)	+5.5 (0.9)	Curncy - NOKUSD	-2.6 (-1.8)	+0.6 (-0.1)	+2.3 (0.9)	+2.2 (0.8)	+1.1 (0.2)
Equity - UK	+1.7 (-0.1)	+5.5 (1.3)	-1.4 (-1.2)	+0.4 (-0.5)	+3.1 (0.5)	Curncy - NZDUSD	-2.4 (-2.3)	+1.8 (0.0)	+0.1 (-0.9)	+3.5 (0.9)	+5.9 (2.3)
Equity - US	+4.8 (0.7)	+6.0 (1.1)	+1.8 (-0.4)	+1.7 (-0.4)	-0.4 (-1.1)	Curncy - SEKUSD	-3.4 (-2.1)	+1.6 (0.6)	+3.3 (1.5)	+0.4 (0.0)	+0.3 (-0.1)
Bond - Australia 10Y	+1.0 (-0.6)	+0.9 (-0.6)	+3.3 (1.3)	+2.1 (0.3)	+1.1 (-0.5)	Comdty - Wheat	+1.9 (1.0)	-7.0 (-1.1)	+3.0 (1.3)	-8.8 (-1.5)	-1.6 (0.2)
Bond - Canada 10Y	+0.7 (-0.9)	+1.4 (-0.2)	+0.7 (-0.9)	+2.0 (0.5)	+3.0 (1.5)	Comdty - Crude Oil	-5.9 (-1.7)	-6.2 (-1.7)	+7.9 (0.9)	+7.8 (0.9)	+10.8 (1.5)
Bond - Germany 5Y	+0.5 (-0.8)	+0.7 (-0.4)	+0.8 (-0.2)	+1.1 (0.5)	+1.4 (1.0)	Comdty - Brent	-5.2 (-2.0)	-2.1 (-1.4)	+8.5 (0.7)	+13.3 (1.7)	+10.3 (1.0)
Bond - Germany 10Y	+2.0 (0.4)	+2.1 (0.5)	+0.8 (-1.1)	+0.9 (-0.9)	+2.6 (1.1)	Comdty - ULSD	-11.6 (-2.8)	-1.9 (-0.9)	+15.0 (2.5)	+12.6 (2.0)	-2.0 (-0.9)
Bond - Japan 10Y	+1.2 (-0.1)	+0.4 (-1.4)	+1.3 (0.0)	+2.7 (2.1)	+0.8 (-0.7)	Comdty - Gasoline	-16.4 (-4.0)	+0.0 (-0.9)	+12.9 (1.6)	+13.6 (1.7)	+13.1 (1.6)
Bond - US 2-Year	+0.2 (-1.8)	+0.7 (0.4)	+0.8 (0.6)	+0.7 (0.5)	+0.7 (0.2)	Comdty - Aluminum	-15.5 (-4.5)	+0.9 (0.7)	+4.7 (1.9)	+3.7 (1.6)	+0.0 (0.4)
Bond - US 5-Year	+0.7 (-0.8)	+2.1 (1.5)	+1.1 (-0.1)	+0.8 (-0.6)	+1.2 (0.0)	Comdty - Copper	-6.2 (-2.5)	+4.4 (0.2)	+3.8 (0.1)	+4.7 (0.3)	+10.7 (1.9)
Bond - US 10-Year	+1.4 (-0.3)	+3.1 (1.6)	+1.1 (-0.6)	+1.0 (-0.6)	+1.5 (-0.1)	Comdty - Gold	-0.4 (-0.5)	-1.5 (-1.0)	-0.2 (-0.5)	+0.1 (-0.3)	+6.8 (2.3)
Bond - US 30-Year	+1.9 (-0.1)	+3.8 (1.2)	+0.3 (-1.1)	+1.4 (-0.5)	+2.8 (0.5)	Comdty - Silver	-0.7 (-0.6)	+2.1 (0.0)	+1.4 (-0.1)	+6.5 (1.0)	+0.3 (-0.4)
Rates - 3m Eurodollar	+0.0 (-2.0)	+0.8 (2.0)	+0.5 (0.6)	+0.4 (0.1)	+0.3 (-0.7)	Comdty - Platinum	+0.3 (-0.7)	+0.9 (-0.4)	+3.9 (0.5)	+2.5 (0.0)	+4.2 (0.6)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* The t-statistic in the bracket is from a two-sample test of returns within a particular weekday and outside that weekday.
** Below-average returns are color-coded red and above-average returns are color coded green.

One should also notice that 'Day-of-the-week' Seasonality usually requires significant portfolio turnover and might not lead to after-cost viable trading strategies. However, they can still be very useful as additional signals in systematic trading strategies. For instance, in a weekly-rebalanced Momentum strategy, if one observes positive Momentum, it could be better to go long on Wednesday or Thursday closes or Friday openings rather than Friday closes due to 'Friday risk-on' effect. On the other hand, if one observes negative Momentum, it could be better to go short on Friday closes.

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Table 43: Average Month-of-the-Year Returns during 1990-2014 (%)

Asset	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
Equity - Canada	+0.4 (0.0)	+0.5 (0.1)	+0.7 (0.3)	+0.4 (0.0)	+1.7 (1.6)	-0.7 (-1.4)	+0.6 (0.2)	-0.5 (-1.1)	-1.6 (-2.5)	+0.8 (0.4)	+0.9 (0.6)	+1.8 (1.7)
Equity - France	+0.2 (-0.1)	+0.8 (0.4)	+1.3 (0.9)	+2.2 (1.7)	+0.2 (-0.2)	-0.6 (-0.9)	+0.1 (-0.2)	-1.5 (-1.7)	-2.5 (-2.8)	+1.7 (1.3)	+0.9 (0.5)	+1.4 (1.0)
Equity - Germany	+0.3 (-0.2)	+0.6 (0.1)	+0.5 (0.0)	+2.8 (2.0)	+0.4 (-0.1)	-0.0 (-0.4)	+1.0 (0.4)	-2.9 (-2.9)	-3.3 (-3.3)	+2.5 (1.7)	+2.1 (1.4)	+2.0 (1.3)
Equity - HK	-0.9 (-1.4)	+2.9 (1.3)	-1.0 (-1.4)	+2.3 (0.9)	+2.2 (0.8)	-0.1 (-0.8)	+2.4 (0.9)	-1.3 (-1.7)	-0.1 (-0.8)	+3.6 (1.8)	+1.0 (0.0)	+1.7 (0.4)
Equity - Japan	-0.4 (-0.3)	+0.4 (0.4)	+0.7 (0.6)	+1.3 (1.2)	-0.4 (-0.3)	-0.4 (-0.3)	-0.4 (-0.2)	-1.8 (-1.4)	-1.3 (-1.0)	-0.8 (-0.5)	+0.6 (0.6)	+1.3 (1.2)
Equity - Netherlands	-0.2 (-0.7)	+1.4 (0.7)	+0.8 (0.2)	+2.7 (1.9)	+0.8 (0.2)	-0.5 (-1.0)	+0.9 (0.3)	-0.8 (-1.2)	-2.8 (-3.1)	+1.1 (0.4)	+1.5 (0.8)	+2.4 (1.6)
Equity - Spain	+1.5 (0.8)	+1.0 (0.4)	-0.8 (-1.2)	+1.7 (1.0)	+0.1 (-0.4)	-0.7 (-1.0)	+0.5 (0.0)	-0.9 (-1.2)	-1.5 (-1.7)	+2.3 (1.5)	+1.7 (1.0)	+1.6 (0.9)
Equity - Switzerland	+0.2 (-0.4)	+0.6 (0.0)	+1.4 (0.9)	+1.6 (1.1)	+1.4 (0.9)	-0.6 (-1.3)	+0.2 (-0.4)	-1.3 (-2.2)	-1.1 (-1.9)	+1.8 (1.3)	+1.2 (0.7)	+1.7 (1.2)
Equity - UK	-1.1 (-1.8)	+0.8 (0.5)	+0.4 (0.1)	+1.8 (1.8)	-0.1 (-0.5)	-1.3 (-2.0)	+0.9 (0.7)	+0.1 (-0.3)	-1.1 (-1.8)	+1.4 (1.3)	+0.9 (0.7)	+1.4 (1.3)
Equity - US	-0.1 (-0.8)	+0.0 (-0.7)	+1.3 (0.9)	+1.5 (1.2)	+1.0 (0.5)	-0.6 (-1.4)	+0.5 (-0.1)	-0.9 (-1.8)	-0.5 (-1.3)	+1.4 (1.1)	+1.4 (1.0)	+1.6 (1.3)
Bond - Australia 10-year	+0.1 (-0.5)	-0.2 (-1.3)	-0.4 (-1.8)	+0.3 (-0.2)	+0.7 (0.8)	-0.3 (-1.5)	+0.9 (1.4)	+0.9 (1.3)	+0.7 (0.8)	+0.1 (-0.6)	+0.8 (1.0)	+0.6 (0.6)
Bond - Canada 10-Year	+0.0 (-0.9)	+0.3 (-0.1)	-0.5 (-2.6)	-0.2 (-1.6)	+0.6 (0.8)	+0.1 (-0.7)	+0.7 (1.0)	+1.1 (2.2)	+0.5 (0.6)	+0.5 (0.6)	+0.6 (0.7)	+0.3 (0.0)
Bond - Germany 5-Year	+0.2 (-0.2)	+0.2 (-0.2)	+0.0 (-0.9)	-0.1 (-1.3)	+0.1 (-0.4)	-0.1 (-1.8)	+0.4 (1.0)	+0.4 (1.3)	+0.5 (1.5)	+0.2 (-0.1)	+0.5 (1.5)	+0.1 (-0.5)
Bond - Germany 10-Year	+0.6 (0.7)	+0.3 (-0.1)	-0.1 (-1.4)	+0.1 (-1.0)	+0.2 (-0.7)	-0.1 (-1.7)	+0.7 (1.3)	+1.0 (2.2)	+0.6 (0.9)	+0.1 (-1.0)	+0.8 (1.4)	+0.2 (-0.7)
Bond - Japan 10-Year	-0.1 (-1.6)	+0.2 (-0.3)	+0.3 (0.2)	-0.0 (-1.3)	+0.6 (1.2)	-0.1 (-1.7)	+0.4 (0.5)	+0.3 (0.2)	+0.7 (1.7)	+0.5 (0.9)	+0.5 (0.9)	+0.1 (-0.7)
Bond - US 2-Year	+0.2 (0.8)	+0.1 (-0.9)	-0.1 (-2.5)	+0.0 (-1.0)	+0.1 (-0.8)	+0.2 (0.2)	+0.3 (1.4)	+0.3 (1.6)	+0.3 (2.1)	+0.1 (0.1)	+0.1 (-0.7)	+0.1 (-0.2)
Bond - US 5-Year	+0.3 (0.1)	+0.1 (-0.8)	-0.3 (-2.7)	-0.0 (-1.3)	+0.3 (0.1)	+0.3 (0.2)	+0.5 (1.2)	+0.7 (1.9)	+0.7 (2.0)	+0.2 (-0.2)	+0.3 (0.1)	+0.1 (-0.6)
Bond - US 10-Year	+0.2 (-0.4)	+0.1 (-0.7)	-0.4 (-2.2)	-0.1 (-1.3)	+0.5 (0.4)	+0.4 (0.1)	+0.6 (0.8)	+1.0 (2.0)	+0.9 (1.6)	+0.1 (-0.8)	+0.6 (0.6)	+0.3 (-0.2)
Bond - US 30-Year	+0.0 (-0.8)	+0.1 (-0.7)	-0.8 (-2.5)	-0.1 (-1.0)	+0.8 (0.7)	+0.5 (0.2)	+0.8 (0.6)	+1.6 (2.3)	+0.9 (0.8)	+0.0 (-0.8)	+1.0 (1.1)	+0.5 (0.1)
Rates - 3M Eurodollar	+0.1 (0.2)	+0.0 (-0.6)	-0.1 (-2.6)	+0.0 (-1.1)	+0.1 (-0.5)	+0.1 (0.5)	+0.2 (1.4)	+0.2 (1.6)	+0.2 (1.8)	+0.1 (0.4)	+0.0 (-1.1)	+0.1 (0.1)
Curncy - AUDUSD	+0.1 (-0.2)	+0.7 (0.6)	+0.4 (0.2)	+1.3 (1.7)	-0.7 (-1.5)	+0.6 (0.5)	+0.5 (0.3)	-0.7 (-1.6)	+0.2 (-0.1)	+0.5 (0.4)	-0.1 (-0.5)	+0.4 (0.3)
Curncy - CADUSD	-0.4 (-1.0)	+0.2 (0.2)	+0.1 (0.0)	+1.0 (2.1)	+0.4 (0.7)	+0.1 (0.0)	-0.1 (-0.3)	-0.1 (-0.3)	+0.4 (0.8)	-0.1 (-0.3)	-0.6 (-1.6)	+0.0 (-0.1)
Curncy - CHFUSD	-1.3 (-2.3)	-0.2 (-0.5)	+0.1 (-0.1)	+0.1 (0.0)	+0.0 (-0.2)	+0.4 (0.5)	+0.8 (1.1)	+0.2 (0.2)	+1.0 (1.5)	-0.4 (-0.8)	-0.7 (-1.3)	+1.3 (1.9)
Curncy - DKKUSD	-1.0 (-2.0)	-0.1 (-0.4)	+0.1 (0.0)	+0.3 (0.3)	-0.2 (-0.7)	+0.4 (0.4)	+0.5 (0.6)	-0.2 (-0.6)	+1.3 (2.0)	-0.1 (-0.4)	-0.4 (-1.0)	+1.2 (1.9)
Curncy - EURUSD	-1.1 (-2.1)	-0.3 (-0.5)	-0.1 (-0.3)	+0.4 (0.5)	-0.3 (-0.6)	+0.3 (0.4)	+0.5 (0.7)	-0.1 (-0.3)	+1.0 (1.7)	-0.2 (-0.4)	-0.6 (-1.1)	+1.2 (2.1)
Curncy - GBPUSD	-0.1 (-0.6)	-0.6 (-1.6)	-0.1 (-0.5)	+1.1 (1.8)	-0.1 (-0.5)	+0.8 (1.2)	+0.8 (1.3)	-0.3 (-0.9)	+0.5 (0.6)	+0.1 (-0.2)	-0.6 (-1.5)	+0.6 (0.8)
Curncy - JPYUSD	-0.4 (-0.5)	-0.4 (-0.5)	-0.7 (-1.1)	+0.1 (0.3)	+0.4 (0.8)	+0.1 (0.3)	+0.0 (0.2)	+0.6 (1.0)	+0.2 (0.4)	+0.8 (1.5)	-1.0 (-1.5)	-0.6 (-0.8)
Curncy - NOKUSD	-0.6 (-1.2)	+0.1 (0.0)	+0.3 (0.3)	+0.8 (1.1)	-0.2 (-0.6)	-0.2 (-0.5)	+0.8 (1.0)	-0.0 (-0.3)	+1.2 (1.8)	-0.2 (-0.5)	-1.0 (-1.9)	+0.7 (0.9)
Curncy - NZDUSD	+0.2 (-0.2)	+0.3 (-0.1)	+0.3 (-0.2)	+1.4 (1.6)	-0.4 (-1.3)	+0.7 (0.5)	+0.3 (-0.1)	-0.4 (-1.3)	+0.3 (-0.1)	+0.5 (0.2)	+0.3 (-0.2)	+1.1 (1.2)
Curncy - SEKUSD	-0.7 (-1.2)	-0.3 (-0.6)	+0.0 (-0.1)	+1.0 (1.3)	-0.5 (-0.9)	+0.1 (0.0)	+0.7 (0.9)	-0.1 (-0.4)	+1.2 (1.8)	-0.2 (-0.4)	-1.2 (-2.1)	+1.1 (1.5)
Comdty - Wheat	-1.0 (-0.3)	-1.0 (-0.3)	-1.6 (-0.7)	-0.3 (0.2)	-0.9 (-0.2)	-2.7 (-1.4)	+1.7 (1.5)	+1.1 (1.1)	-0.9 (-0.2)	-0.2 (0.2)	-0.6 (-0.1)	-0.2 (0.2)
Comdty - Crude Oil	+0.1 (-0.2)	+1.4 (0.4)	+3.6 (1.6)	+1.7 (0.6)	+0.1 (-0.3)	+1.2 (0.4)	+2.1 (0.8)	+2.2 (0.9)	+2.7 (1.2)	-3.4 (-2.2)	-3.5 (-2.2)	-1.2 (-1.0)
Comdty - Brent	+1.2 (0.1)	+1.8 (0.4)	+4.1 (1.7)	+2.9 (1.0)	+0.7 (-0.2)	+1.4 (0.2)	+2.5 (0.8)	+3.2 (1.2)	+2.9 (1.0)	-3.0 (-2.2)	-3.0 (-2.3)	-2.1 (-1.7)
Comdty - ULSD	-1.1 (-0.9)	+1.8 (0.7)	+3.3 (1.6)	+1.9 (0.8)	-0.2 (-0.4)	+1.9 (0.8)	+1.3 (0.5)	+3.7 (1.8)	+2.2 (1.0)	-4.0 (-2.6)	-2.9 (-1.9)	-2.0 (-1.4)
Comdty - Gasoline	+2.2 (0.6)	+1.3 (0.1)	+5.3 (2.2)	+2.6 (0.8)	+0.8 (-0.1)	-0.5 (-0.8)	+3.0 (1.1)	+4.4 (1.7)	-0.2 (-0.7)	-3.4 (-2.3)	-2.9 (-2.1)	-0.2 (-0.6)
Comdty - Aluminum	+1.4 (1.5)	+0.1 (0.4)	-1.1 (-0.8)	-0.3 (0.0)	-2.2 (-1.8)	+0.4 (0.6)	+1.3 (1.4)	-1.9 (-1.5)	-1.3 (-1.0)	-0.5 (-0.2)	+0.7 (0.9)	+0.1 (0.4)
Comdty - Copper	+0.4 (-0.2)	+2.7 (1.4)	+2.1 (1.0)	+1.3 (0.4)	-0.2 (-0.7)	+1.0 (0.2)	+3.1 (1.7)	+0.1 (-0.5)	-1.9 (-1.9)	-0.8 (-1.2)	+0.9 (0.1)	+0.4 (-0.3)
Comdty - Gold	+0.7 (0.5)	+0.7 (0.6)	-1.2 (-1.6)	-0.0 (-0.3)	-0.0 (-0.3)	-0.8 (-1.1)	+0.2 (0.1)	+0.5 (0.4)	+2.1 (2.2)	-1.3 (-1.8)	+1.4 (1.3)	+0.1 (-0.1)
Comdty - Silver	+2.2 (1.1)	+2.7 (1.5)	+1.0 (0.4)	-0.2 (-0.4)	-1.3 (-1.1)	-2.3 (-1.7)	+1.8 (0.9)	-0.6 (-0.6)	+0.9 (0.3)	-2.0 (-1.5)	+1.5 (0.7)	+1.1 (0.4)
Comdty - Platinum	+2.9 (2.2)	+3.6 (2.8)	+0.0 (-0.4)	-0.1 (-0.6)	+1.0 (0.4)	-0.6 (-1.0)	+0.6 (0.0)	-0.9 (-1.3)	-1.6 (-1.9)	-1.0 (-1.3)	+1.6 (1.0)	+0.5 (0.0)

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* The t-statistic in the bracket is from a two-sample test of returns within a particular month and outside that month.
** Below-average returns are color-coded red and above-average returns are color coded green.

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Table 43 shows 'Month-of-the-Year' effect across assets over the past 25-years (from 1990 to 2014). One can observe the following patterns:

(1) Developed Market equities performed well during October – December and April, and less so during February – March periods; on the other hand, January, June, August and September saw average negative performances.

(2) Government bond futures performed well during July - September and November, but suffered during March - April periods; Bond performance was below average in December and February as well (opposite to Equities).

(3) G10 currencies (relative to USD) were strong in April, July, September, December and relatively weak in January, May, August, November.

(4) Commodities also exhibited Seasonality effects: For instance, energy was strong during February – April and July – September periods, but weak in October - December period; copper was strong in February, March, July and weak in September, October; etc.

With these results, one again has to keep in mind limitations related to sample data size. In particular, studying monthly Seasonality over a 30-year period just barely meets the criteria of having a significant sample. Table 44 below shows Equity Seasonality effect in different 30-year periods going back to 1871. One can see that 'Sell in May' was a good strategy before the 1990s as S&P 500 generally returned negatively in May. However, selling in May turned out to be a less successful strategy in the most recent three decades: S&P 500 posted positive returns in every May during 1985-1996 and the anticipated 'May-selling' event seems to have been postponed to June.

Table 44: Non-Overlapping 30-Year Average Monthly Returns (%) of S&P 500 by Month-of-Year during 1871-2014

Period	Average	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
1871-1899	0.14	1.17	0.42	-0.29	0.07	-0.52	-0.56	0.06	1.01	0.85	-0.56	0.27	-0.28
1900-1929	0.42	1.55	-0.49	0.28	1.02	-0.32	0.07	0.41	1.51	0.52	-0.38	0.68	0.25
1930-1959	0.53	1.46	-0.35	-0.78	0.93	-0.40	2.21	3.25	1.07	-1.86	0.10	-0.55	1.28
1960-1989	0.59	1.85	0.02	0.92	1.14	-0.63	0.10	0.25	1.15	-0.82	0.54	1.25	1.27
1990-2014	0.68	0.13	0.09	1.41	1.68	1.03	-0.46	0.68	-0.82	-0.39	1.51	1.47	1.83
1871-2014	0.47	1.27	-0.07	0.27	0.95	-0.21	0.30	0.95	0.84	-0.34	0.20	0.60	0.85

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg, Robert Shiller.

Additionally, one can notice that the 'January effect' has gradually moved earlier in the year. During 1871-1929, January returned more than 1% above average (117bps in Jan vs 14bps average during 1871-1899, and 155bps in Jan vs 42bps average during 1900-1929). Perhaps in anticipation of this seasonality, the average December returns increased during the 1930-1959 time period. During 1960-1989, November outperformed ahead of December, while in 1990-2014, October outperformed ahead of November.

Overall, we find the 'Halloween effect' to be more persistent than a fixed 'month-of-the-year' Seasonality such as the 'January effect' and it exists in both absolute and relative terms. Indeed one can show that equity cumulative returns from November to December, and from February to April, were significantly higher than bond returns over the same time period. In addition, bonds happened to outperform equities during May-September (see Table 43).

Based on these seasonalities in bond and equity markets, one can design a simple asset allocation strategy. Figure 70 below shows a simple weight allocation based on 'Sell Equities in May and Buy in November', and 'Sell Bonds in November and Buy in May'.

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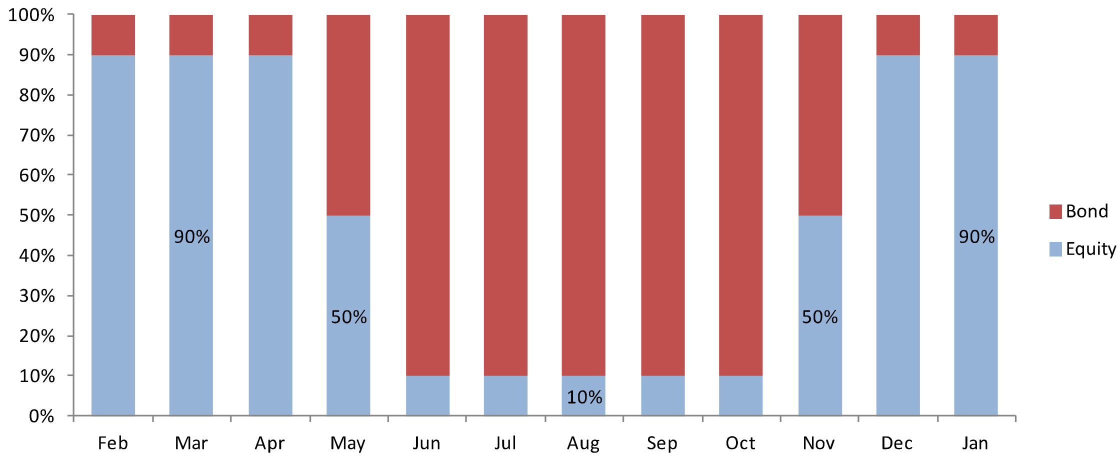
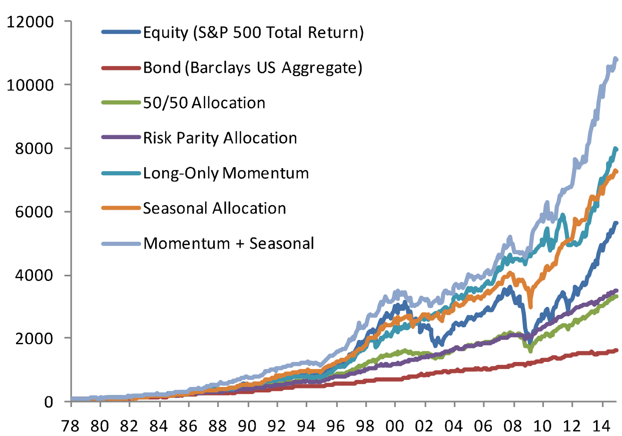
Figure 70: An Example of a 'Seasonality Inspired' Equity-Bond Allocation



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 71 shows performance of this 'Seasonality' allocation as well as performance of other popular bond-equity allocation methods: 50/50 fixed weight, Risk Parity allocation, 12-month price Momentum-based allocation.[94] We also show results for an allocation that combines Seasonality and Momentum. For equities we used the S&P 500 Index, and for bonds we used the Barclays US Aggregate Bond Index. Table 45 summarizes related performance-risk metrics during 1978-2014.

Figure 71: Equity/Bond Allocation during 1978-2014: A comparison of asset allocation methods



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 45: Performance/Risk Stats for Various Asset Allocation Methods during 1978-2014 (Monthly Rebalance)

	50/50	Risk Parity	MOM	Seasonal	Seasonal + MOM
Excess Return (%)	4.8	5.0	7.3	7.0	8.2
STDev (%)	8.6	5.9	11.5	9.4	10.0
MaxDD (%)	-28.7	-21.8	-30.7	-28.6	-21.4
MaxDDur (in yrs)	4.8	5.3	4.9	5.8	4.7
***t*-Statistic**	**3.6**	**5.1**	**4.1**	**4.7**	**5.1**
Sharpe Ratio	**0.56**	**0.83**	**0.64**	**0.75**	**0.82**
Hit Rate (%)	60.1	65.3	62.8	64.2	64.2
Skewness	-0.39	-0.06	-0.82	-0.06	-0.02
Kurtosis	1.27	2.34	6.37	2.14	1.62

Source: J.P. Morgan Quantitative and Derivatives Strategy.

A prototype Momentum strategy that allocates 100% of notional to the best performing asset is inherently riskier than a 50/50 allocation strategy (annualized volatility of 11.5% for the former vs 8.6% for the latter). Over the entire test period during 1978-2014, the Momentum based tactical allocation delivered an excess return of +7.3% per annum, outperforming 50/50 by +2.5% each year. In addition, the Momentum strategy delivered a Sharpe ratio of 0.64, +14% higher than that of 50/50.

[94] In the Risk Parity allocation program, rebalance weights are inverse proportional to the volatility of the underlying assets over the past month; In the 12-month price Momentum based allocation program, 100% of notional is allocated to the best performing asset (based on 12-month total return) among S&P 500 Index, Barclays US Aggregate Bond Index and 1-Month US Treasury Bill (Cash).

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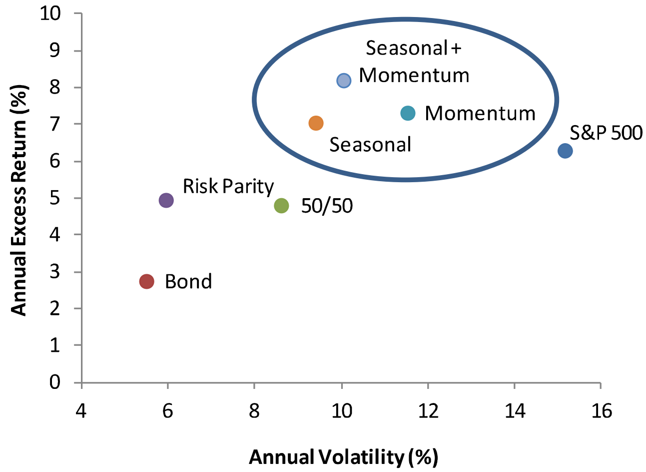
Seasonal tactical allocation based on the 'Halloween effect' (Figure 70) delivered comparable return to a Momentum strategy (+7% per annum over Treasury bill) with less strategy risk. As a result, the Seasonality allocation strategy had a comparably high Sharpe ratio of 0.75 over the past four decades. Finally, given Momentum and Seasonality captures different dimensions of asset return persistence, one could further enhance portfolio return/risk profile by combining these two allocations.[95]

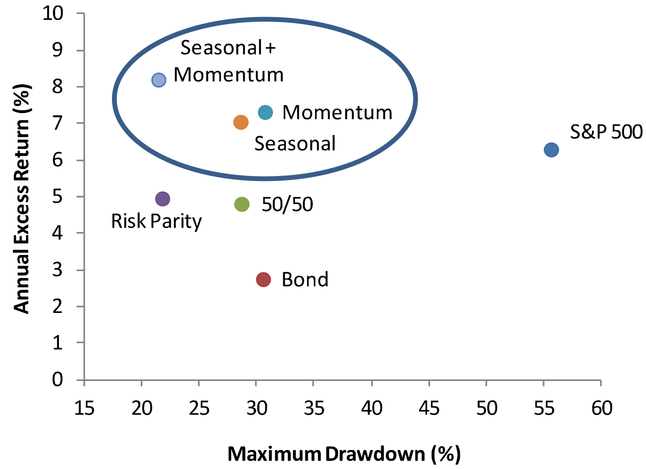
Figure 72 and Figure 73 below plot risk-return diagrams for five allocation schemes (50/50, Risk Parity, Momentum, Seasonal, Seasonal/Momentum rotation). We compared strategies based on two risk metrics: asset volatility and maximum drawdown. In particular, the strategy outperformed Risk Parity approach by +3.2% per annum for a similar drawdown risk. We would stop short of declaring Momentum and Seasonality allocation to be the best performing as one has to keep in mind statistical limitations of the Seasonality signal. In particular, the Seasonality signal was selected based on the bond/equity performance over the full data sample (i.e. in-sample).

Figure 72: Risk/Return Comparison of Bond-Equity Allocation Strategies: 1978-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 73: Risk/Return Comparison of Bond-Equity Allocation Strategies: 1978-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy.

[95] We tested a simple rotation between Momentum and Seasonality which pursues the best performing strategy over the past month and this strategy delivered an excess return and Sharpe ratio of +8.2% and 0.82 respectively during 1978-2014.

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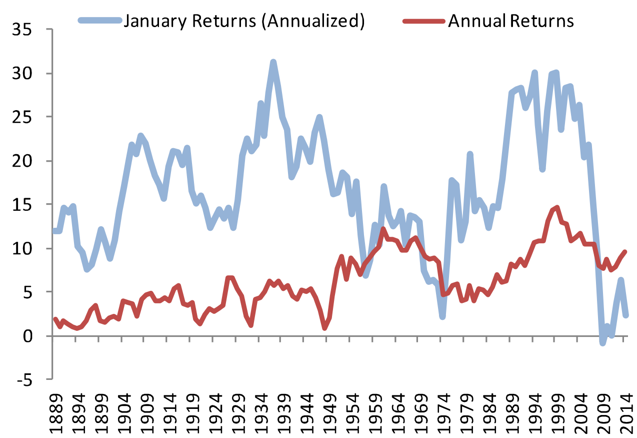
Prototype Seasonality Risk Factors

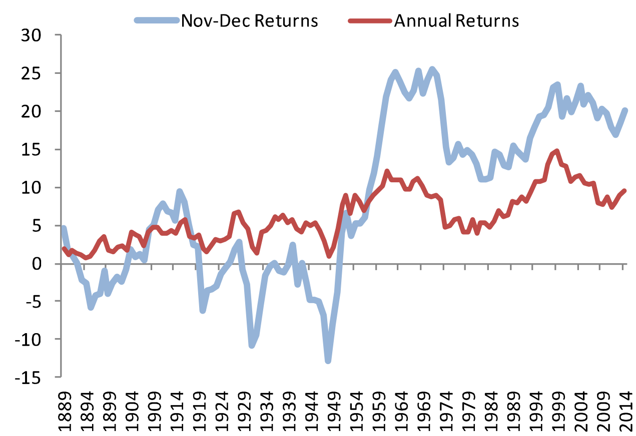
Given the potential pitfalls of using full sample calibration of Seasonality signals, one should prefer a dynamic Seasonality strategy that is constantly calibrated from recent, out of sample data. Using a constant, full sample Seasonality prescription may fail when investors change their behavior, and a dynamic Seasonality strategy may be able to adapt to such changes. For instance, Figure 74 shows that the 'January effect' in the US stock market lost effectiveness during the past 20 years.[96] Figure 75 shows that the Nov-Dec effect became significant since the 1940s, potentially as a result of investors positioning early for the 'January trade'.

Figure 74: Trailing 20-year Average Returns of S&P 500 Index in January (Annualized) vs Annual Averages



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 75: Trailing 20-year Average Returns of S&P 500 Index in Nov-Dec (Annualized) vs Annual Averages



Source: J.P. Morgan Quantitative and Derivatives Strategy.

A dynamic Seasonality strategy considers recent price patterns and adjusts seasonal allocations accordingly. For instance, instead of overweighting Equities during the fixed window during November-April period, one could compare historical performance over a certain lookback window (e.g. 10 or 20 years) and identify the time-varying Seasonality. Based on this idea, we test prototype Seasonality models for the same set of assets used in our prototype Momentum Factors in Chapter 2.

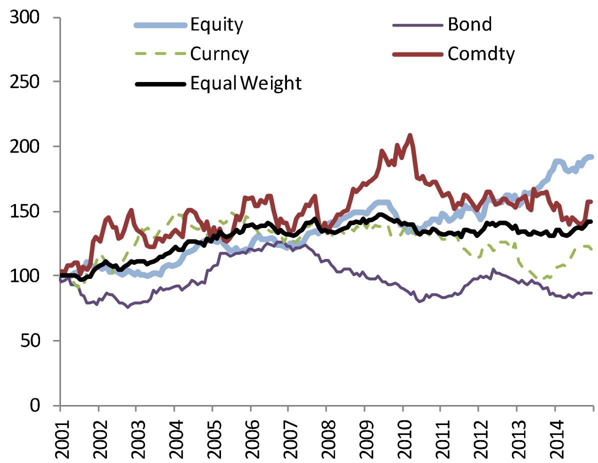
For prototype Seasonality models, we calculate average month-of-the-year returns during the past 10-years for each underlying asset and rebalance the portfolio to go long top-N assets and short bottom-N assets according to the average seasonal performance over the next month ($N = 3$ to be consistent with prototype Momentum models in Chapter 2). We have also applied a target volatility of 5% for each asset in the long/short portfolio.[97]

Historical performance of the prototype Seasonality models is shown in Figure 76, and related performance and risk statistics in Table 46. Among different asset classes, only the equity Seasonality Risk Factor has consistently generated positive risk-adjusted returns since 2001 (return of +4.8% and Sharpe Ratio of 0.67). By comparison, bond and currency prototype Seasonality Factors performed poorly since 2007, while commodity prototype Seasonality Risk Factor failed to perform since 2010.

[96] Average January returns during 1995-2014 was only 0.2%, while S&P 500 returned an average annual return of roughly +10%.

[97] Unlike Trend-Following models based on price Momentum, our tests find that volatility targeting doesn't necessarily help enhance portfolio performance for a seasonality Risk Factor. A marginal volatility target is applied to make cross-asset strategies more comparable and make the seasonality models consistent with our prototype Trend factors.

Figure 76: Prototype Seasonality Risk Factors by Asset Class



Source: J.P. Morgan Quantitative and Derivatives Strategy.

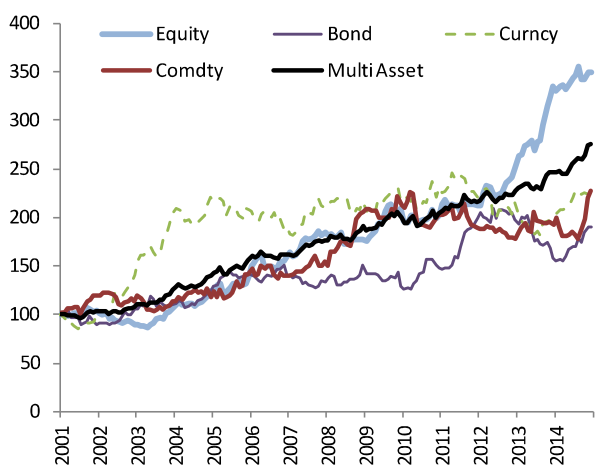
Table 46: Performance/Risk Stats for Prototype Seasonality Factors

	Equity	*Bond*	*Curncy*	*Comdty*	*Equal Weight*
Excess Ret (%)	4.8	-1.0	1.4	3.3	2.5
STDev (%)	7.1	9.3	10.5	15.0	5.7
MaxDD (%)	-15.0	-36.3	-36.7	-33.0	-11.7
MaxDDur (yrs)	2.8	8.2	10.9	4.8	5.5
***t*-Statistic**	**2.6**	**-0.2**	**0.7**	**1.1**	**1.8**
Sharpe Ratio	**0.67**	**-0.11**	**0.13**	**0.22**	**0.45**
Hit Rate (%)	59.5	48.2	52.4	51.2	56.5
Skewness	0.09	0.52	-0.03	0.18	-0.06
Kurtosis	0.23	2.06	1.13	1.73	0.22

Source: J.P. Morgan Quantitative and Derivatives Strategy.

The poor performance of bond, currency, and commodity prototype Seasonality Risk Factors is not surprising given we discovered similar poor performance of prototype Relative Momentum Risk Factors before. The major culprit is again the short portfolio, which often contributed to drag on performance while increasing overall strategy volatility. As a result, in designing enhanced prototype Seasonality Risk Factors, we overlay an element of Absolute Momentum in the short portfolios: a bottom-ranked asset by historical seasonal return enters the short portfolio only if it's past three month return[98] is negative. Figure 77 shows the Absolute Momentum enhanced Seasonality Risk Factors and Table 47 summarizes related performance and risk statistics.

Figure 77: Enhanced Prototype Seasonality Risk Factors by Assets



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 47: Perf/Risk Stats for Enhanced Prototype Seasonality Factors

	Equity	*Bond*	*Curncy*	*Comdty*	*Multi Asset*
Excess Ret (%)	9.3	4.7	5.8	6.1	7.5
STDev (%)	9.4	11.5	12.1	12.7	5.9
MaxDD (%)	-18.1	-25.8	-26.2	-21.7	-7.0
MaxDDur (yrs)	2.3	2.6	4.6	4.7	0.9
***t*-Statistic**	**3.8**	**1.7**	**2.0**	**2.0**	**4.7**
Sharpe Ratio	**1.00**	**0.41**	**0.48**	**0.48**	**1.27**
Hit Rate (%)	64.9	58.3	54.8	58.3	64.9
Skewness	-0.41	-0.22	0.06	0.01	-0.37
Kurtosis	0.60	0.83	0.84	1.50	0.16

Source: J.P. Morgan Quantitative and Derivatives Strategy.

98 We tested other window sizes for the Absolute Momentum requirement and found similar overall results. In general, a longer window makes it more difficult to short equity/bond and thus makes the overall strategy more long-biased. A three-month Absolute Momentum window strikes some balance between overall performance and market-neutrality.

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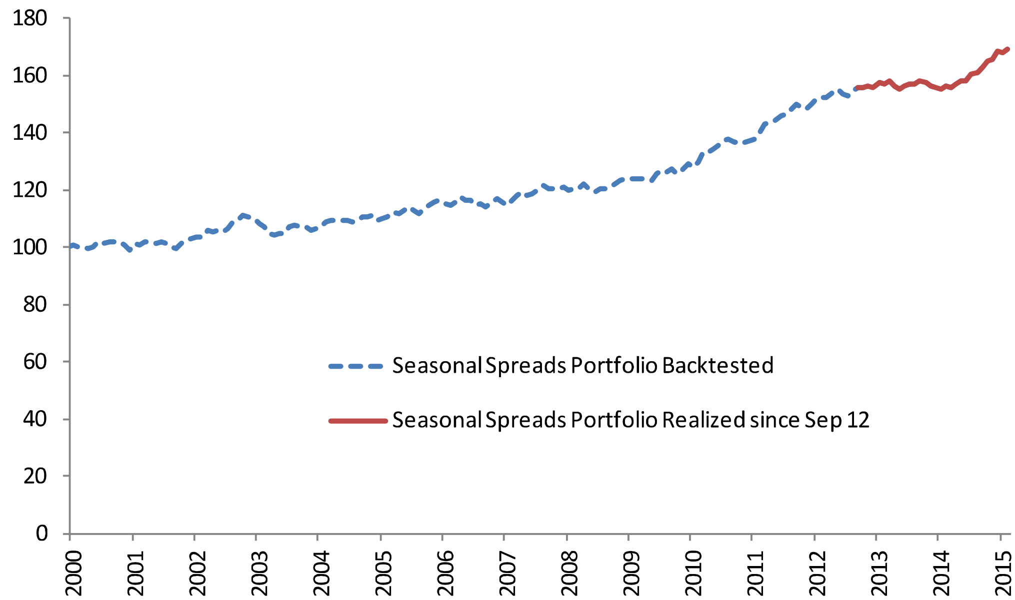
Modifying the short leg of the Seasonality factor leads to significant improvement across asset classes. Cross asset diversification helped reduce asset-specific risks in Seasonality strategies - this multi-asset Seasonality model delivered quite consistent performance (+7.5% per annum) during 2001-2014 with low risk of drawdown.[99]

Note that our Seasonality indices were constructed in a very simple fashion. One can create more advanced strategies by including only assets or spreads between assets that are known to have seasonal patterns. **J.P. Morgan Seasonal Spreads Commodity Strategy** (Bloomberg ticker: JMABSSPE<Index>) is based on this approach. The commodity market is first split into 27 fundamental pairs (commodity groups). For each pair, a +1/54 allocation is made to the commodity that exhibits historical outperformance in the relevant month, and a -1/54 allocation is made for the other in the pair. Aggregate exposures to all underliers are risk managed and market-neutrality maintained in order to make the aggregate portfolio well-diversified and less prone to market risk[100].

Figure 78: J. P. Morgan Commodity Seasonal Spreads Portfolio Strategy



Source: J.P. Morgan Quantitative and Derivatives Strategy

Having analyzed historical performance, we next examine correlation between the prototype Seasonality models and their correlation with prototype Absolute Momentum factors introduced in Chapter 2.

Table 48 shows that Seasonality Factors are positively correlated with Momentum within an asset class, while correlations are low between different asset classes. While the correlation between equity Seasonality Factor and equity Momentum Factor is positive (+37%), there is also a considerable diversification benefit by combining these two strategies given both of them performed strongly (an equally weighted portfolio has a higher Sharpe ratio of 1.11 and lower drawdown at -11.6% than Momentum or Seasonality strategy alone). This generalizes our findings in the section 'Correlation of Momentum Strategies' on page 30 and makes the case that cross-asset diversification is an essential element in constructing an efficient Momentum and Seasonality portfolio.

[99] In the example of multi-asset seasonality model, we assigned a 40% weight to the equity enhanced Seasonality Factor and 20% weights to bond/currency/commodity enhanced Seasonality Factors.
[100] For more information on the strategy design, please contact your J.P. Morgan salesperson or the Structuring Desk.

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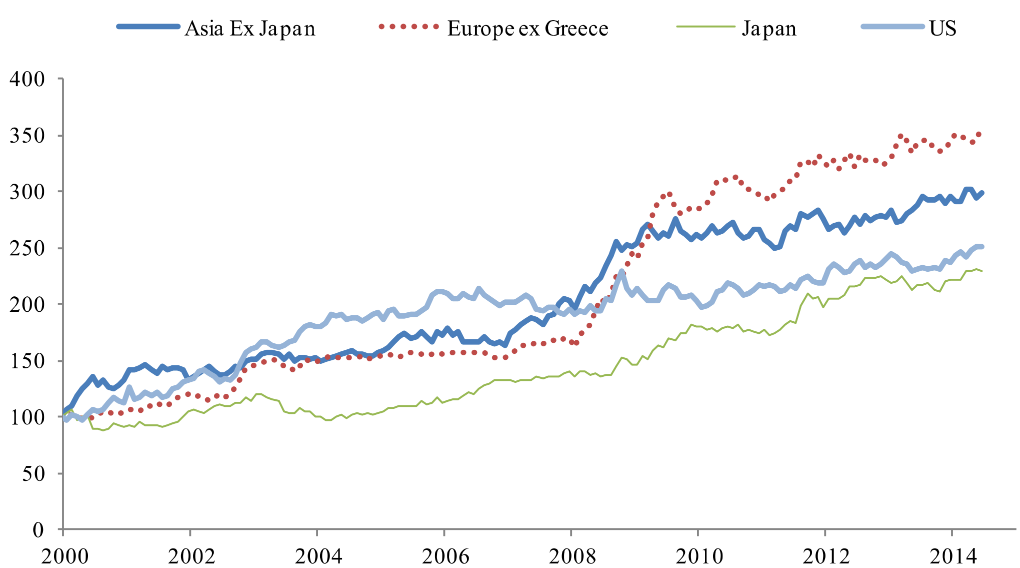
Table 48: Correlation Between Momentum and Seasonality Risk Factors Across Assets (2001-2014)

	Momentum - Equity	Momentum - Bond	Momentum - Curncy	Momentum - Comdty	Seasonality - Equity	Seasonality - Bond	Seasonality - Curncy	Seasonality - Comdty
Momentum - Equity	100%	8%	25%	18%	**37%**	-1%	11%	11%
Momentum - Bond	8%	100%	16%	10%	-13%	**65%**	8%	-2%
Momentum - Curncy	25%	16%	100%	32%	4%	12%	**35%**	13%
Momentum - Comdty	18%	10%	32%	100%	7%	9%	12%	**51%**
Seasonality - Equity	**37%**	-13%	4%	7%	100%	-11%	14%	8%
Seasonality - Bond	-1%	**65%**	12%	9%	-11%	100%	4%	0%
Seasonality - Curncy	11%	8%	**35%**	12%	14%	4%	100%	6%
Seasonality - Comdty	11%	-2%	13%	**51%**	8%	0%	6%	100%

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Similar to Momentum, Seasonality is not only useful for macro-level allocations between equity indices, bonds, currencies and commodities, but can also be employed on a micro-level such as in the selection of individual stocks. Seasonality of individual stocks can be defined in the same way as for indices (i.e. calculating performance of stock relative to a benchmark. in a specific calendar month). As we argued in our research piece Stock Seasonality Trading Model: How to Use Stock Periodic Seasonality to Improve Quant Model Performance, stocks which outperformed/underperformed in a particular period of the year tend to keep on doing so in future years. Academic studies have also established evidence of stock-level seasonality both in US and international markets[101]. Figure 79 shows the performance of such a Seasonality strategy in the US, Europe, Asia ex-Japan and Japan. Interested readers can refer to our primer on Equity Risk Premia Strategies for more information and analysis on stock-related Momentum and Seasonality factors.

Figure 79: Performance of the Stock Seasonality Factor in the US, Europe, Asia ex-Japan, and Japan



Source: J.P. Morgan Quantitative and Derivatives Strategy, MSCI, Factset, IBES.

[101] See, for example, Heston, Steven L. and Sadka, Ronnie (2004), Seasonality in the Cross-Section of Expected Stock Return. AFA 2006 Boston Meetings Paper. Available at SSRN: http://ssrn.com/abstract=687022. And Heston, Steven L. and Sadka, Ronnie (2007), Common Patterns of Predictability in the Cross-Section of International Stock Returns. Available at SSRN: http://ssrn.com/abstract=971141 .

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Seasonality and Momentum Factor Portfolios

In this section, we will further explore how to combine Seasonality and Momentum factors. To start with, we apply a broad set of asset allocation methods[102] to the prototype 12-Month Absolute Momentum and Seasonality factors in Equities, Bonds, Currencies and Commodities (eight prototype models in total). Base on the results, we could compare performance of allocation methods (similar to our studies in Cross Asset Systematic Strategies and Equity Risk Premia Strategies reports).

Specifically, we tested the following allocation methodologies, where factor weights are rebalanced on a monthly basis:

1. Equal Weighted portfolio (EW),
2. Equal Marginal Volatility portfolio (EMV),
3. Mean-Variance Optimized portfolio (MVO),
4. Global Minimum Variance portfolio (GMV),
5. Most Diversified portfolio (MDP),
6. Risk Parity or Equal Risk Contribution portfolio (RP).

To calculate the weights at each of the month-end rebalance dates, we use a covariance matrix estimated by trailing 24-month factor returns. For MVO return estimates, we use the annualized average of past 6-month returns.

Table 49 below shows the performance and risk of the six methodologies over the tested time period (from Jan 2003 to Dec 2014). Figure 80 on the next page plots the performance.

Table 49: Performance and Risk Metrics for Portfolios of Prototype Momentum and Seasonality Factors

	EW	EMV	MVO	GMV	MDP	RP
Ann. Ex Ret (%)	7.2	7.4	10.2	7.8	7.6	7.6
CAGR (%)	7.2	7.4	10.2	7.9	7.7	7.7
STDev (%)	5.8	5.7	9.7	6.2	6.3	5.7
MaxDD (%)	-4.9	-5.2	-11.0	-5.2	-5.1	-4.8
MaxDDur (in yrs)	1.5	1.5	1.1	0.9	0.7	0.8
***t*-Statistic**	**4.3**	**4.5**	**3.7**	**4.4**	**4.2**	**4.6**
Sharpe Ratio	**1.24**	**1.29**	**1.06**	**1.26**	**1.20**	**1.32**
Hit Rate (%)	65.3	67.4	64.6	71.5	67.4	67.4
Skewness	-0.18	-0.23	-0.16	-0.43	-0.37	-0.23
Kurtosis	0.10	0.21	0.93	0.66	0.41	0.13

Source: J.P. Morgan Quantitative and Derivatives Strategy. * Performance is calculated during the backtesting period from Jan 2003 to Dec 2014.

Based on the historical backtest, we can observe the following[103]:

1) EW had the lowest return (CAGR at +7.2%) while MVO had the worst drawdown (-11%) and Sharpe ratio (1.06). On the other hand, MVO had the highest return (CAGR at +10.2%), while Risk Parity had the smallest drawdown (-4.8%) and highest Sharpe ratio (1.32).

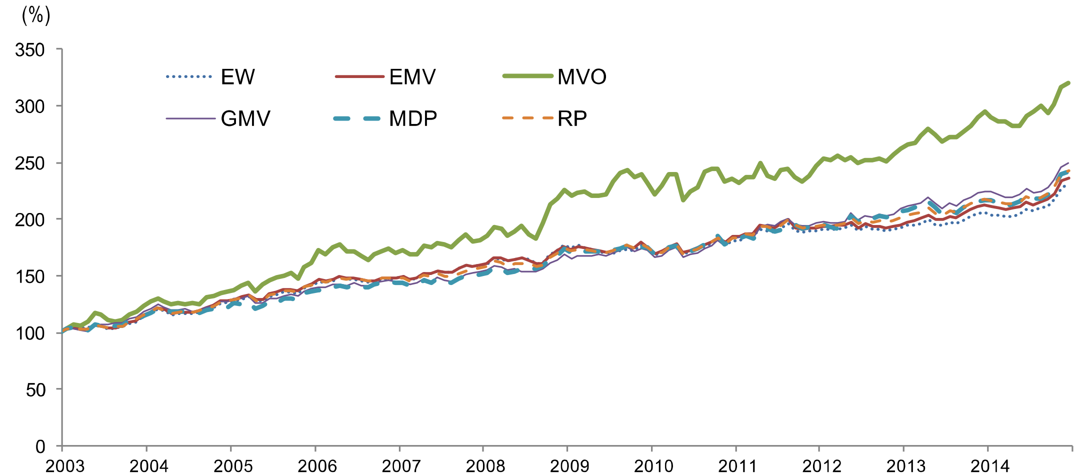
2) Performance of EW is in line with other methods (such as EMV, Risk Parity, GMV and MDP). This is because the marginal risks of these prototype models were similar to each other by construction.

[102] See the Appendix on page 166 for a brief summary of asset allocation and risk management methods and Chapter 3 (pages 59-118) of Cross Asset Systematic Strategies for more detailed explanations and illustrations.
[103] These results are broadly in line with our findings for Cross Asset Risk Factor and Equity Risk Factor portfolios. See Page 101-107 in our primer report on Cross Asset Systematic Strategies and Page 71-76 on Equity Risk Premia Strategies.

3) MVO generated the highest return (CAGR at +10.2%) but also had the highest volatility and max drawdown (almost double the others). MVO also had the highest Kurtosis.

4) All the six allocation methods had negative skewness and above-normal kurtosis. However, their levels of excess kurtosis (above normal distribution) were far lower than the prototype Momentum strategies in Chapter 2.

Figure 80: Historical Performance of Portfolio Construction Methods for prototype Momentum and Seasonality Factors



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Overall, we find that the risk-based methods (GMV, MDP, EMV, RP) delivered similar returns and volatility profiles. On the other hand, MVO delivered higher return (+11% per annum) at a higher volatility without resorting to factor leverage.

Figure 81-Figure 86 shows the monthly weights of factors in different risk models. For instance, GMV (Figure 83) is closely related to MDP (Figure 84): both try to minimize ex-ante portfolio variance with the former applying a larger penalty on higher volatility factors. In addition, EMV shown in Figure 85 is a special case of Risk Parity shown in Figure 86 (EMV disregards asset correlation when calculating risk contributions). Similar to GMV, the Risk Parity method tries to manage portfolio risk by overweighting assets with lower contribution to portfolio risk (lower average correlation with other assets and lower marginal volatility). Overall, EMV/RP had the lowest factor turnover (aside for EW that has no weight turnover by construction) and MVO had the highest factor turnover.

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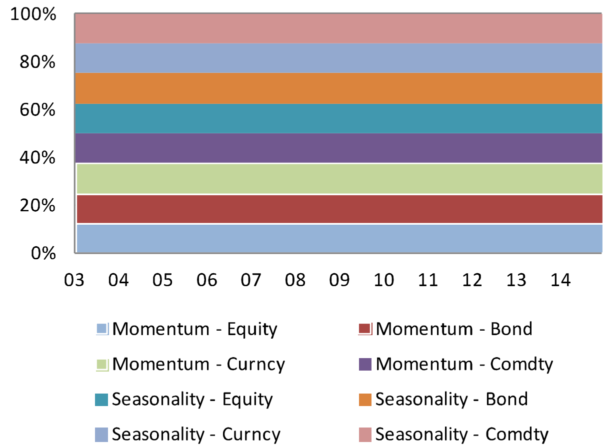
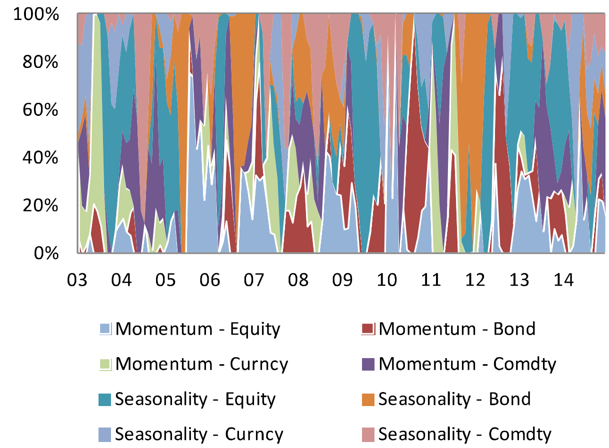
Figure 81: Portfolio Weights of EW



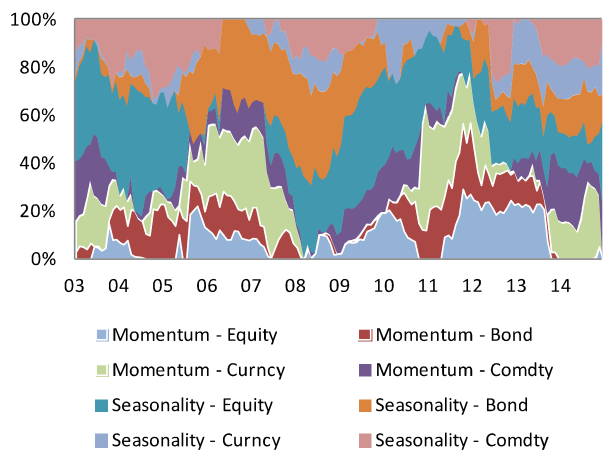
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 82: Portfolio Weights of MVO



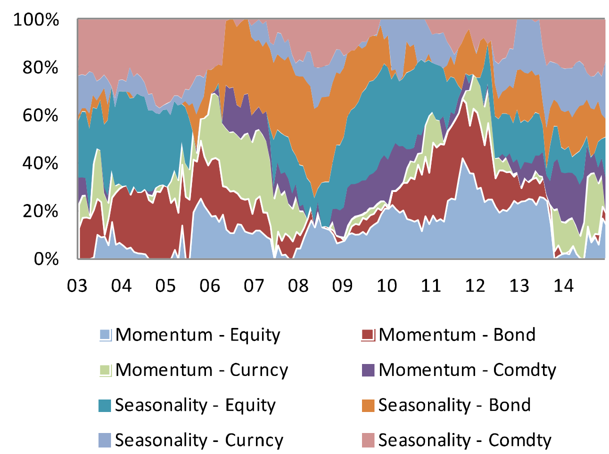
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 83: Portfolio Weights of GMV



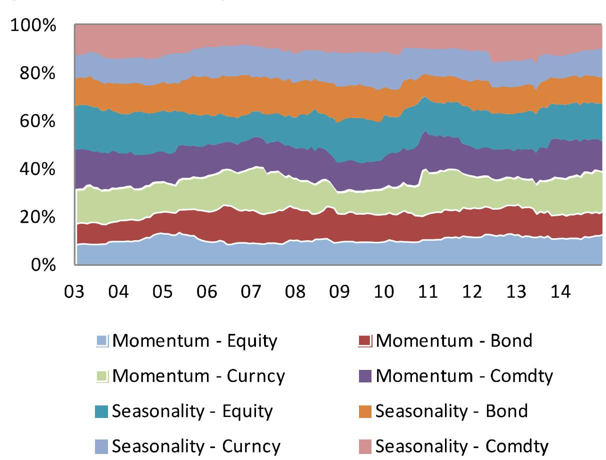
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 84: Portfolio Weights of MDP



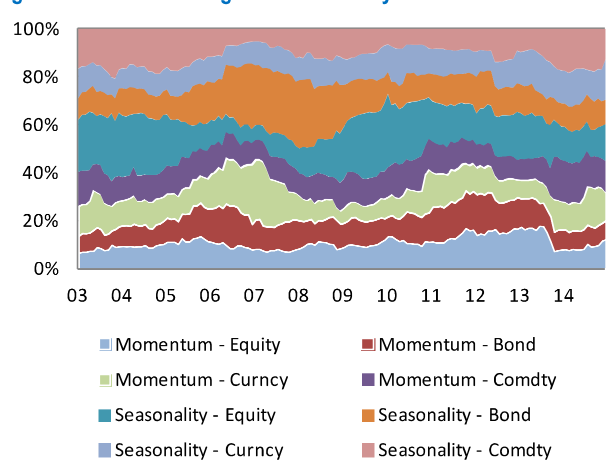
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 85: Portfolio Weights of EMV



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 86: Portfolio Weights of Risk Parity



Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Finally, we would like to show another example of a portfolio that includes prototype Momentum factors and a more advanced Seasonality factor. In this example, we included four Risk Factors: prototype 12-Month Equity Momentum Factor (see Figure 10), prototype 12-Month Bond Momentum Factor (see Figure 10), Commodity Seasonality Factor based on J.P. Morgan Seasonality Spreads Portfolio (Figure 78), and prototype Equity Seasonality Factor (see Figure 77 and Table 47).

Table 50 shows sample correlation of the four Risk Factors along with a Cross Asset long-only Momentum Factor based on J. P. Morgan Mozaic Strategy (see section 'Long Only Momentum' on page 69) during 2001-2014. We find Equity Seasonality and Equity Momentum Factors are positively correlated, whereas Bond Momentum and Commodity Seasonality Factors showed roughly zero correlation with the other strategies.

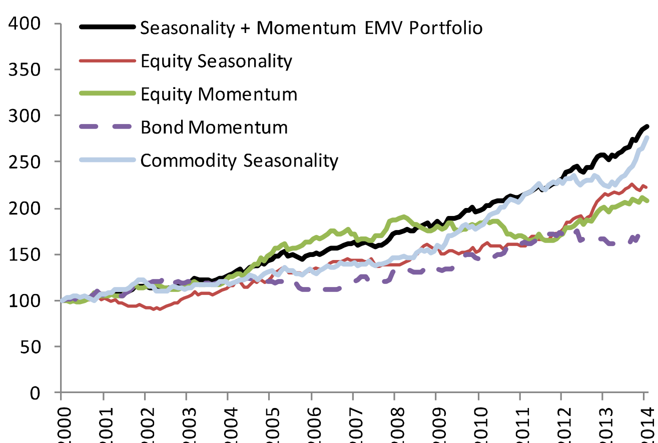
Table 50: Sample Correlation among Selected Cross Asset Momentum and Seasonality Risk Factors during 2001-2014

	Equity Seasonality	*Equity Momentum*	*Bond Momentum*	*Commodity Seasonality*	*Cross Asset LO Momentum*
Equity Seasonality	100.0%	37.2%	-13.3%	6.9%	27.6%
Equity Momentum	37.2%	100.0%	8.0%	-4.9%	31.0%
Bond Momentum	-13.3%	8.0%	100.0%	3.6%	42.4%
Commodity Seasonality	6.9%	-4.9%	3.6%	100.0%	4.1%
Cross Asset Long-only Momentum (Mozaic)	27.6%	31.0%	42.4%	4.1%	100.0%

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 87 shows historical performance of the four Seasonality/Momentum Risk Factors (with 6% volatility target) and an Equal-Marginal-Volatility (EMV) Portfolio with marginal volatility target of 8%.

Figure 87: Performance of Seasonality/Momentum Risk Factors and an Equity-Marginal-Volatility (EMV) Portfolio



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 51: Perf/Risk Stats for Cross Asset Seasonality and Momentum Factors with EMV portfolio during 2001-2014

	Equity Seasonality	Equity Momentum	Bond Momentum	Commodity Seasonality	Seasonality /Momentum Portfolio
Excess Ret (%)	5.9	5.4	4.1	7.5	7.9
STDev (%)	6.4	6.1	6.2	6.1	4.5
MaxDD (%)	-13.9	-13.8	-11.1	-10.1	-6.0
MaxDDur (in yrs)	2.3	4.6	4.8	2.3	0.9
***t*-Statistic**	**3.5**	**3.3**	**2.6**	**4.6**	**6.4**
Sharpe Ratio	**0.92**	**0.89**	**0.67**	**1.23**	**1.76**
Hit Rate (%)	64.9	60.7	61.9	63.1	72.0
Skewness	-0.54	0.13	-0.21	-0.02	-0.54
Kurtosis	1.20	-0.07	1.13	-0.51	0.19

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* Performance/Risk Stats are based on monthly index levels; Past performance is no indication of future results.

Table 51 summarizes related performance/risk statistics for the Seasonality/Momentum Risk Factors as well as the Equal-Marginal-Volatility (EMV) Portfolio[104]. During 2001-2014, the EMV portfolio delivered an excess return of +7.9% per annum, Sharpe ratio of 1.76 with a small maximum drawdown of -6%, which recovers in less than a year.

[104] Volatility targeting and EMV portfolio are based on monthly rebalance and volatility estimate from trailing 24-month returns.

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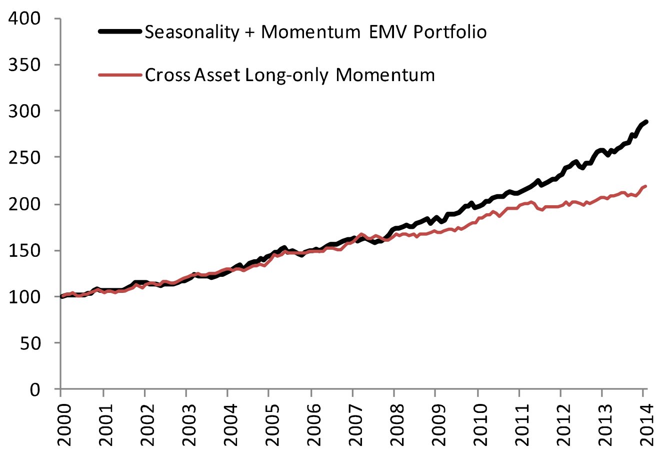
Figure 88 compares the performance of a Equal-Marginal-Volatility (EMV) weighted Portfolio of Seasonality and Momentum factors with the performance of a portfolio of Long-only Momentum Factors across assets.[105] Table 52 shows performance/risk statistics during full sample period (2001-2014) and after-GFC period (2009-2014). Before 2009, both portfolios delivered roughly similar return/risk profiles. After 2009, the portfolio that includes Momentum and Seasonality outperformed the Momentum only portfolio in both absolute and risk-adjusted terms. This demonstrates the advantage of including Seasonality factors into a Momentum portfolio.

Figure 88: Performance of Seasonality/Momentum EMV Portfolio and a Long-Only Momentum Portfolio



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 52: Performance Statistics for Seasonality/Momentum Portfolio vs. Long-Only Momentum Portfolio

	Seasonality + Momentum Portfolio (2001-2014)	Cross Asset Long-only Momentum (2001-2014)	Seasonality + Momentum Portfolio (2009-2014)	Cross Asset Long-only Momentum (2009-2014)
Excess Ret (%)	7.9	5.7	8.8	4.5
STDev (%)	4.5	4.2	4.4	3.8
MaxDD (%)	-6.0	-4.8	-2.7	-4.3
MaxDDur (in yrs)	0.9	1.6	0.3	0.9
***t*-Statistic**	**6.4**	**5.1**	**4.7**	**2.9**
Sharpe Ratio	**1.76**	**1.37**	**1.99**	**1.20**
Hit Rate (%)	72.0	67.3	76.4	66.7
Skewness	-0.54	-0.06	-0.78	-0.41
Kurtosis	0.19	-0.13	0.74	0.20

Source: J.P. Morgan Quantitative and Derivatives Strategy.
* Performance/Risk Stats are based on monthly index levels; Past performance is no indication of future results.

105 Strictly speaking, a long-only cross-asset Momentum strategy may not be a proper benchmark for a portfolio of long/short Momentum/Seasonality Risk Factors, given the latter is essentially an absolute return strategy with no intentional market tilts.

Appendices

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J.P. Morgan Investable Momentum Indices

Our Structuring Desks around the globe created a suite of single-asset and multi-asset investable Momentum indices. The design of these investable indices is based on our discussion of prototype as well as enhanced Momentum/Seasonality models in this report. Investors can make use of these investable indices to access/benchmark Momentum risk premium across different assets and to build well-diversified portfolios. The table below lists Bloomberg tickers along with the names, asset class and regional focus of each investable strategy[106].

Table 53: J.P. Morgan Investable Momentum/Seasonality Indices

Ticker	Index Name	Strategy Family	Launch Date	Asset Class	Regional Focus	Currency
CIJPAER5	Asia Pacific Equity Rotator Index (USD)	Aero	Aug-11	Equities	Asia	USD
CIJPAEB5	Asian EM Equity Rotator 5	Aero	Mar-12	Equities	Emerging Mkts	USD
AIJPMEEE	Equity Momentum Europe	AIS	Nov-09	Equities	EMEA	EUR
AIJPMEJJ	Equity Momentum Japan	AIS	Nov-09	Equities	Asia	JPY
AIJPMEUU	Equity Momentum US	AIS	Nov-09	Equities	Americas	USD
QTJPXPMS	Asia ex Japan Price Momentum (Long Only)	ERP	Dec-14	Equities	Asia	USD
RPJPXPMS	Asia ex Japan Price Momentum (Long Short)	ERP	Dec-14	Equities	Asia	USD
QTJPPMEL	Europe Price Momentum (Long Only)	ERP	Jun-14	Equities	EMEA	EUR
RPJPPMEU	Europe Price Momentum (Long/Short)	ERP	Jun-14	Equities	EMEA	EUR
QTJPSYEL	Europe Price Seasonality (Long Only)	ERP	Jun-14	Equities	EMEA	EUR
RPJPSYEU	Europe Price Seasonality (Long/Short)	ERP	Jun-14	Equities	EMEA	EUR
FTUSXLUT	US Extended Price Momentum (Long Only)	ERP	Dec-14	Equities	Americas	USD
QTJPXBLS	US Extended Price Momentum (Long/Short Beta Matched)	ERP	Jan-15	Equities	Americas	USD
FTUSXSUT	US Extended Price Momentum (Short Only)	ERP	Dec-14	Equities	Americas	USD
FTUSMLUT	US Price Momentum (Long Only)	ERP	Dec-14	Equities	Americas	USD
QTJPMBLS	US Price Momentum (Long/Short Beta Matched)	ERP	Jan-15	Equities	Americas	USD
FTUSMSUT	US Price Momentum (Short Only)	ERP	Dec-14	Equities	Americas	USD
FTUSNLUT	US Price Seasonality (Long Only)	ERP	Dec-14	Equities	Americas	USD
QTJPNBLS	US Price Seasonality (Long/Short Beta Matched)	ERP	Jan-15	Equities	Americas	USD
FTUSNSUT	US Price Seasonality (Short Only)	ERP	Dec-14	Equities	Americas	USD
JPMZKRNS	J.P.Morgan Kronos Index	Kronos	Jun-13	Equities	Americas	USD
JPMZKRMO	J.P.Morgan Kronos Index - Momentum	Kronos	Jun-13	Equities	Americas	USD
CIJPAESR	J.P. Morgan Asia ex Japan Sector Rotator	SectorRotator	Dec-14	Equities	Asia	USD
JPUSSCTE	J.P.Morgan U.S. Sector Rotator	SectorRotator	Jun-13	Equities	Americas	USD
JPUSSC5E	J.P.Morgan U.S. Sector Rotator 5% Vol Budget	SectorRotator	Jun-13	Equities	Americas	USD
AIJPMMEE	Momentum Money Market Europe	AIS	Nov-09	Rates	EMEA	EUR
AIJPMMJJ	Momentum Money Market Japan	AIS	Nov-09	Rates	Asia	JPY
AIJPMMUU	Momentum Money Market US	AIS	Nov-09	Rates	Americas	USD
JPCVHUS	Curve Trader H+ USD	CurveTrader	Jan-10	Rates	Global	USD
JPCVTOEU	CurveTrader M+ sub EUR Index	CurveTrader	Feb-08	Rates	Global	EUR
JPCVTOUS	CurveTrader M+ sub USD Index	CurveTrader	Feb-08	Rates	Global	USD
JPCVTUS	CurveTrader M+ USD	CurveTrader	Feb-08	Rates	Global	USD
JPFSGMUS	FSI - Gemini in USD	FSI	Feb-12	Rates	EMEA	USD
JPFSMMLE	FSI - Multi Momentum Long Only EUR	FSI	Feb-12	Rates	EMEA	EUR

[106] For more information, please contact your J.P. Morgan salesperson or the Structuring Desk.

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JPFSMMEU	FSI - Multi.Momentum EUR	FSI	Feb-12	Rates	EMEA	EUR
JHLXHUS	Helix - Basket Hedged in USD	Helix	May-09	Rates	Global	USD
JHLXH2US	Helix2 - Basket Hedged in USD	Helix	Feb-13	Rates	Global	USD
JMOMUUU	Momentus Quattro Duo in USD	Momentus	Jun-07	Rates	Global	USD
JMOMQTO	Momentus Quattro in USD	Momentus	Jun-07	Rates	Global	USD
JMOZFIGU	Mozaic Global Rates	Mozaic	Jul-12	Rates	Global	USD
JCREMOXO	Credit Europe Crossover Momentum	Credit Strategy	Jan-12	Credit	EMEA	EUR
JCREMOEU	Credit Europe Main Momentum	Credit Strategy	Jan-12	Credit	EMEA	EUR
JCREMOHY	Credit NA HY Momentum	Credit Strategy	Jan-12	Credit	Americas	USD
JCREMOIG	Credit NA IG Momentum	Credit Strategy	Jan-12	Credit	Americas	USD
AIJPMF5U	Momentum FX AUDUSD	AIS	Nov-09	Currencies	Global	USD
AIJPMF6U	Momentum FX EURGBP	AIS	Nov-09	Currencies	Global	USD
AIJPMF3U	Momentum FX EURJPY	AIS	Nov-09	Currencies	Global	USD
AIJPMF1U	Momentum FX EURUSD	AIS	Nov-09	Currencies	Global	USD
AIJPMF4U	Momentum FX USDCAD	AIS	Nov-09	Currencies	Global	USD
AIJPMF2U	Momentum FX USDJPY	AIS	Nov-09	Currencies	Global	USD
AIJPMCEU	Commodity Momentum Energy	AIS	Nov-09	Commodities	Global	USD
AIJPMCNU	Commodity Momentum Non-Energy	AIS	Nov-09	Commodities	Global	USD
JMABALOC	Commodity Allocator	Allocator	Apr-13	Commodities	Global	USD
CMDT9CER	C-IGAR 9 Conditional Long Short	C-IGAR	May-09	Commodities	Global	USD
CMDT9YER	C-IGAR 9 Long Only	C-IGAR	May-09	Commodities	Global	USD
CMDT9SER	C-IGAR 9 Long Short	C-IGAR	May-09	Commodities	Global	USD
CMZSLSTR	C-IGAR Sigma	C-IGAR	Jun-10	Commodities	Global	USD
JMAB053E	Commodity Continuum Basket of 16	Continuum	Jun-11	Commodities	Global	USD
JMAB052E	Fast Continuum	Continuum	Nov-10	Commodities	Global	USD
JMABCCLE	WTI Continuum	Continuum	Nov-10	Commodities	Global	USD
CMDTO1ER	Optimax Alternative 1	Optimax	May-08	Commodities	Global	USD
CMDTOMER	Optimax Market-Neutral	Optimax	May-08	Commodities	Global	USD
CMDTOPER	Optimax Plus	Optimax	May-08	Commodities	Global	USD
JMABSSPE	Seasonal Spreads Portfolio	Seasonal Spreads	Sep-12	Commodities	Global	USD
EFJPEH8I	Efficace (EUR Hedged)	Efficiente	Mar-08	Multi Asset	Global	EUR
EEJPR5SW	Efficient Allocation (CHF)	Efficiente	Jan-12	Multi Asset	Global	CHF
EFJPEH8E	Efficiente (EUR Hedged)	Efficiente	Aug-07	Multi Asset	Global	EUR
EFJPUS8E	Efficiente (USD)	Efficiente	Aug-07	Multi Asset	Global	USD
EFJPUS8E	Efficiente (USD)	Efficiente	Jul-07	Multi Asset	Global	USD
EFJPAU5E	Efficiente Absolute Return (USD)	Efficiente	Jun-09	Multi Asset	Global	USD
EFJPEM5E	Efficiente EM 5	Efficiente	May-13	Multi Asset	Global	USD
EFJP5GUE	Efficiente Global 5% (USD)	Efficiente	May-12	Multi Asset	Global	USD
EFJPIU8E	Efficiente Islamic	Efficiente	Jun-09	Multi Asset	Global	USD
EEJPUS5E	ETF Efficiente 5 Index	Efficiente	Oct-10	Multi Asset	Global	USD
EEJPUS5M	ETF Efficiente 5 MOD	Efficiente	Mar-12	Multi Asset	Global	USD
EEJPUS5P	ETF Efficiente 5 Price Return	Efficiente	May-12	Multi Asset	Global	USD
EEJPUS5T	ETF Efficiente 5 Total Return	Efficiente	May-12	Multi Asset	Global	USD
EEJPUS8E	ETF Efficiente 8 Index	Efficiente	Oct-10	Multi Asset	Global	USD
EEJPRC8E	ETF Efficiente 8 RC	Efficiente	Nov-12	Multi Asset	Global	USD
EEJPDS5E	ETF Efficiente Daily Series 5	Efficiente	Nov-12	Multi Asset	Global	USD

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IEJPRC4E	ETF Efficiente Income Focus DS 4	Efficiente	Aug-12	Multi Asset	Global	USD
IEJPUS4E	J.P. Morgan Income Focus Efficiente DS 4 Index	Efficiente	Aug-12	Multi Asset	Global	USD
IEJPRC6E	J.P. Morgan Income Focus Efficiente DS 6 Risk Control	Efficiente	Aug-12	Multi Asset	Global	USD
IEJPUS6E	J.P.Morgan Income Focus Efficiente DS 6 Index	Efficiente	Aug-12	Multi Asset	Global	USD
EEJPRC5E	JPMorgan ETF Efficiente 5 RC Index	Efficiente	Jan-13	Multi Asset	Global	USD
JMOZ5USD	Mozaic 5	Mozaic	Jul-12	Multi Asset	Global	USD
JMOZUSD	Mozaic USD	Mozaic	Apr-09	Multi Asset	Global	USD

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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J.P. Morgan Research on Momentum Strategies

The research teams at J.P. Morgan have put together a rich collection of papers on Cross-Asset Momentum Strategies and related topics. Table below list a selected portfolio of papers which we believe would be educational and beneficial to various types of investors[107].

Publication Date (dd/mm/yyyy)	Headline	Abstract/Highlights
04/09/2014	Equity Risk Premia Strategies: Risk Factor Approach to Portfolio Management	The concept of Risk Factors has been at the center of Quantitative Equity Investing for many years. Equity Risk Factor exposures are expected to deliver positive long-term returns (also called Equity Risk Premia), and the correlation between Equity Risk Factors is expected to be low across market cycles.
15/07/2014	Framework for Regional Equity Allocation: Country Selection based on Fundamental, Macro and Technical Signals	A new systematic framework for regional equity allocation is initiated in this report. Ten uncorrelated traditional and proprietary signals that show predictive ability for allocating across country equity markets are introduced and their robustness is examined under various economic regimes
11/12/2013	Systematic Strategies Across Assets: Risk Factor Approach to Asset Allocation	In this guide we will explain a non-traditional approach of Risk Factor Investing. The goal of the approach is to create systematic trading strategies that can access new sources of alpha while exhibiting low and stable correlations.
10/12/2013	Investment Strategies No. 104: Market Impact of Derivatives Hedging - Weekly Patterns	Investigates the impact of expiry week delta hedging and month-end asset rebalances on weekly S&P 500 price patterns. Also included is a 'Momentum-enhanced' S&P 500 overwriting strategy that mitigates this market impact.
10/12/2013	Investment Strategies No. 103: Equity Factor Reference Handbook	A compilation of quant factor reference books across the US, Europe, Asia ex-Japan, Australia and GEM regions.
10/12/2013	Investment Strategies No. 90: Earnings Factors	Examines the relationship between Earnings Momentum and Price Momentum and outline s strategies that can be developed to improve eanrings-based signals. Also included is an analysis of how investing based on changes in analyst target prices has proved to be a profitable strategy.
10/12/2013	Investment Strategies No. 89: Equity Momentum	Reviews various enhancements to a basic Price Momentum strategy. Also includes a backtest of the Trend Factor in various markets to understand the effect of Momentum on stock returns.
10/12/2013	Investment Strategies No. 88: Signals from Options Markets	Illustrates how signals from the options market, such as implied volatility skew, can be used to improve risk management of a portfolio.
10/12/2013	Investment Strategies No. 79: Market Impact of Derivatives Hedging - Daily Patterns	This compilation of reports estimates the market impact of gamma hedging of derivative products (options and levered ETFs) and discusses how to construct systematic trading strategies around this.

[107] Investors can log in J. P. Morgan's Global Research portal to view latest publications of Cross Asset Systematic Strategies.

12/1/2012	Investment Strategies No. 69: REVISITING: Using the Global PMI as trading signal	In Sep 2009, we published a trading rule that goes long Global Cyclical vs. Defensive sectors if the Global Manufacturing PMI improves and vice versa. Out of sample, since mid 2009, this trading rule has performed well but only when using the...
16/11/2011	Investment Strategies No. 67: Using unemployment to trade bonds	Unemployment rates provide a profitable signal for trading government bonds. Overweighting government bonds in countries where unemployment is rising most against those where unemployment is rising least would have produced a return to risk of up...
28/03/2011	Investment Strategies No. 65: Trading on economic data releases: What works? What does not?	We examine the profitability of a range of signals for trading stock and bond markets in a half-hour window around major US data releases. Basic models can predict data surprises, but this is not exploitable for trading as the market seems to...
28/10/2009	Investment Strategies No. 59: Economic and Price Signals for Commodity Allocation	Economic activity signals, such as global IP growth and global manufacturing PMI, are leading indicators of future commodity performance. Simple rules that use economic activity signals have performed well in the past decade, delivering Sharpe...
8/9/2009	Investment Strategies No.58: Trading Cyclical vs Defensive equity sectors	A trading rule that goes long Global Cyclical vs Defensive sectors if the global manufacturing PMI new orders-to-stocks ratio rises and vice versa, produced a good information ratio of 0.65 since 1998. The global PMI has also provided a profitable...
29/04/2009	Investment Strategies No. 56: The EM vs Developed Markets equity allocation	A return Momentum strategy that goes long EM equities vs Developed Markets (DM) if the former outperformed in the previous 2 months and vice versa, produced an information ratio of 0.86 since 1988 An economic Momentum strategy based on the...
26/02/2009	Investment Strategies No. 53. Combining Directional and Sector Momentum	We use a simple directional Momentum signal to determine whether to invest in the long-only or the long-short sector Momentum strategy, and obtain Sharpe ratios of up to 0.9 since 1996 vs 0.0 for the MSCI World index.
20/11/2008	Investment Strategies No 51: Volatility signals for asset allocation	Deleveraging in periods of high volatility, and releveraging in periods of low volatility, i.e., risk-budgeting, generates higher risk-adjusted returns with lower tail risk for equities, commodities, and bonds.
14/08/2008	Investment Strategies No. 48: Global bond Momentum	An equally-weighted basket of individual bond Momentum strategies across countries produces high information ratios of up to 1.2
13/05/2008	Investment Strategies No. 44: Momentum in Emerging Markets Sovereign Debt	Momentum in Emerging Markets is particularly pervasive because of difficulty in assessing value and higher information search costs across various economies, in our opinion
20/05/2008	Investment Strategies No. 43: Trading the US Curve	Monetary policy Momentum, curve Momentum, positions on 10y UST and economic sentiment are profitable signals in trading the US curve
19/05/2008	Investment Strategies No. 42: Cross-Momentum for EM equity sectors	We find evidence of Momentum in EM equity sectors, but it is more profitable to invest across EM sectors according to past global sector performance
9/5/2008	Investment Strategies No. 41: Momentum in Global Equity Sectors	Active Momentum-based strategies in global equity sectors offer high returns to risk, and perform well in both bull and bear markets; Buying the top-third performing global sectors over the past year outperforms an equal sector allocation by...

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29/04/2008	Investment Strategies No. 40: Optimizing Commodities Momentum	We show that dynamic mean-variance optimization enhances the return to risk of commodities Momentum strategies
10/3/2008	Investment Strategies No. 39: Risk Management Fund Alternatives	We analyze the pros and cons of Risk Management fund replication and rule-based investing.
7/8/2007	Investment Strategies No. 35: Markowitz in tactical asset allocation	Classical mean variance portfolio optimization, conceived by Harry Markowitz in 1952, is used frequently for long-term strategic asset allocation, but not for tactical asset allocation.
2/8/2007	Investment Strategies No. 34: A simple rule to trade the curve	The strategy: invest in flatteners when central banks tighten and steepeners when central banks ease, look for carry when policy rates are on hold
17/05/2007	Investment Strategies No. 32: Momentum in Money Markets	Momentum-based trading strategies offer attractive risk-adjusted returns on Euro area and US money markets.
10/11/2006	Investment Strategies Series No.27: Euro Fixed Income Momentum Strategy	Momentum-based strategies provide attractive risk-adjusted trading returns in European fixed income.
8/11/2006	Investment Strategy Series No. 26: Equity Style Rotation	We evaluate index-based equity style rotation strategies using Momentum, valuations and macro data in the search for the most robust and profitable rules...
19/09/2006	Investment Strategies No. 25: Momentum in Commodities	Active Momentum-based strategies in commodities offer high returns to risk and outperform passive investment in the asset class
8/2/2006	Investment Strategies No. 14: Exploiting Cross-Market Momentum	We propose an innovative strategy that achieves high returns with low risk by exploiting Momentum in relative returns across a wide set of asset classes.

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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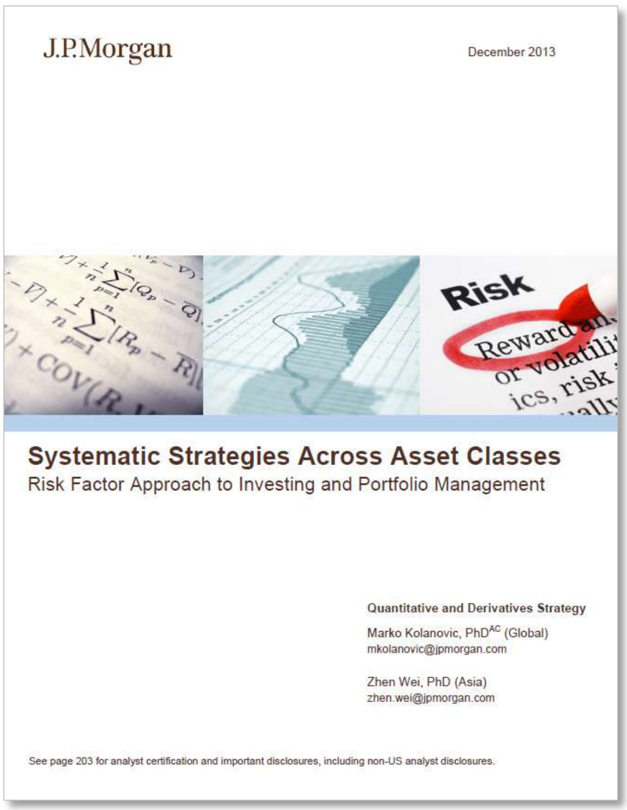
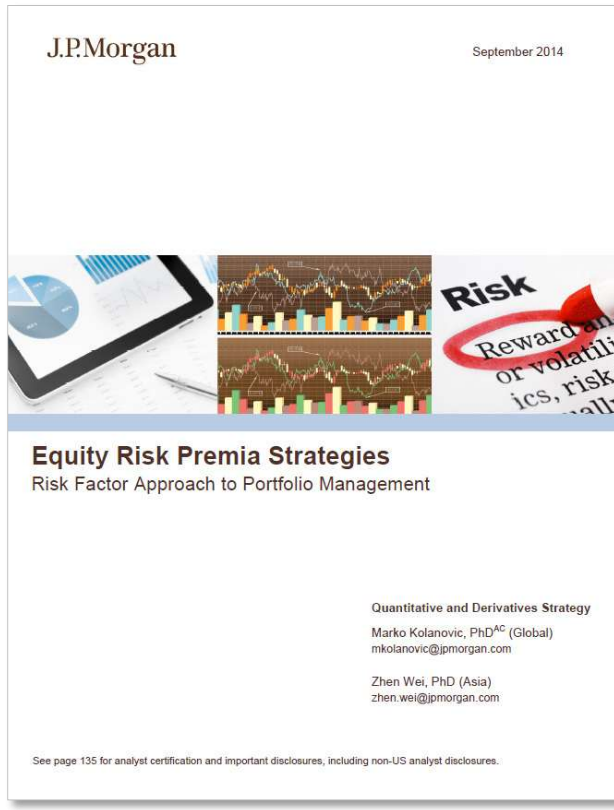
J. P. Morgan Cross Asset Systematic Strategy Primer Books

The J.P. Morgan Quantitative and Derivatives Strategy team has produced primer books on Cross Asset Systematic Strategies and Equity Risk Premia Strategies. Both primer books examine performance/risk properties of prototype Risk Factors, Factor Correlations and Portfolio Construction/Risk Management models.

Primer Book on Systematic Strategies Across Assets



Primer Book on Equity Risk Premia Strategies



Source: J.P. Morgan Quantitative and Derivatives Strategy.

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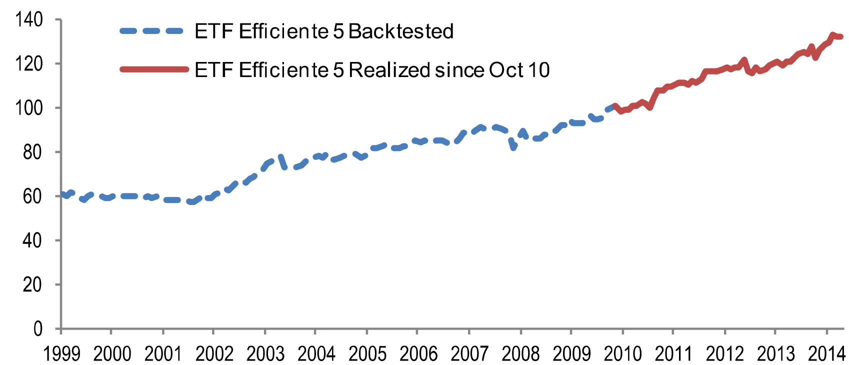
J.P. Morgan ETF Efficiente Strategy – Multi Asset Long-Only Momentum

Strategy Index Profile[108]

Index Name	ETF Efficiente 5
Strategy Type	Enhanced Beta
Asset Class	Multi Asset
Regional Focus	Multi Region
Strategy Style	Momentum
Risk Method	Risk Budgeting
Launch Date	October 2010
Bloomberg Ticker	EEJPUS5E Index



Summary of Historical Performance/Risk Statistics[109]

	Past 1-year	Past 3-year	Past 5-year	Past 10-year	Since Launch	During GFC**
Ann. Excess Return (%)	**9.2**	**6.0**	**6.9**	**5.6**	**6.4**	**2.0**
Ann. Volatility (%)	6.7	5.7	5.5	5.9	5.5	8.7
Max Draw Down (%)	-3.8	-5.1	-5.1	-10.3	-5.1	-10.3
Max DD Duration (in yrs)	0.2	0.9	0.9	1.5	0.9	1.1
Sharpe Ratio	**1.36**	**1.06**	**1.26**	**0.95**	**1.17**	**0.23**
***t*-Statistics**	**1.4**	**1.8**	**2.8**	**3.0**	**2.4**	**0.3**
Skewness	-1.1	-0.9	-0.6	-0.6	-0.6	-0.4
Kurtosis	1.7	1.7	1.2	1.9	1.4	1.2

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg.
* Performance/risk statistics are based on monthly data and calculated as of March 2015. ** GFC (Global Financial Crisis) refers to Aug 2007 - Mar 2009 period.

Strategy Description/Rules[110]

1) The index seeks to provide exposure to a range of asset classes and geographic regions based on the modern portfolio theory approach to asset allocation.

2) The Index selects from a basket of 12 cross asset ETFs and the JPMorgan Cash Index USD 3 Month. The ETFs includes SPY, IWM, EFA, TLT, LQD, HYG, EEM, EMB, IYR, GSG, GLD and TIP.

3) The Index seeks to identify the weights for each Basket Constituent that would have resulted in the hypothetical portfolio with the highest return over the previous six months while realizing an annualized volatility over the same period of 5% or less.

[108] Strategy classification is according to our framework introduced in the primer to Cross Asset Systematic Strategies.
[109] Definitions of the performance/risk analytics can be found in the Appendix 'Performance-Risk Analytics' on page 121.
[110] For more information, please contact your J.P. Morgan salesperson or the Structuring Desk.

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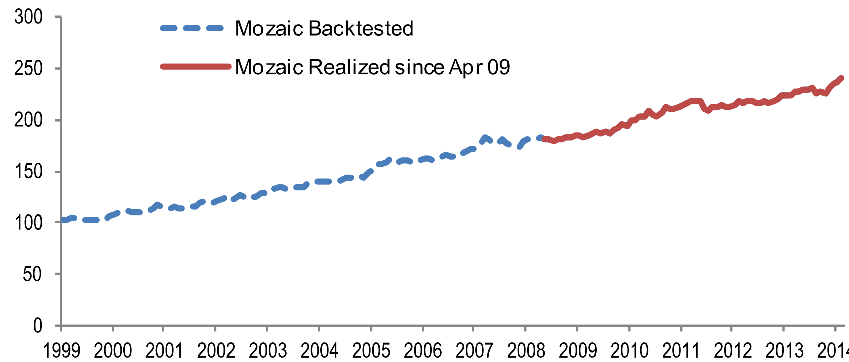
J.P. Morgan Mozaic Strategy – Multi Asset Long-Only Momentum

Strategy Index Profile

Index Name	Mozaic
Strategy Type	Enhanced Beta
Asset Class	Multi Asset
Regional Focus	Multi Region
Strategy Style	Momentum
Risk Method	None
Launch Date	April 2009
Bloomberg Ticker	JMOZUSD Index



Summary of Historical Performance/Risk Statistics

	Past 1-year	Past 3-year	Past 5-year	Past 10-year	Since Launch	During GFC**
Ann. Excess Return (%)	**7.4**	**3.7**	**5.4**	**5.6**	**5.2**	**6.7**
Ann. Volatility (%)	4.1	3.9	3.9	4.1	3.8	5.2
Max Draw Down (%)	-2.2	-4.3	-4.3	-4.8	-4.3	-4.8
Max DD Duration (in yrs)	0.3	1.0	1.0	1.6	1.0	1.1
Sharpe Ratio	**1.81**	**0.94**	**1.38**	**1.37**	**1.38**	**1.29**
***t*-Statistics**	**1.8**	**1.6**	**3.1**	**4.3**	**3.3**	**1.7**
Skewness	-1.4	-0.8	-0.5	0.0	-0.5	0.2
Kurtosis	2.3	0.7	0.3	-0.1	0.3	-1.1

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg.
* Performance/risk statistics are based on monthly data and calculated as of March 2015. ** GFC (Global Financial Crisis) refers to Aug 2007 - Mar 2009 period.

Strategy Description/Rules

1) The Index is a notional rules-based proprietary index that tracks the excess return of a synthetic portfolio of up to five constituents that are each an Asian/EM equity index or a futures tracker (selected from Asian/EM equity indices or equity futures trackers) and, if fewer than five Equity Constituents have been selected, the J.P. Morgan U.S. Treasury Notes Futures Tracker (the "Bond Constituent") above the return of the JPMorgan Cash Index USD 3 Month.

2) The Index rebalances the synthetic portfolio monthly. Each month, the Index will select the top five positive performing Equity Constituents based on their past month's performance for inclusion in the synthetic portfolio.

3) As part of this rebalancing process, the Index will assign weights to the Basket Constituents. The Index uses a volatility budgeting approach to assign weights to the Non-Cash Constituents based on a total volatility allocation of 5%.

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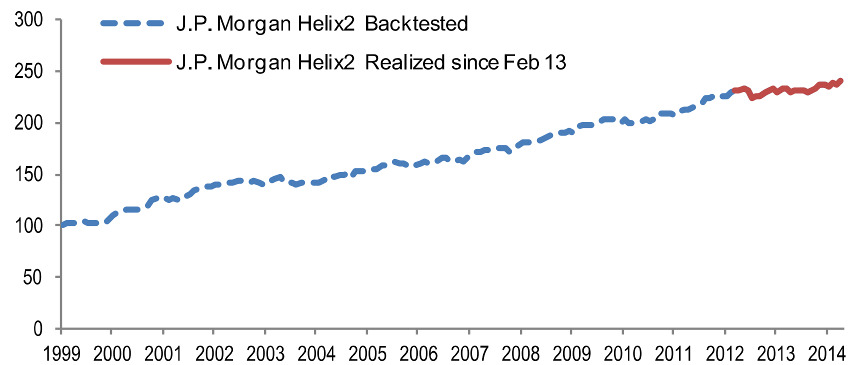
J.P. Morgan Helix2 Strategy – Fixed Income (Rates) Momentum

Strategy Index Profile	
Index Name	J.P. Morgan Helix2
Strategy Type	Alternative Beta
Asset Class	Rates
Regional Focus	Multi Region
Strategy Style	Momentum
Risk Method	Risk Timing
Launch Date	February 2013
Bloomberg Ticker	JHLXH2US Index



Summary of Historical Performance/Risk Statistics

	Past 1-year	Past 3-year	Past 5-year	Past 10-year	Since Launch	During GFC**
Ann. Excess Return (%)	**4.5**	**4.2**	**3.9**	**4.9**	**2.0**	**7.5**
Ann. Volatility (%)	2.6	3.7	3.7	3.7	3.9	3.8
Max Draw Down (%)	-0.9	-4.4	-4.4	-4.4	-4.4	-1.8
Max DD Duration (in yrs)	0.3	0.8	0.8	0.8	0.8	0.3
Sharpe Ratio	**1.76**	**1.15**	**1.06**	**1.35**	**0.51**	**2.00**
t-Statistics	**1.8**	**2.0**	**2.4**	**4.3**	**0.7**	**2.6**
Skewness	-0.1	-1.4	-0.7	-0.3	-1.5	0.2
Kurtosis	-0.9	3.6	1.7	1.2	2.9	0.3

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg.
* Performance/risk statistics are based on monthly data and calculated as of March 2015. ** GFC (Global Financial Crisis) refers to Aug 2007 - Mar 2009 period.

Strategy Description/Rules

1) Seeks to take advantage of trends in short-term EUR and USD interest rates by creating exposure to a synthetic basket of EURIBOR and Eurodollar futures trackers.
2) Index can provide dynamic long and/or short exposure to the front four EURIBOR and Eurodollar exchange-traded quarterly money market futures.
3) Stop loss cut-out feature if returns are persistently negative over a rolling 1-week observation window.
4) Volatility target of 3.5%.
5) Leverage factor determined as a function of the index's volatility.

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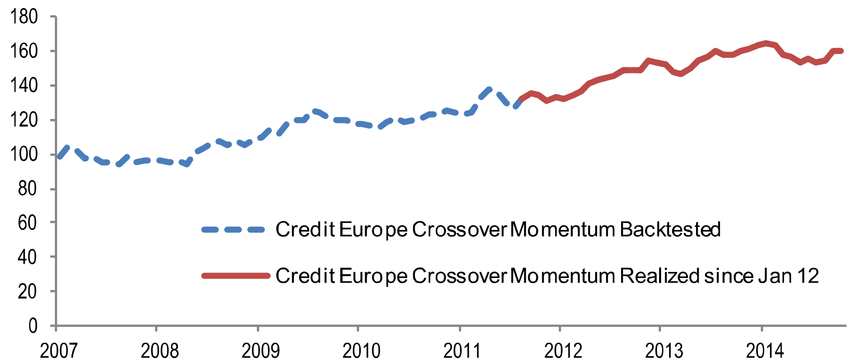
J.P. Morgan Credit Europe Crossover Momentum Strategy – Credit Momentum

Strategy Index Profile	
Index Name	Credit Europe X-Over Momentum
Strategy Type	Alternative Beta
Asset Class	Credit
Regional Focus	EMEA
Strategy Style	Momentum
Risk Method	N/A
Launch Date	January 2012
Bloomberg Ticker	JCREMOXO Index



Summary of Historical Performance/Risk Statistics

	Past 1-year	Past 3-year	Past 5-year	Past 8-year	Since Launch	During GFC**
Ann. Excess Return (%)	**-0.2**	**5.9**	**6.0**	**6.4**	**6.2**	**1.6**
Ann. Volatility (%)	6.3	6.5	7.5	8.3	6.4	8.9
Max Draw Down (%)	-7.4	-7.4	-8.2	-9.8	-7.4	-9.8
Max DD Duration (in yrs)	0.8	0.8	0.9	1.6	0.8	1.3
Sharpe Ratio	**-0.03**	**0.90**	**0.80**	**0.78**	**0.97**	**0.18**
t-Statistics	**0.0**	**1.6**	**1.8**	**2.2**	**1.7**	**0.2**
Skewness	-0.4	-0.3	0.2	0.4	-0.3	0.7
Kurtosis	0.0	-0.3	0.9	0.1	-0.3	0.3

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg.
* Performance/risk statistics are based on monthly data and calculated as of March 2015. ** GFC (Global Financial Crisis) refers to Aug 2007 - Mar 2009 period.

Strategy Description/Rules

J. P. Morgan Credit Momentum Strategy Indices track trending behaviour in the main credit default swap indices:

1) Strategy is harnessed using 5-day and 50-day moving averages on the Underlying Index ("Short Term Average" or "STA" and "Long Term Average" or "LTA" respectively)

2) On each Index Business Day:

If STA ≥ LTA: Strategy increases the long exposure (or decreases the short exposure) by 0.25x subject to a cap of 1x long

If STA < LTA: Strategy increases the short exposure in the Underlying Index by 0.25x subject to a cap of 1x short

3) Exposure is changed in steps of 0.25x

4) Strategy can start reacting quickly to a potential signal but limit the execution costs in case the signal is not persistent

5) Execution are assumed to be done at the closing level of the Underlying Index

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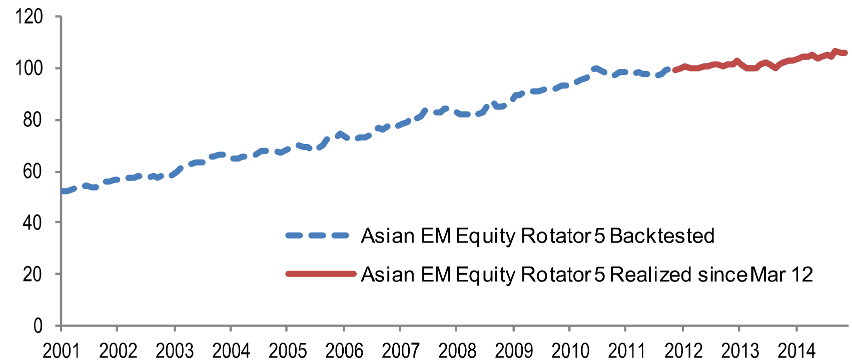
J.P. Morgan Asian EM Equity Rotator 5 Strategy – Equity Momentum

Strategy Index Profile	
Index Name	Asian EM Equity Rotator 5
Strategy Type	Alternative Beta
Asset Class	Equities
Regional Focus	Emerging Markets
Strategy Style	Momentum
Risk Method	Risk Timing
Launch Date	March 2012
Bloomberg Ticker	CIJPAEB5 Index



Summary of Historical Performance/Risk Statistics

	Past 1-year	Past 3-year	Past 5-year	Past 10-year	Since Launch	During GFC**
Ann. Excess Return (%)	**3.0**	**2.2**	**2.7**	**4.7**	**2.2**	**3.7**
Ann. Volatility (%)	3.5	3.1	3.3	3.9	3.1	4.8
Max Draw Down (%)	-1.5	-3.1	-3.1	-3.1	-3.1	-99.9
Max DD Duration (in yrs)	0.3	0.9	1.3	1.3	0.9	1.3
Sharpe Ratio	**0.86**	**0.72**	**0.82**	**1.20**	**0.72**	**0.77**
t-Statistics	**0.9**	**1.3**	**1.8**	**3.8**	**1.3**	**1.0**
Skewness	0.1	-0.2	0.2	0.3	-0.2	0.4
Kurtosis	0.8	0.2	0.8	0.6	0.2	-0.4

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg.
* Performance/risk statistics are based on monthly data and calculated as of March 2015. ** GFC (Global Financial Crisis) refers to Aug 2007 - Mar 2009 period.

Strategy Description/Rules

1) The Index is a notional rules-based proprietary index that tracks the excess return of a synthetic portfolio of up to five constituents that are each an Asian/EM equity index or a futures tracker (selected from Asian/EM equity indices or equity futures trackers) and, if fewer than five Equity Constituents have been selected, the J.P. Morgan U.S. Treasury Notes Futures Tracker (the "Bond Constituent") above the return of the JPMorgan Cash Index USD 3 Month.

2) The Index rebalances the synthetic portfolio monthly. Each month, the Index will select the top five positive performing Equity Constituents based on their past month's performance for inclusion in the synthetic portfolio.

3) As part of this rebalancing process, the Index will assign weights to the Basket Constituents. The Index uses a volatility budgeting approach to assign weights to the Non-Cash Constituents based on a total volatility allocation of 5%.

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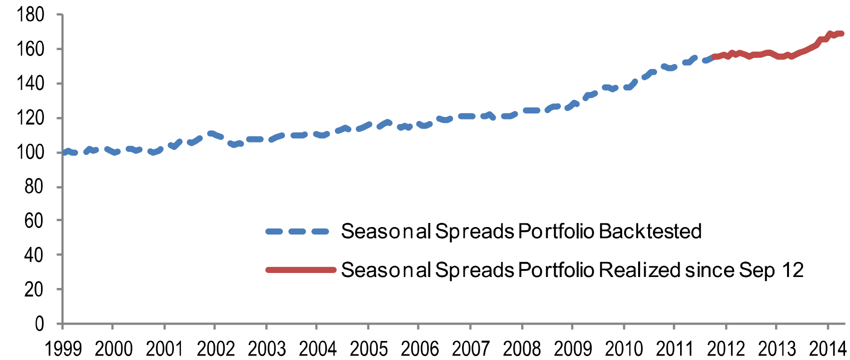
J.P. Morgan Seasonal Spreads Portfolio Strategy – Commodity Seasonality/Momentum

Strategy Index Profile

Index Name	Seasonal Spreads Portfolio
Strategy Type	Alternative Beta
Asset Class	Commodities
Regional Focus	Global
Strategy Style	Momentum
Risk Method	Risk Budgeting
Launch Date	September 2012
Bloomberg Ticker	JMABSSPE Index



Summary of Historical Performance/Risk Statistics

	Past 1-year	Past 3-year	Past 5-year	Past 10-year	Since Launch	During GFC**
Ann. Excess Return (%)	**8.6**	**3.5**	**4.9**	**4.2**	**3.3**	**2.1**
Ann. Volatility (%)	2.5	2.6	2.6	3.0	2.6	2.8
Max Draw Down (%)	-0.3	-1.8	-1.8	-3.1	-1.8	-2.3
Max DD Duration (in yrs)	0.1	0.7	0.7	0.8	0.7	0.6
Sharpe Ratio	**3.52**	**1.32**	**1.86**	**1.38**	**1.28**	**0.74**
***t*-Statistics**	**3.5**	**2.3**	**4.2**	**4.4**	**2.0**	**1.0**
Skewness	0.3	0.1	-0.1	-0.1	0.3	-0.4
Kurtosis	-0.4	-0.6	-0.7	-0.7	-0.4	-0.1

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg.
* Performance/risk statistics are based on monthly data and calculated as of March 2015. ** GFC (Global Financial Crisis) refers to Aug 2007 - Mar 2009 period.

Strategy Description/Rules

The strategy Invests monthly in a portfolio of 23 S&P GSCI ER single commodity indices, based on 27 well known fundamental commodity spreads. Each month for each commodity pair:

1) Simulate historical spread positions using S&P GSCI spot indices

2) The spread only contains the data from the relevant month that we want to invest in (e.g. if we want to invest for June, then create a spread with S&P GSCI spot data over all historical Junes only)

3) If the spread cumulative performance line of best fit has a positive slope, the relevant long-commodity gets a positive vote, while the relevant short-commodity a negative vote and vice versa

4) Each commodity in each spread then gets a +1/54 allocation for the month for each positive vote and a -1/54 allocation for each negative vote. In other words, spreads are equally weighted

5) Any commodity with an aggregate absolute weight of more than 5% is capped. Exposure across any commodities with offsetting positions are scaled down to maintain the market-neutrality of the portfolio

6) Rebalancing occurs over the last five business days of each month in order to reduce market impact and to be fully invested with the new weights as soon as the month begins.

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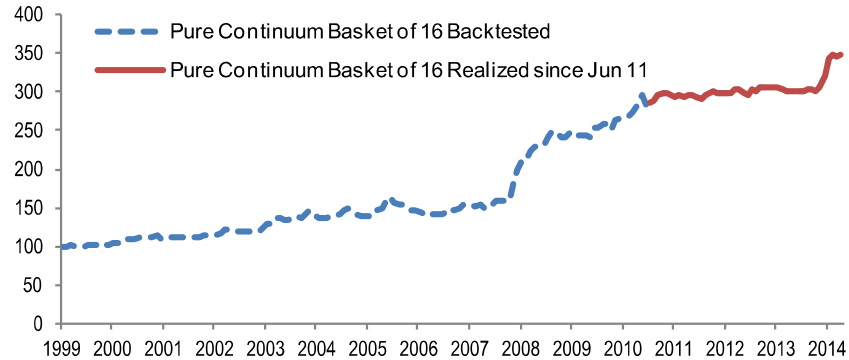
J.P. Morgan Pure Continuum Basket of 16 – Commodity Momentum

Strategy Index Profile	
Index Name	Pure Continuum Basket of 16
Strategy Type	Alternative Beta
Asset Class	Commodities
Regional Focus	Global
Strategy Style	Momentum
Risk Method	N/A
Launch Date	June 2011
Bloomberg Ticker	JMAB053E Index



Summary of Historical Performance/Risk Statistics

	Past 1-year	Past 3-year	Past 5-year	Past 10-year	Since Launch	During GFC**
Ann. Excess Return (%)	**15.4**	**5.5**	**7.4**	**9.6**	**5.2**	**29.8**
Ann. Volatility (%)	7.8	5.6	6.5	9.1	5.3	14.0
Max Draw Down (%)	-1.3	-2.6	-3.7	-15.0	-2.6	-4.0
Max DD Duration (in yrs)	0.2	0.9	0.9	2.3	0.9	0.4
Sharpe Ratio	**1.97**	**1.00**	**1.14**	**1.06**	**0.99**	**2.13**
***t*-Statistics**	**2.0**	**1.7**	**2.6**	**3.4**	**1.9**	**2.8**
Skewness	1.7	2.2	1.2	1.4	2.1	1.4
Kurtosis	2.0	6.0	2.1	4.6	6.0	1.8

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg.
* Performance/risk statistics are based on monthly data and calculated as of March 2015. ** GFC (Global Financial Crisis) refers to Aug 2007 - Mar 2009 period.

Strategy Description/Rules

Continuum takes an equally weighted basket of S&P GSCI constituents using the Fast Continuum Methodology for each Commodity. Continuum strategy seeks to adjust its allocation approach to different market regimes; it employs rolling semi-annual Calibration Periods followed by monthly (FAST) Implementation Periods:

1) Continuum determines the optimal pair of moving averages based on historical patterns during the respective Calibration Period and defines the nature of the regime which can be either Trending or Range bound

2) During the Implementation Period, allocation signals are generated when the leading moving average (MA1) crosses the lagging moving average (MA2)

3) The strategy monitors the market daily by means of Adaptive Regime Monitoring (ARM) to determine if sub-regimes are present. Three different ARM lookback periods are used, generating diversification across different time frames.

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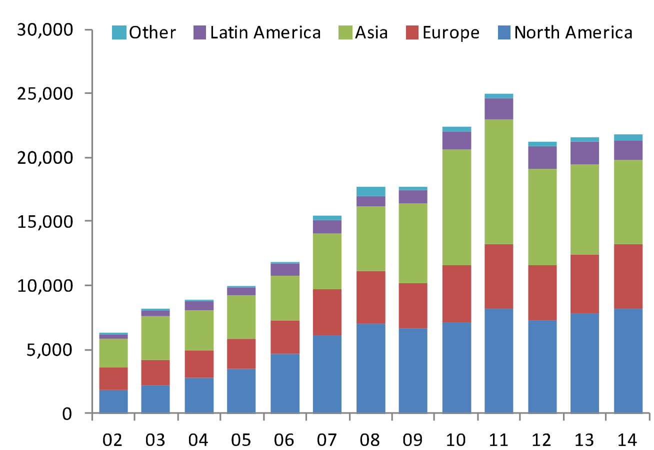
An Introduction to Commodity Trading Advisors (CTAs)

According to the National Futures Association[111] (NFA) of the United States, a **Commodity Trading Advisor** (CTA) is an individual or organization which, for compensation or profit, advises others as to the value of or the advisability of buying or selling futures contracts, options on futures, retail off-exchange forex contracts or swaps. Although firms outside the U.S. employing similar techniques are not required to register with Commodity Futures Trading Commission (CFTC) through NFA, many still use the same label "CTA" to describe the group of managed futures funds. In this short introduction, we discuss CTA funds' historical background, current institutional investor base, classification, indexation, performance and Seasonality properties.

Historical Background

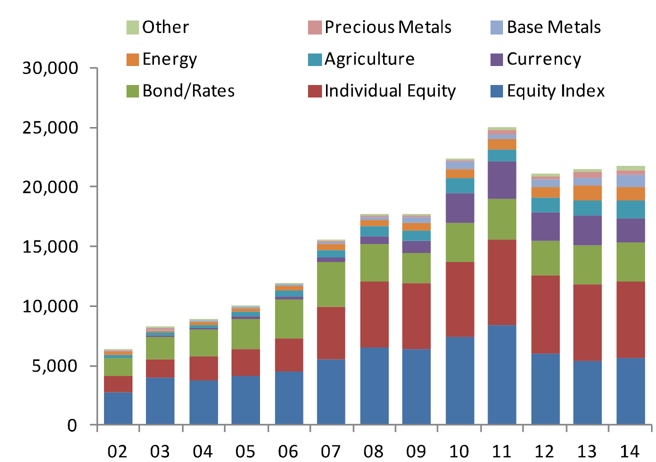
Since an organized futures market was established in the United States during the mid 19th century[112], it has become a place to satisfy the financial needs of producers, merchants and speculators in agricultural commodities. In fact, until the 1960s, global futures markets were mainly comprised of agricultural commodity products. With the collapse of 'Bretton Woods' System in early 1970s and introduction of financial market reforms in developed markets led by the US (notably the passage of Commodity Futures Trading Commission Act of 1974), futures markets were created for precious metals[113], currencies[114], government bonds, interest rates, as well as equity indices. Back to 1980, total trading volume of futures contracts in US exchanges was at 92.5 million contracts[115], up 21% from the year of 1979. With the development of international futures exchanges and introduction of financial futures contracts, total futures trading volume reached 12.2 billion contracts in 2013 around the globe[116] or a +16% compounded annual growth during a 33-year period.

Figure 89: Trading Volume of Exchange Traded Futures and Options by Region (No of Contracts in Millions)



Source: FIA, J.P. Morgan Quantitative and Derivatives Strategy.

Figure 90: Trading Volume of Exchange Traded Futures and Options by Asset Class (No of Contracts in Millions)



Source: FIA, J.P. Morgan Quantitative and Derivatives Strategy.

[111] National Futures Association (NFA) is the self-regulatory organization for the U.S. derivatives industry, including on-exchange traded futures, retail off-exchange foreign currency (forex) and OTC derivatives (swaps). NFA Website: http://www.nfa.futures.org

[112] The Chicago Board of Trade (CBT), the oldest futures exchange in the world which was founded in 1848 by a group of 83 merchants, adopted its first rules and procedures to trade futures on agriculture commodities in 1863. According to some authors, the first recorded instance of futures (forward) trading occurred with rice in 17th Century Japan, and there is some evidence that rice futures has been traded in China 6,000 years ago.

[113] Silver futures were created in 1969 and gold futures began trading in 1974.

[114] Currency futures were first created in 1970 at the International Commercial Exchange in New York. But the contracts were not live for trades until May 16, 1975 due to the fact that the Bretton Woods system was still in effect.

[115] See http://www.nytimes.com/1981/01/05/business/1980-a-swell-year-for-futures.html

[116] According to the 2013 annual volume survey conducted by Futures Industry Association (FIA): http://www.futuresindustry.org/downloads/FIA_Releases_2013_Volume_Report.pdf

According to Futures Industry Association (FIA), total trading volume of global exchange traded futures and options stood at 21.8 billion contracts in 2014, which was held relatively stable during 2012-2014. North America, Europe and Asia accounted for roughly 37.7%, 23.3% and 30% of the total trading volume in 2014. By asset class, Equity Index (25.9%) and Individual Equities (29.4%) together accounted for more than half of the total trading volume, followed by Bond/Rates (14.9%), Currencies[117] (9.5%) and Agriculture Commodities (7.0%).

The first publicly held commodity CTA fund, Futures Inc., was established in 1948 by Richard Donchian, who developed Trend-Following systems such as the Donchian Channel and is an early pioneer of systematic trading in commodity futures. However, his concepts on systematic trend following and diversification were not widely adopted until decades later, partly because of limited products in global futures markets. One year later, Alfred Winslow Jones[118] established the first investment partnership structure, later known as a Hedge Fund, to invest in long/short stock strategies.

The development of the managed futures/CTA industry and global currencies and futures market over the past four decades is full of anecdotes of financial/technological innovations, regulatory reforms, academic influences, century-old pattern of boom/bust cycles and related legends of traders/researchers/policy makers etc. A number of events shaped the development of the futures market, education of CTA managers, and the proliferation of systematic Trend-Following strategies.

On Oct 23-24, 1974, US Congress passed the **Commodity Futures Trading Commission Act of 1974**, which overhauled the Commodity Exchange Act and created the Commodity Futures Trading Commission (CFTC). This event was viewed as another catalyst for the development of CTAs/managed futures industry, which created enormous opportunity for the first few generation of macro/CTA managers.

Commodities Corporation, which was co-founded by Nobel laureate Paul Samuelson’s student Helmut Weymar along with several of his MIT classmates/Professors in 1969 to focus on trading opportunities in commodities, became a training ground for many of the hedge fund stars such as Paul Tudor Jones, Bruce Kovner, Louis Bacon, Ed Seykota, and Jack D. Schwager[119] etc. With strong academic background and right timing, employees of Commodities Corporation were able to experiment with various Trend-Following systems on commodity futures as well as the newly created financials futures markets.

Another meaningful event in the history of CTA is about legendary traders Richard Dennis and William Eckhardt’s experiment on training exceptional traders in 1983. Dennis, the winner of the experiment, proved that successful trading could be sustained by applying a set of systematic trading rules: after two weeks of training, many of his students, referred to as ‘Turtles’, ended up generating significant returns. The story of ‘Turtles’ and the publicizing of Dennis’ systematic trading rules have since inspired many people in the field of trading and systematic strategies.

Technological advancement also re-shaped the CTA industry and the proliferation of scientific Trend-Following strategies. Before the 1980s, most futures traders relied on ‘tape reading’ and charting patterns to identify certain trend. With easier access to computers and programming languages, many of the trading rules are written as computer codes and charting patterns are summarized as technical signals such as Relative Strength Indicator, Stochastics, William’s R, and Moving Average Convergence Divergence etc. With latest development in statistical science, especially in the field of machine learning and pattern recognition during the past three decades, more and more funds designed their own procedures to identify cross-asset trends and trade a diversified pool of futures. In addition, the introduction of electronic trading technology is making a positive impact on CTAs by increasing execution efficiency and reducing trading slippages.

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[117] Given less capacity and limited contract variety in currency futures, many CTAs actually prefer to use of more liquid OTC currency contracts rather than exchange traded currency futures for their trading strategies. According to BIS, notional outstanding of OTC currency contracts (including forward, FX swaps, currency swap and options) stood at USD 75 trillion in June 2014, whereas notional outstanding for exchange traded currency futures and options were only at USD 379 billion at the same period, or 0.5% of the comparable OTC market size.

[118] In his 1949 article in Fortune, Alfred analyzed many then-popular stock forecasting techniques, such as Mansfield Mills’ buying and selling curves, Dow Theory, and others Trend Following techniques. He then explained the ‘Trend Following’ concept by ‘the undoubted fact of Momentum in psychological trends’.

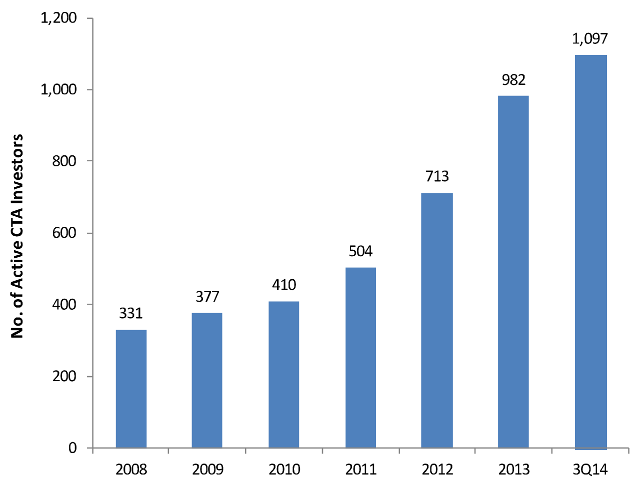
[119] Jack D. Schwager later authored a best-selling ‘Market Wizard’ series by interviewing world’s top traders (including several colleagues of Commodities Corp), whose long-term track record rebuffs the notion of ‘Efficient Market Hypothesis’.

Active Institutional Investor Base

According to BarclayHedge, AUM for the CTA industry was only at USD 310 million as of 1980. In 30 years, it grew more than 1000 times and surpassed the USD 300 billion mark in 2011. Earlier take-off in the industry subscribes to the liberalization of financial markets and the development of financial theories supporting the benefit of managed futures strategies[120].

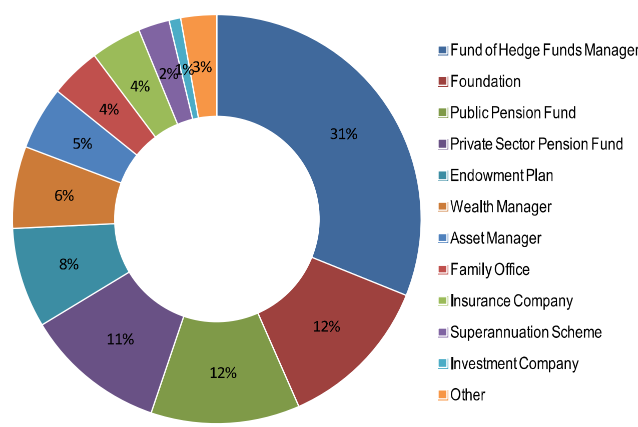
Despite slowdown of asset growth[121] since 2011 (Figure 6 on page 15 of the main text), the number of active CTA investors has been on the increasing trend in recent years. According to a latest survey done by Preqin, a data provider for alternative assets, there are 1097 active institutional investors in CTAs as of 3Q 2014, doubling from three years ago and tripling from five years ago (Figure 91). Among the institutional investors with a preference for CTA funds, fund of hedge funds managers account for roughly a third, followed by pension funds, foundations, endowment plans, wealth managers/family offices and asset managers (Figure 92).

Figure 91: No. of Active CTA Investors (Institutional)



Source: Preqin, J.P. Morgan Quantitative and Derivatives Strategy

Figure 92: Investors with a Preference for CTA Funds by Type



Source: Preqin, J.P. Morgan Quantitative and Derivatives Strategy

With the revival of CTA performance since 2Q 2014 and disappointments from traditional hedge funds, the CTA industry and related strategies could see more interests from different type of investors looking for exposures to liquid alternatives.

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[120] John Lintner, one of the co-creators of Capital Asset Price Model (CAPM), wrote a paper in 1983 titled "The Potential Role of Managed Commodity-Financial Futures Accounts (and/or Funds) in Portfolios of Stocks and Bonds", which shows substantial diversification benefits that accrue when managed futures are added to institutional portfolios of stocks/bonds. Major investment firms added managed futures to their retail offerings based on the findings of this academic study.

[121] According to BarclayHedge, asset under management for the CTA industry (including Systematic Trend Following Fund and Discretionary CTA Managers) stands at USD 312.6bn as of 3Q 2014. This figure may understate the true AUM of the CTA industry given some of the trend followers classify themselves into Global Macro hedge funds and many managed accounts uses CTA strategies. In addition, many of the latest CTA funds operating in domestic markets such as China's Shanghai and Zhengzhou Futures exchanges may not be captured by international CTA databases. Since 2007, there are also managed futures strategies operating under '40 Act Liquid Alternative Mutual Fund categories, which are not in the CTA databases.

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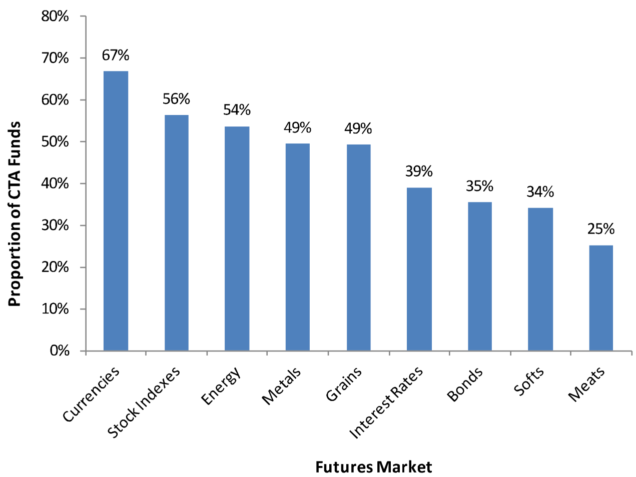
Classification of CTA Funds and CTA Sector Trends

Before analyzing performance statistics, we first look at the generic classification of the CTA industry and related development trends. Given the limited information provided by reporting funds, there are roughly two ways to classify a CTA. First of all, a fund can be classified by its specific **asset sector of operation** according its manager's specialty. For instance, while a currency specialist may prefer to trade in currency futures, spots or OTC currency forwards and swaps, an agricultural commodity trader could specialize in dealing with futures contracts in corn, wheat, soybeans, cotton etc. According to Preqin, currency futures, stock index futures and energy commodity futures are traded by more than half of the active CTA funds (Figure 93).

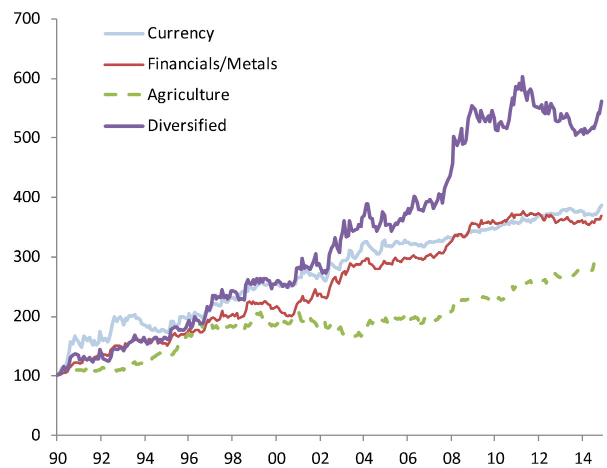
With increasing recognition of cross-asset diversification benefit, more and more CTA funds are operating with diversified exposure to different asset classes - this can either be achieved by hiring asset-sector specialist traders/strategists or running systematic multi-asset Trend-Following programs similar to those introduced in our main text. According to Figure 94 below depicting BarclayHedge CTA sector indices since 1990, diversified CTA funds have outperformed sector-specialists over the past two decades.

Figure 93: Top Futures Markets Traded by CTA Funds



Source: Preqin, J.P. Morgan Quantitative and Derivatives Strategy

Figure 94: Historical Performance of CTA Fund Sectors



Source: J.P. Morgan Quantitative and Derivatives Strategy, BarclayHedge, Bloomberg.

Another method of classifying CTA funds is according their **Style of Trading**. Generally speaking, CTA funds implement trading strategies either through trader/PM's discretion or automatic trading programs executing pre-determined systematic strategy. Some systematic traders may also have the discretion to override trading signals and/or position sizes based on experience or unmodeled market information. According to Preqin, 70%-80% of the CTAs launched during 2011-2014 employ systematic trading, 10%-20% focus on discretionary trading, and roughly 10% use both styles. Figure 96 shows that CTAs with systematic trading styles outperformed those with discretionary trading over the past 25 years.

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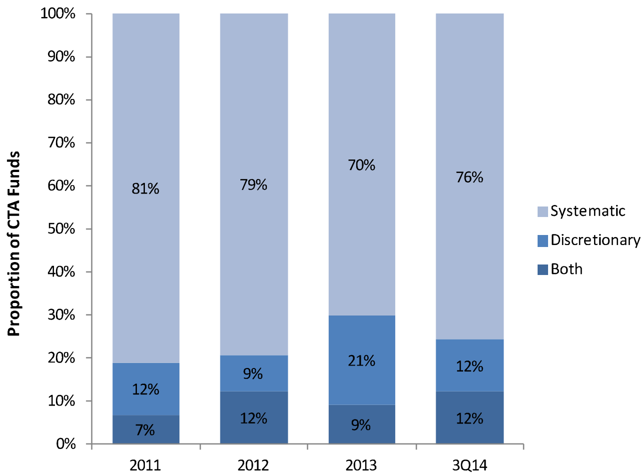
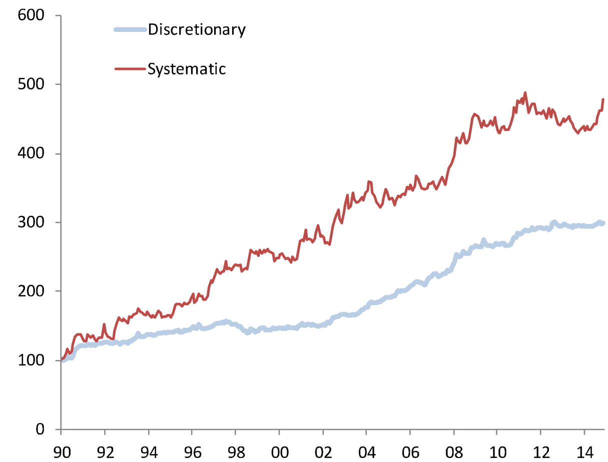
Figure 95: Systematic vs. Discretionary Trading Styles of New CTAs



Source: Preqin, J.P. Morgan Quantitative and Derivatives Strategy

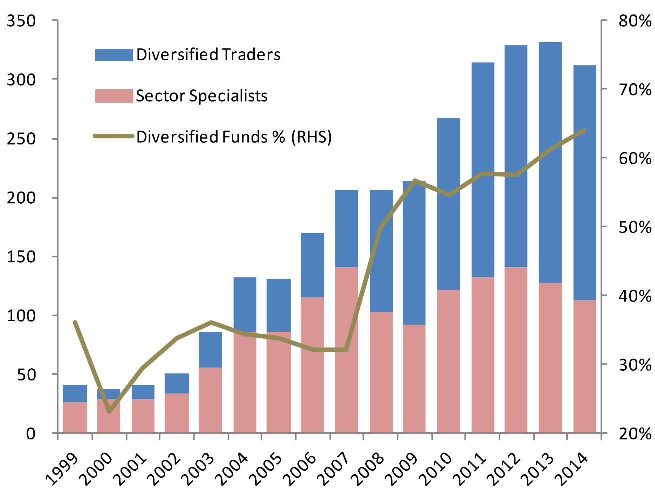
Figure 96: Historical Performance of CTA Fund by Trading Styles



Source: J.P. Morgan Quantitative and Derivatives Strategy, BarclayHedge, Bloomberg.

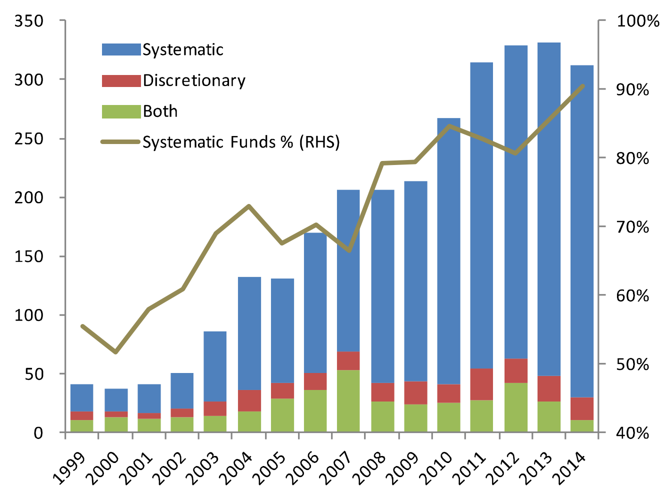
In terms of assets, diversified CTAs (USD 200.4bn as of 3Q 2014 according to BarclayHedge) account for roughly two thirds of all CTA funds, up from roughly 20% in 2000. In addition, more than 90% CTAs focuses on systematic trading, compared with only 51.8% in 2000. The trend towards diversified Trend-Following strategies seems to be welcomed by both CTA fund managers and their investor base.

Figure 97: AUM trends of Sector Specialists vs Diversified CTAs



Source: BarclayHedge, J.P. Morgan Quantitative and Derivatives Strategy

Figure 98: AUM trends of Systematic vs Discretionary CTAs



Source: BarclayHedge, J.P. Morgan Quantitative and Derivatives Strategy.

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CTA Indexation and Performance

According to our findings in the section 'CTA Exposure to Prototype Momentum Factors' on page 48, CTA funds are significantly exposed to a common set of systematic Trend Risk Factors. Compared with time-varying Risk Factor style exposure of generic Hedge Funds, this feature makes CTA a more homogenous alternative asset class and brings indexation of CTA industry/sector performance a meaningful exercise. One explanation for this homogeneity is that similar CTA funds within certain asset sectors generally pursue similar Trend-Following strategies[122]. Similar to Hedge Funds, CTAs doesn't report to a unified database and as a result there are a few popular database/index providers catering to different end users. Table 54 below summarizes several major providers of CTA data: each of them designs a suite of indices tracking aggregate as well as sector performances of the CTA industry. [123]

Table 54: Popular Data/Index providers for CTAs

Data/Index Provider	Start Date	Index Weight	Region/Sector	Website
Hedge Fund Research*	1990	Equal Weight	Yes	www.hedgefundresearch.com
Dow Jones Credit Suisse	1994	Asset Weight	No	www.hedgeindex.com
Morningstar CISDM	1980	Equal Weight	No	hedgefunds.datamanager.morningstar.com
EurekaHedge	2000	Equal Weight	Yes	www.eurekahedge.com
BarclayHedge	1980	Equal Weight	Yes	www.barclayhedge.com
Newedge	2000	Equal Weight	Yes	www.newedge.com/

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg.
* HFRI Macro/CTA aggregate and sector indices also include global macro trading style.

Table 55 below shows historical return-risk profiles for the Dow Jones Credit Suisse (DJCS), Morningstar CISDM, EurekaHedge, BarclayHedge and Newedge CTA indices during Jan 2000 - Dec 2014 based on monthly data. Given each database tracks different sets of funds, observed performances do differ by index provider. For instance, CTA Funds tracked by EurekaHedge delivered an annualized excess return (above US$ cash) and Sharpe ratio of +8% and 1.15 respectively, while the BarclayHedge CTA index showed an annualized excess return and Sharpe ratio of +1.8%, and 0.30 respectively.

Table 55: Performance/Risk Statistics for CTA Benchmarks during 2000-2014

	DJCS	*CISDM*	*EurekaHedge*	*BarclayHedge*	*Newedge*
Ann. Ex Ret (%)	3.7	4.7	7.9	2.0	3.2
CAGR (%)	3.1	4.5	8.0	1.8	2.9
STDev (%)	11.6	8.3	6.9	6.6	8.6
MaxDD (%)	-18.6	-13.2	-6.9	-11.2	-13.3
MaxDDur (in yrs)	3.6	3.5	1.9	3.8	3.9
***t*-Statistic**	**1.3**	**2.2**	**4.4**	**1.2**	**1.5**
Sharpe Ratio	**0.32**	**0.57**	**1.15**	**0.30**	**0.38**
Hit Rate (%)	53.9	52.8	60.6	51.1	54.4
Skewness	0.02	0.46	0.57	0.33	0.15
Kurtosis	-0.53	0.06	0.93	0.57	0.50

Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg. * Statistics are calculated from monthly data.

Figure 99 plots 1st quartile, median, and 3rd quartile for monthly returns of the five CTA indices and we find the returns of Dow Jones Credit Suisse and Newedge Indices are more dispersed than the returns of the other three indices. Asset/trend horizon tilts and the use of leverage of constituent funds as well as index methodology are the major reasons behind the difference in return dispersions. For instance, the asset weight method used by DJCS could be one of the reasons for its higher return volatility since a few large funds could have high impacts on the index return.

[122] Despite differences in the use the specific trend signal and risk management system, the outcome of Trend-Following strategies generally have high correlations as illustrated by the section on 'Correlation of Momentum Strategies' on page 34.

[123] Biases (such as survivorship, look-back, backfill, selection biases etc) in Hedge Fund/CTA indexes are reported by various authors.

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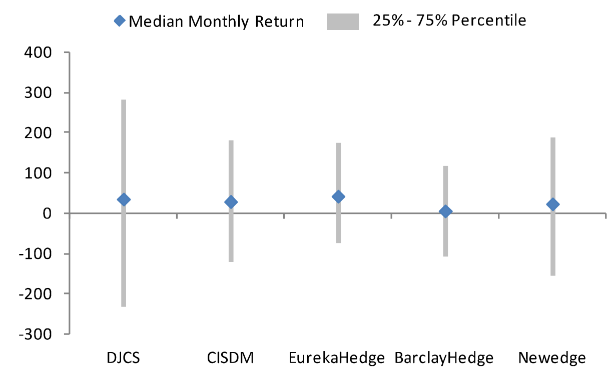
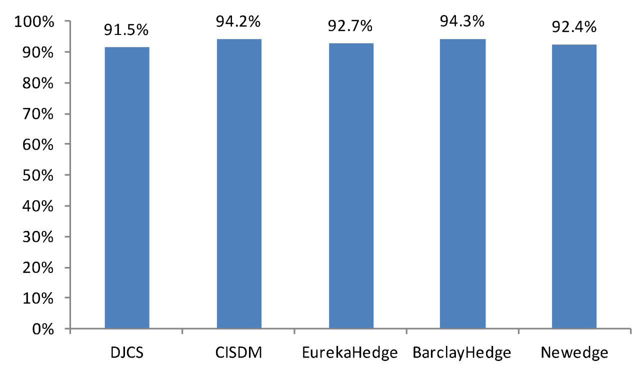
Despite differences in returns and returns dispersions, the CTA indices are highly correlated with each other. Figure 100 shows that the average correlation between any CTA index with all the other major benchmarks was more than 90% during 2000-2014, an evidence

Figure 99: Return Distributions of Different CTA Indices



Source: J.P. Morgan Quantitative and Derivatives Strategy

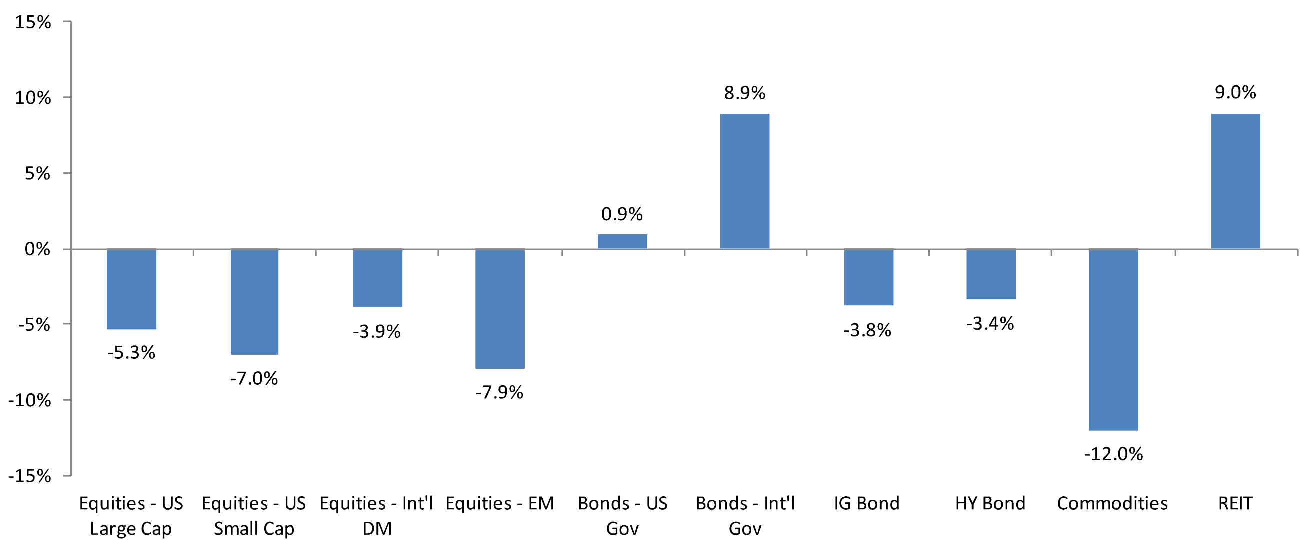
Figure 100: Average correlation of a CTA Index with others



Source: J.P. Morgan Quantitative and Derivatives Strategy.

Given high correlation among CTA benchmarks, we use the Newedge CTA index, which is designed to tracker the largest twenty CTA fund (by asset) performances, to calculate the correlation between CTA and major assets in institutional investors' portfolio. Shown in Figure 101 below, CTA as an alternative asset class displayed low correlation with US/International Equities, US/International Government Bonds, Investment Grade Bond, High Yield Bond, Commodities and REIT. This low correlation over a full business cycle arises from the fact that CTAs are exposed to systematic trend factors that are anti-crisis - positive correlation with risky assets during up markets and negative correlation with risky assets during down markets.

Figure 101: CTA's correlation with major assets during 2000-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy.

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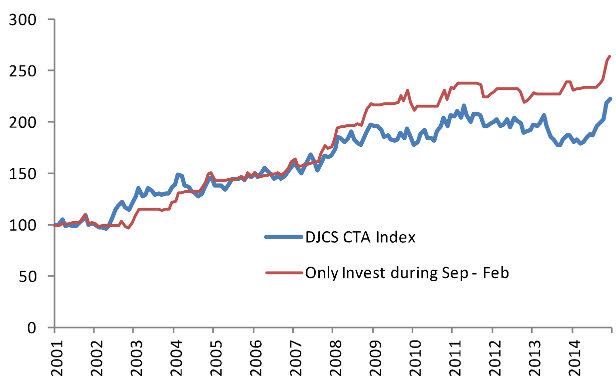
CTA Return Seasonality

After a brief review of CTA benchmark's return/risk as well as correlation properties, we next look at an interesting feature of CTA indices: **Seasonality**. In the equity space, there are a few well-known seasonal anomalies such as the January effect, the Halloween effect, just to name a few; in commodities, seasonality often relates to weather changes and the supply/demand of agricultural/energy products; in G10 currencies, there are also few documented seasonality effects such as the July/August turn in USD/JPY cross etc. We discussed these Seasonality effects and related systematic strategies in Chapter 4 of this report.

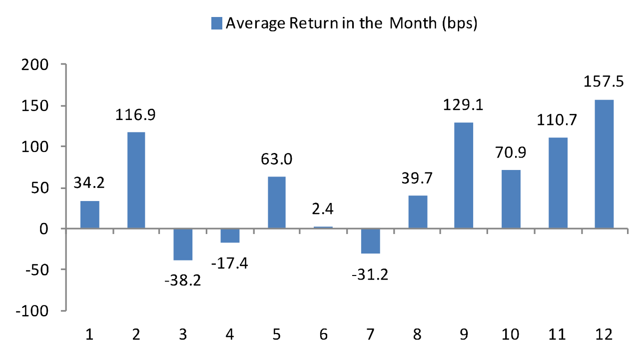
We find there are two notable Seasonality effects for CTAs. First, on a **medium-term horizon**, an investment strategy that only puts money into CTAs from September to February the following year and stay in cash otherwise would have generated similar returns to a buy-and-hold strategy. In other words, holding an investment into an average CTA fund during the semi-annual periods from March to August doesn't seem to contribute to portfolio total return[124]. This suggests that CTA as an asset class may follow an investment cycle two months ahead of the famous 'Halloween effect' in stock markets. Figure 102-Figure 109 below shows that this 'Buy in August and Sell in March' effect exists for the major CTA indices in our study and except for CISDM index (which shows inline performances), a Sep-Feb seasonal investment strategy in CTA benchmarks outperformed a buy-and-hold CTA strategy during 2001-2014.

Figure 102: Cumulative total return of a Sep-Feb investment vs buy-and-hold strategy in DJCS CTA Index



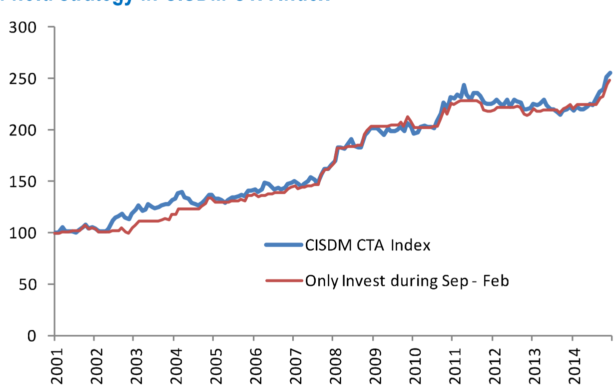
Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 103: Average return of DJCS CTA index by month during 2000-2014



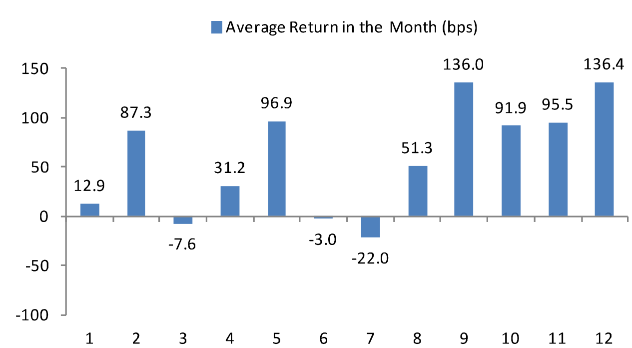
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 104: Cumulative total return of a Sep-Feb investment vs buy-and-hold strategy in CISDM CTA Index



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 105: Average return of CISDM CTA index by month during 2000-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy.

[124] The only exception is the EurekaHedge CTA index, which shows a positive average return in average month.

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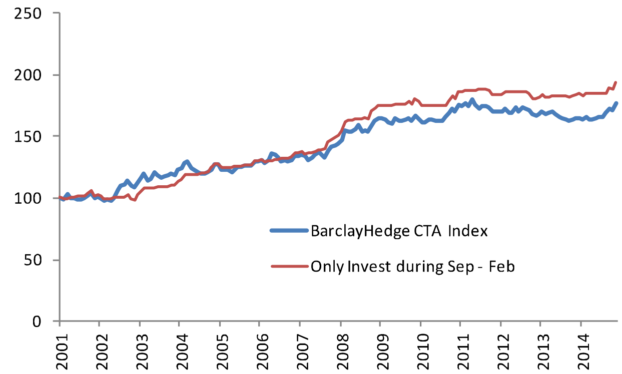
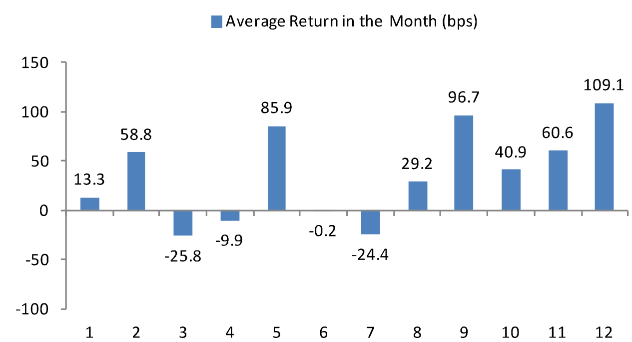
Figure 106: Cumulative total return of a Sep-Feb investment vs buy-and-hold strategy in BarclayHedge CTA Index



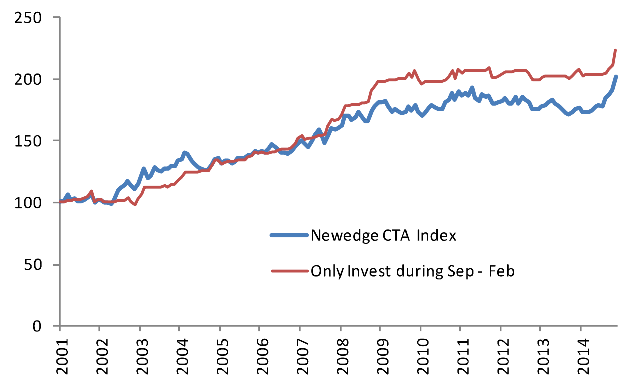
Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 107: Average return of BarclayHedge CTA index by month during 2000-2014



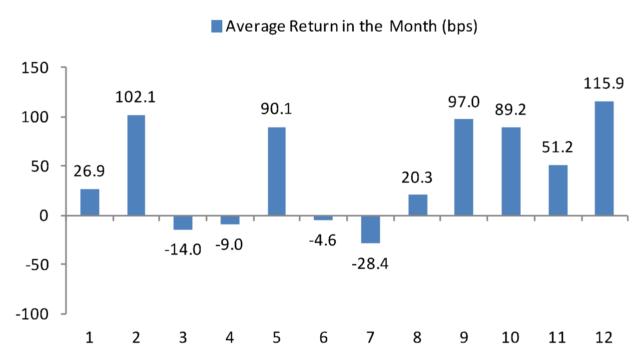
Source: J.P. Morgan Quantitative and Derivatives Strategy.

Figure 108: Cumulative total return of a Sep-Feb investment vs buy-and-hold strategy in Newedge CTA Index



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 109: Average return of Newedge CTA index by month during 2000-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy.

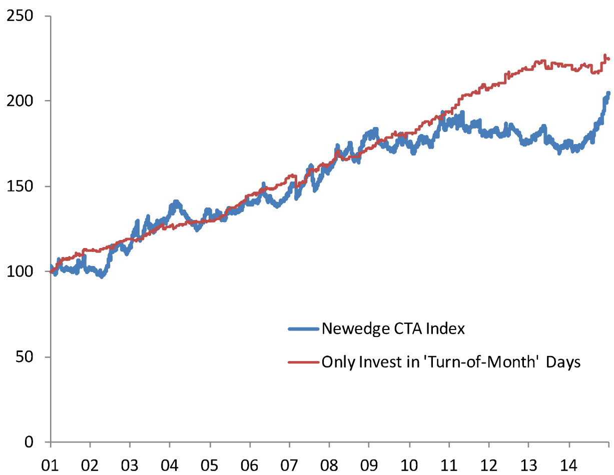
Second, on a **short-term horizon**, there is a noticeable 'turn of the month' effect for large CTAs: An investment strategy that only puts money into CTAs from one-day before month ends to one-day after and stay in cash otherwise would have generated similar returns to a buy-and-hold strategy. Figure 110 and Figure 111 below validate this thesis by examining average daily returns of the Newedge CTA index[125] around month ends and test a 'turn-of-the-month' investment strategy[126]. We find that average daily return for the Newedge CTA index were +10.6 bps, +10.9 bps and +11.1 bps respectively during 2001-2014, significantly higher than the average returns on other business days.

A possible reason is related to the monthly/quarterly liquidity of these funds and short-term market impact of investor subscriptions. Given larger CTAs pursue longer-term trends, inflows of investor assets during end of month/quarter rebalances would likely reinforce the current trend and the performance of existing strategy. Another explanation of the turn-of-month effect relates to the 'Window Dressing' behavior of CTAs – return enhancement activities are usually occurred during the ending days of performance measurement window. This is also consistent with the finding that Day 2-3

[125] Among major CTA indices, only Newedge provides daily levels and hence our analysis focuses on the Newedge CTA index, which tracks performances of 20 largest CTAs by assets.
[126] This strategy only demonstrates short-term seasonality effect of CTA funds. Given lockout period and possible fees related to subscription/redemption, it is not recommended to be implemented in practice.

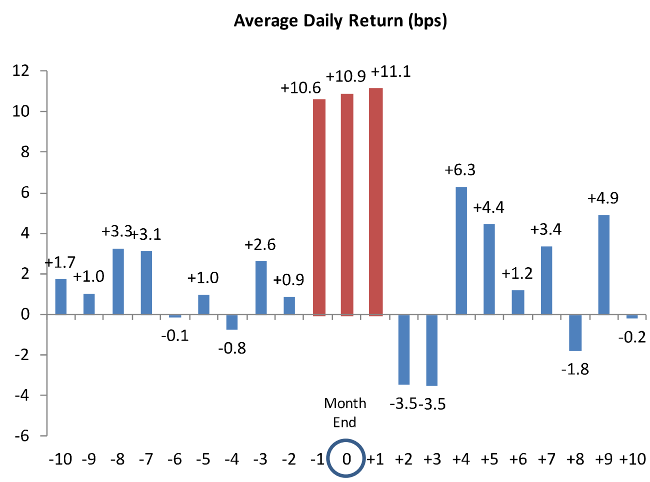
after month-end/month beginning rebalances turned out to be the worst performing days in a month, possibly arising from the unwind of month/quarter-end window-dressing activities.

Figure 110: Cumulative total return of a 'Turn-of-Month' investment vs buy-and-hold strategy in Newedge CTA Index



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 111: Average return of Newedge CTA index by Days around the Month End



Source: J.P. Morgan Quantitative and Derivatives Strategy.

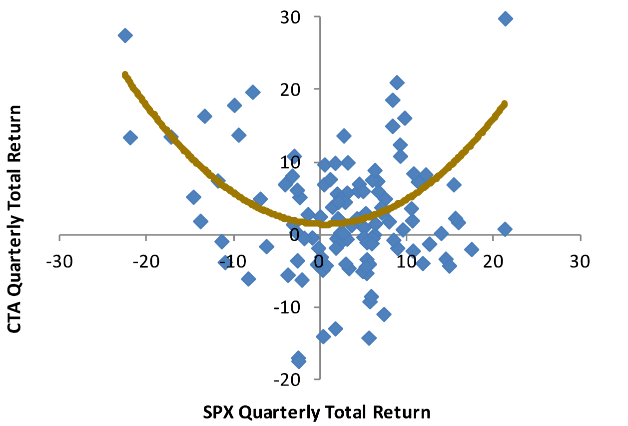
CTA Return Convexity and Crisis Alpha

A desired feature for the CTA asset class is its return convexity with regard to traditional risky assets such as Equities, High Yields and Commodities: it delivers high returns during both bull and bear markets and low returns during range bound (non-directional) markets[127]. For instance, Figure 112 below shown such return convexity relative to S&P 500 index during the past 30 years from 1984 to 2014 (quarterly return scatter-plot with quadratic regression fit of relationship) and Figure 113 calculates the average return of CTAs[128] during increasing order of SPX return buckets.

One could find that during Equity market crisis (quarterly return less than -10%), CTAs returned strongly (in fact, the CTA index never had a negative quarterly when SPX returned less than -12% in the same quarter). One the other hand, when equity markets were in bull phase, CTAs still delivers decent return, but not as strong as a long-only position in equities.

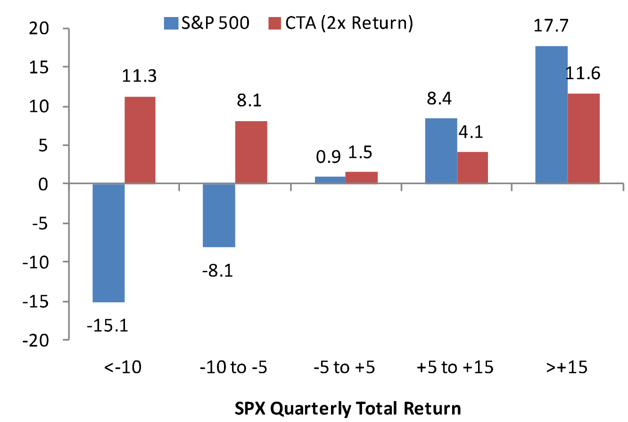
[127] We identified similar properties for prototype Momentum factors in the section 'Correlation of Momentum Strategies' on page 35.
[128] The average return is based on 2x leverage to make the return comparison in similar scale given CTAs displayed roughly half the volatility of SPX.

Figure 112: Historical Quarterly Total Returns of CTAs vs SPX during 1984-2014 (%)



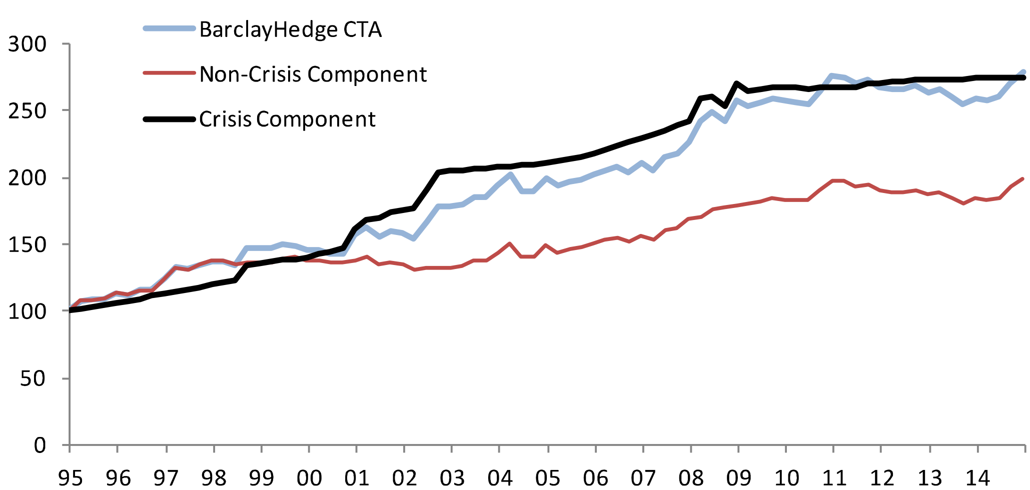
Source: J.P. Morgan Quantitative and Derivatives Strategy
* CTA returns are calculated based on BarclayHedge CTA Index.

Figure 113: Average Quarterly Return of CTAs vs SPX ranked by SPX returns during 1984-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy.
* CTA returns are calculated based on BarclayHedge CTA Index.

Figure 114: CTA Return Decomposition into Crisis and Non-Crisis Components Based on SPX Returns



Source: J.P. Morgan Quantitative and Derivatives Strategy. * Crisis Mode is when SPX quarterly total return < -5%.

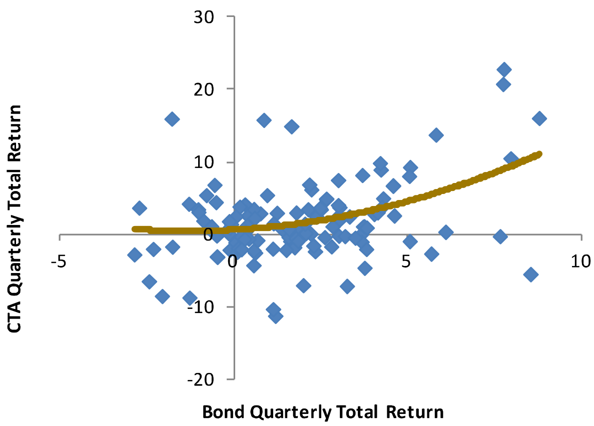
Figure 114 decomposes CTA returns into equity market crisis (SPX returned less than -5% in a quarter) and non-crisis components during the past 20 years and one could find that almost all the cumulative CTA returns were earned during equity market crisis. This phenomenon is often called the 'Crisis Alpha' or 'Crisis Seasonality' of CTAs. Given 'Alpha' is usually defined against a certain benchmark index (either a cash or equity index), another interpretation of CTAs' Crisis Alpha is that the intercept of a conditional regression of CTA returns vs equities (or the conditional average return of CTAs) is statistically significant when we only consider equity market drawdown periods. This conclusion is self-evident in Figure 113 given CTAs are shorting risk assets in a down-trending market.

Another interesting point is about CTA's Crisis Alpha from a Bond perspective. Figure 115 and Figure 116 show the relationship between the quarterly returns of CTA and US Bonds[129] during 1984-2014. Over this 30-year period, one could

[129] We use Barclays US Aggregate Bond Index, which is a benchmark of US Treasury and investment grade corporate bonds.

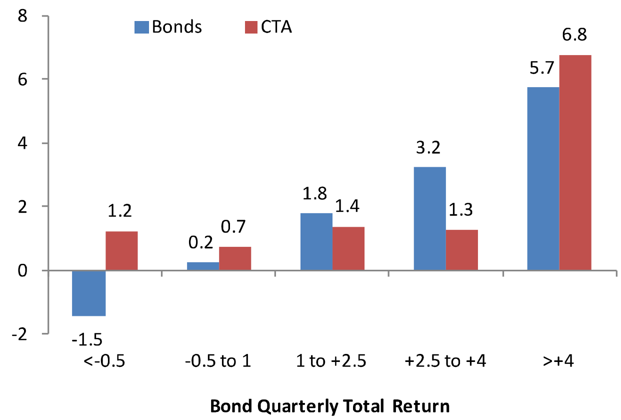
identify overall positive relationship between bond and CTA returns. However, if one only focuses on normal periods when bonds returned less than 4% in a quarter, we find the correlation between CTA and bonds are roughly zero - this suggests that CTAs did offer good diversification to a bond portfolio. Indeed, during periods of bond distress, CTAs most often returned positively and protects a bond portfolio.

Figure 115: Historical Quarterly Total Returns of CTAs vs US Aggregate Bond Index during 1984-2014 (%)



Source: J.P. Morgan Quantitative and Derivatives Strategy
* CTA returns are calculated based on BarclayHedge CTA Index.

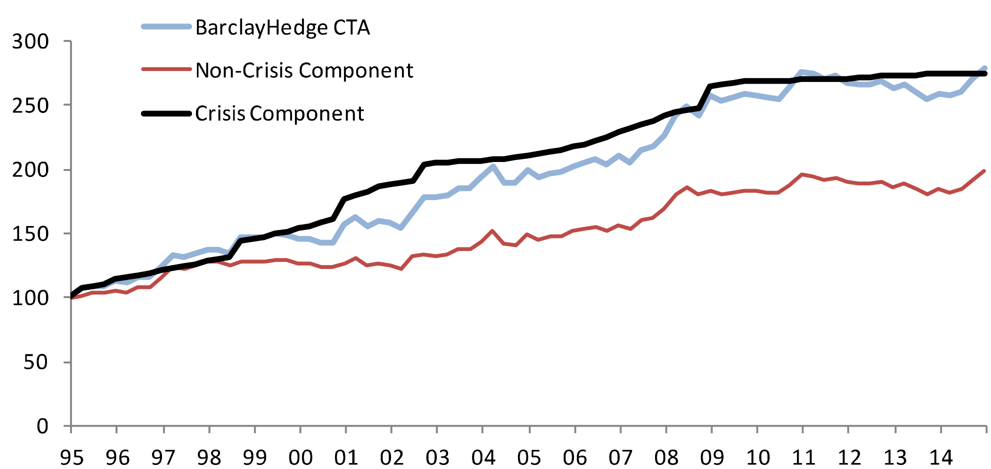
Figure 116: Average Quarterly Return of CTAs vs Bond ranked by US Aggregate Bond Index returns during 1984-2014 (%)



Source: J.P. Morgan Quantitative and Derivatives Strategy.
* CTA returns are calculated based on BarclayHedge CTA Index.

Figure 117 resurrects CTA's 'Crisis Alpha' from a bond perspective: the bulk of CTA returns can be mostly explained by episodes of 'flight to quality' during which bonds returned more than 4% in a quarter.

Figure 117: CTA Return Decomposition into Crisis and Non-Crisis Components Based on Bond Returns



Source: J.P. Morgan Quantitative and Derivatives Strategy. * Crisis Mode is when Barclays US Aggregate Bond index quarterly total return > 4%.

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Mathematics of Trend Filtering Methods

In this Appendix, we briefly describe main methods in the field of statistical trend filtering without going into technical details. Technicalities could be found in standard books on machine learning and technical trading.

Mathematical Box (Methods of Trend Filtering and Trend Signals)

Let y_t be a normalized continuous process of security price (e.g. log of daily close price) with the following "trend cycle" decomposition:

$$y_t = x_t + \epsilon_t$$

where x_t is the unobservable price trend and ϵ_t is the noise factor. **Trending filtering** is a process to uncover x_t from the observations of y_t.

Constant "first derivative" of x_t indicates up or down price trends. Let $\mu_t = \mathrm{d}x_t/dt$, the trend filtering equation could be written as:

$$dy_t = \mu_t dt + d\epsilon_t$$

If we assume $d\epsilon_t = \sigma_t dW_t$ to be while noise, y_t follows a Gaussian stochastic process[130] whose randomness is characterized by the white noise term $\sigma_t dW_t$.

Theoretically, Trend Filtering amounts to identify the functional form of $\hat{x}_t = f(t, \boldsymbol{y}_t)$ or $\hat{\mu}_t = g(t, \boldsymbol{y}_t)$. Generally, there are two approaches in solving the trend filtering problem:

(1) By making assumptions on functional form of $f(t, \boldsymbol{y}_t)$ or $g(t, \boldsymbol{y}_t)$, and solving for the function parameters by optimizing an objective function designed to balance between (in-sample) goodness of fit and degree of freedom.

(2) By making assumptions on additional stochastic drivers of x_t or μ_t and solve for the system of parameters by optimizing a certain objective function such as the likelihood function or cross-validated mean squared error function.

Popular trend filtering methods/signals include the following:

1) Past Price Returns

If we assume $y_t = \log(S_t)$, where S_t is the close price of a certain security. Then the past price return during a certain window L is defined by $R_{t,\Delta t} = S_t/S_{t-\Delta t}$. Trend filtering based on $R_{t,\Delta t}$ is equivalent to use

$$\log(R_{t,\Delta t}) = \log(S_t/S_{t-\Delta t}) = y_t - y_{t-\Delta t}$$

This makes sense if we assume $\mu_t \equiv \mu$ held roughly stable during the window $(t, t-\Delta t)$ and the error term $(\epsilon_t - \epsilon_{t-\Delta t})$ roughly canceled out, which can be seen from:

$$y_t - y_{t-\Delta t} = \int_{t-\Delta t}^{t} \mu_s ds + \epsilon_t - \epsilon_{t-\Delta t} \approx \Delta t \times \mu$$

[130] In the case that price level is modeled by Geometric Brownian Motion and its various extensions, one could apply logarithm on prices to get similar Gaussian processes with some convexity adjustment for drift/trend.

2) Past Price Returns Skipping Recent History

As some securities have the tendency for near-term reversal, the calculation of price trend could be usually enhanced via skipping a certain short window in recent history. Specifically for : $\Delta s < \Delta t$

$$y_{t-\Delta s} - y_{t-\Delta t} = \int_{t-\Delta t}^{t-\Delta s} \mu_s ds + \epsilon_{t-\Delta s} - \epsilon_{t-\Delta t} \approx (\Delta t - \Delta s) \times \mu$$

3) Simple Moving Averages

Similar to above, if we assume $\mu_t \equiv \mu$ held roughly stable during the window $[t, t - L + 1]$ of length L, then

$$MA(y_t^L) = \frac{1}{L}\sum_{i=0}^{L-1} y_{t-i} \approx y_0 + \frac{1}{L}\sum_{i=0}^{L-1}\int_0^{t-i} \mu_s ds \approx y_0 + \left(t - \frac{L-1}{2}\right)\mu$$

4) Simple Moving Average Crossovers

Similar to above, if we assume $\mu_t \equiv \mu$ held roughly stable during the window $[t, t - L_2 + 1]$ of length L_2, then for any $0 < L_1 < L_2$, we have

$$MA\left(y_t^{L_1}\right) - MA\left(y_t^{L_2}\right) \approx \frac{L_2 - L_1}{2}\mu$$

5) Kernel Smoothing Methods

One could regard the simple moving average as a linear operation on the Time Series data of $\boldsymbol{y}_t = (y_0, y_1, \dots, y_t)$. In fact, we could assume generic functional forms of $f(t, \boldsymbol{y}_t)$ and optimize the parameters based a certain objective functions.

Exponentially Weighted Moving Averages

Unlike Simple Moving Averages which use equal weights for past observations, the Exponentially Weighted Moving Averages uses exponential decay to give more weight to more recent observations:

$$MA(y_t^L) = \theta \sum_{i=0}^{\infty} e^{-\delta(t-i)} y_{t-i}$$

where $\delta > 0$ controls the speed of exponential decay and θ is a normalizing constant. Exponentially Weighted Moving Averages may be implemented with a fixed window cutoff by considering only the most recent data.

Linear Least Square Filters

If we assume $f(t, \boldsymbol{y}_t) = \alpha + \beta t$, then the parameters (α, β) could be estimated via minimizing the sum of squared errors:

$$\left(\hat{\alpha}, \hat{\beta}\right) = \underset{(\alpha,\beta)}{\operatorname{argmin}} \sum_{i=1}^{t} (y_t - \alpha - \beta t)^2$$

Smoothing Splines

One could directly extend the linear least square filter above to include polynomial terms for better in-sample fit. However, the behavior of polynomials fit to data tends to be erratic near the boundaries, and hence extrapolation of trends can be dangerous. Spline basis functions are designed to achieve boundary continuity and smoothness. For example, a natural cubic spline with K knots $(\xi_1, \dots, \xi_K)$ is represented by K basis functions $N_k(\boldsymbol{y}_t)$ for $k = 1,2, \dots, K$ and $f(t, \boldsymbol{y}_t)$ could be expressed as a functional expansion:

$$f(t, \boldsymbol{y}_t) = \sum_{j=1}^{K} \beta_j N_k(y_j)$$

where $N_1(y) = 1$, $N_2(y) = y$, $N_{k+2}(y) = d_k(y) - d_K(y)$, where $d_k(y) = [(y - \xi_k)_+^3 - (y - \xi_K)_+^3]/(\xi_K - \xi_k)$.

As a result, the parameters could be solved from the following penalty function:

$$(\hat{\alpha}, \hat{\beta}) = \underset{(\alpha,\beta)}{\operatorname{argmin}} \sum_{i=1}^{t} \left(y_t - \sum_{j=1}^{K} \beta_j N_k(y_j) \right)^2 + \lambda \|W\boldsymbol{\beta}\|_p$$

where W is a weight matrix constraining the smoothness of the parameters, λ is a parameter balancing the goodness of fit, parameter smoothness and degree of freedom (function regularization). $\|\cdot\|_p$ is the L_p norm[131].

6) Kalman Filters

Another group of methods try to solve the trend filtering problem by assuming additional dynamics of trends. For example, in addition to $y_t = x_t + \epsilon_t$, one could assume the underlying trend follows another stochastic process: $x_{t+1} = x_t + \eta_t$, which models the smoothness of the trend. It terms out that if the noise terms (ϵ_t, η_t) are independent Gaussian variables, a process called **Kalman Filtering** could give the optimal solution.

7) Other Single-Variable Methods

Involves different extensions of **technical trading indicators** beyond simple moving averages (such as volume weighted moving averages, MACD, DMI, Parabolic Stop and Reversals, Ichimoku etc); different definitions of **stochastic behaviors** of Time Series based on certain modeling assumptions such as Half-life, Hurst exponent etc; different extension of **basis functions** in kernel-based smoothing methods; different **extensions of Kalman filters** to handle non-normality/ non-linear cases (e.g. Particle Filters); different **machine-learning** related tools such as Neural Networks, Graphical Models, Genetics Algorithm, Support Vector Machines etc.

8) Multi-Variate Trend Filtering

There are also trend filtering methods taking advantage of Relative information from contemporaneous variables. For instance, we define the trend signals $\widetilde{TS}_{j,t-1}(L_i)$ as scaled moving average of the *j*-th underlier and model asset returns via the Relative regression relationship:

$$R_{j,t} = \beta_{0,t} + \sum_i \beta_{i,t} \widetilde{TS}_{j,t-1}(L_i) + \epsilon_{j,t} \quad \text{for all } j$$

where

$$\begin{aligned} R_{j,t} &= \text{Return of the } j\text{th underlier in month } t, \\ \widetilde{TS}_{j,t-1}(L_i) &= \text{Trend signal at the end of month } t-1 \text{ with lag } L_i, \\ \beta_{k,t} &= \text{Intercept and coefficents for the trend signals.} \end{aligned}$$

Similar Relative relationship was proposed, for instance, by Han and Zhou (2014)[132] and we discussed this topic in the section 'Dynamically Rebalanced Signals' on page 46.

Finally, multi-variate extension of technical systems, Kalman Filters, high-dimensional machine learning methods are among the recipe of more complicated trend-followers.

[131] L_0 norm equals to the number of parameters, L_1 norm equals to the sum of absolute values and L_2 norm equals to the sum of squared values. L_p norm are usually employed to regularize functions. See Hastie et. al (2008) and Bishop (2007) for more general treatment of statistical functional approximations and regularization methods.

[132] Han and Zhou (2014), "Trend Factor: A New Determinant of Cross-Section Stock Return". Available at SSRN.

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CTA Exposure to Fung and Hsieh Factors

Fung and Hsieh (2001) argued that Trend-Following strategies should have straddle-like payoffs and we validated this assumption (in a statistical sense) in the section 'Correlation of Momentum Strategies' on page 30. The two authors created straddle-based factors (Primitive Trend-Following Factors or PTF factors) on Bonds, Currencies, Commodities, Rates and Equities to explain CTA/Hedge Fund returns. The regression results based on historical Time Series returns during 1994-2014 below (Table 56) do show that the PTF factors are significant explanatory variables for CTA benchmark index returns.

However, compared with Table 18 in the section 'CTA Exposure to Prototype Momentum Factors' on page 48, we find the PTF factors had a much less significant goodness of fit than our 'prototype trend factors': the Adjusted R-squared ranged from 16 to 31 for the PTF regression whereas our 'prototype trend factors' generated an Adjusted R-squared in the range of 45-49. Moreover, the asset exposure across different CTA benchmark indices is less stable based on PTF factors (e.g. Bond exposure ranged from +8% to +17%) than based on our 'prototype trend factors'.

Table 56: Performance Attribution of CTA Benchmarks to Look-back Straddle Factors of Fung and Hsieh (2001)

	After Fee CTA Benchmarks				Before Fee CTA Benchmarks			
	Barclay	**BTOP 50**	**DJCS**	**CISDM**	**Barclay**	**BTOP 50**	**DJCS**	**CISDM**
Ann. Alpha (%)	3.35	4.61	5.28	6.12	6.53	8.03	8.62	9.77
	(2.32)	(2.58)	(2.09)	(3.64)	(4.53)	(4.49)	(3.41)	(5.80)
PTF Bond	0.02	0.03	0.03	0.02	0.02	0.03	0.03	0.02
	(2.39)	(2.63)	(1.96)	(2.41)	(2.44)	(2.66)	(1.95)	(2.46)
PTF Currency	0.04	0.04	0.04	0.04	0.04	0.04	0.04	0.04
	(5.97)	(4.55)	(3.41)	(5.68)	(5.91)	(4.50)	(3.43)	(5.61)
PTF Comdty	0.04	0.03	0.04	0.04	0.04	0.03	0.04	0.04
	(4.37)	(2.72)	(2.75)	(4.21)	(4.40)	(2.76)	(2.79)	(4.22)
PTF Rates	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01	-0.01
	(-2.23)	(-1.37)	(-1.74)	(-2.12)	(-2.18)	(-1.35)	(-1.74)	(-2.06)
PTF Equity	0.02	0.02	0.04	0.02	0.02	0.02	0.04	0.02
	(1.81)	(1.83)	(2.36)	(2.06)	(1.83)	(1.83)	(2.35)	(2.08)
Adjusted R2 (%)	**30.65**	**21.24**	**16.16**	**29.62**	**30.69**	**21.31**	**16.27**	**29.61**

Loading By Assets	After Fee CTA Benchmarks				Before Fee CTA Benchmarks			
	Barclay	**BTOP 50**	**DJCS**	**CISDM**	**Barclay**	**BTOP 50**	**DJCS**	**CISDM**
Equity	16.4	20.1	29.0	18.7	16.5	19.9	28.8	18.8
Bond/Rates	7.9	16.5	9.4	8.6	8.4	16.9	9.2	9.2
Currency	38.4	35.3	29.7	36.6	37.8	34.8	29.8	36.0
Commodity	37.4	28.1	31.9	36.1	37.3	28.3	32.2	36.0

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Rebalancing and Investment Horizons

This Appendix summarizes performance/risk metrics for prototype Absolute and Relative Momentum strategies with various rebalancing frequency (Daily, Weekly, Monthly), trend-window length (1-, 3-, 6-, 12- and 24-months) and invest horizon (from 1-day to 24-months) assumptions. See Chapter 2 for more analysis.

Table 57: Performance-Risk of Absolute Momentum Strategies by Rebalancing and Investment Horizons: Multi-Asset

Trend Window (Months)	Invest Horizon (Months)					Invest Horizon (Months)					Invest Horizon (Weeks)					Invest Horizon (Weeks)					Invest Horizon (Days)					Invest Horizon (Days)				
	1	3	6	12	24	1	3	6	12	24	1	4	13	26	52	1	4	13	26	52	1	5	21	130	261	1	5	21	130	261
	Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)					Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)					Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)				
1	3.1	3.2	2.4	2.6	1.4	-3.2	-0.4	0.4	1.2	1.5	0.8	1.1	2.9	2.4	2.7	-11.4	-5.6	-0.7	0.6	1.1	-2.3	0.3	1.1	2.3	2.7	-14.8	-10.3	-4.4	0.6	1.1
3	5.6	4.7	3.7	3.7	2.2	-1.0	0.7	2.0	2.3	2.6	4.6	4.9	4.7	3.7	3.8	-4.3	-2.8	-0.2	1.3	2.1	1.9	4.5	4.9	3.7	3.8	-8.6	-4.1	-2.1	1.4	2.0
6	6.4	5.8	5.3	4.4	2.6	0.3	0.9	0.6	1.9	2.5	4.9	5.7	5.4	5.1	4.4	-1.5	0.3	0.5	0.7	2.2	3.4	4.9	5.6	5.2	4.4	-4.1	-1.7	0.6	0.8	2.1
12	8.6	7.3	5.8	4.3	2.7	3.4	3.7	3.6	4.1	3.8	8.3	8.1	7.0	5.7	4.2	3.0	2.6	3.0	3.3	4.0	7.0	8.0	8.1	5.7	4.2	1.3	2.1	2.8	3.2	3.9
24	4.9	4.6	3.5	2.5	1.7	5.0	4.7	4.0	3.8	5.0	4.1	4.4	4.2	3.3	2.5	2.5	3.7	3.9	3.6	3.6	3.6	4.0	4.4	3.4	2.5	2.0	2.5	3.8	3.6	3.7

Trend Window (Months)	Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)					Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)					Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)				
1	0.5	0.7	0.7	1.0	0.6	-0.4	-0.1	0.1	0.6	**1.1**	0.2	0.2	0.7	0.7	1.0	-1.6	-0.9	-0.2	0.2	0.5	-0.3	0.1	0.2	0.7	1.0	-2.2	-1.6	-0.8	0.2	0.5
3	0.8	0.8	0.8	0.9	0.6	-0.1	0.1	0.5	0.7	**1.1**	0.7	0.7	0.8	0.8	0.9	-0.6	-0.4	0.0	0.3	0.7	0.3	0.7	0.7	0.8	0.9	-1.2	-0.5	-0.3	0.4	0.7
6	0.9	0.9	0.9	0.8	0.6	0.1	0.2	0.1	0.4	0.7	0.7	0.8	0.8	0.9	0.8	-0.2	0.1	0.1	0.2	0.5	0.5	0.7	0.8	0.9	0.8	-0.6	-0.2	0.1	0.2	0.5
12	**1.2**	**1.1**	0.9	0.7	0.5	0.6	0.6	0.6	0.8	0.8	**1.2**	**1.2**	**1.0**	0.9	0.7	0.5	0.5	0.5	0.6	0.7	**1.0**	**1.2**	**1.2**	0.9	0.7	0.3	0.4	0.5	0.6	0.7
24	0.7	0.7	0.5	0.4	0.3	0.9	0.8	0.7	0.7	**1.1**	0.6	0.6	0.6	0.5	0.4	0.5	0.7	0.7	0.6	0.7	0.5	0.6	0.6	0.5	0.4	0.4	0.5	0.7	0.6	0.7

Trend Window (Months)	t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)					t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)					t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)				
1	**2.3**	**3.4**	**3.2**	**4.5**	**2.8**	-0.8	-0.1	0.3	1.1	**2.0**	0.7	1.0	**3.1**	**3.3**	**4.5**	-3.0	-1.7	-0.3	0.4	1.0	-1.4	0.4	1.0	**3.3**	**4.5**	-4.0	-3.0	-1.4	0.4	1.0
3	**3.8**	**3.7**	**3.6**	**4.1**	**2.7**	-0.2	0.3	0.9	1.3	**2.0**	**3.1**	**3.5**	**3.7**	**3.5**	**4.2**	-1.0	-0.7	0.0	0.6	1.2	1.4	**3.2**	**3.5**	**3.5**	**4.2**	-2.2	-1.0	-0.5	0.7	1.2
6	**4.4**	**4.3**	**4.2**	**3.8**	**2.5**	0.1	0.3	0.3	0.8	1.4	**3.4**	**3.9**	**4.0**	**4.1**	**3.8**	-0.3	0.2	0.2	0.3	0.9	**2.5**	**3.4**	**3.9**	**4.1**	**3.8**	-1.1	-0.4	0.2	0.3	0.9
12	**5.7**	**5.1**	**4.2**	**3.4**	**2.4**	1.1	1.2	1.1	1.4	1.5	**5.6**	**5.5**	**4.9**	**4.1**	**3.3**	1.0	0.9	1.0	1.1	1.4	**4.8**	**5.4**	**5.5**	**4.1**	**3.3**	0.5	0.7	0.9	1.1	1.4
24	**3.3**	**3.1**	**2.4**	1.8	1.4	1.7	1.6	1.3	1.2	2.0	**2.8**	**2.9**	**2.8**	**2.3**	1.8	0.9	1.3	1.3	1.2	1.2	**2.5**	**2.8**	**3.0**	**2.3**	1.8	0.8	0.9	1.3	1.2	1.2

Trend Window (Months)	Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)					Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)					Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)				
1	-22.6	-12.3	-6.5	-4.8	-10.7	-22.4	-12.3	-4.9	-2.8	-1.8	-40.7	-27.2	-10.0	-6.0	-5.1	-34.5	-20.1	-10.0	-3.9	-3.1	-51.3	-38.8	-23.5	-5.8	-5.0	-42.5	-31.8	-16.4	-3.7	-2.9
3	-20.3	-13.0	-9.1	-8.6	-15.6	-20.3	-13.0	-5.0	-4.6	-2.8	-23.5	-20.0	-13.0	-10.2	-8.9	-23.5	-20.0	-13.0	-6.0	-4.9	-33.5	-23.1	-18.5	-10.0	-8.7	-33.5	-23.1	-18.5	-5.7	-4.7
6	-12.4	-10.5	-12.0	-15.8	-19.4	-12.4	-8.0	-10.8	-7.0	-5.2	-11.9	-10.8	-11.0	-13.5	-16.0	-11.8	-10.5	-8.8	-11.5	-6.9	-19.8	-12.2	-11.3	-14.0	-16.1	-19.8	-12.2	-10.7	-11.5	-6.8
12	-12.6	-14.3	-17.0	-17.7	-25.9	-7.8	-7.3	-8.0	-6.9	-6.2	-12.3	-12.9	-14.8	-17.7	-17.8	-8.7	-8.8	-7.8	-8.5	-7.5	-13.3	-12.7	-13.0	-17.7	-17.6	-9.0	-8.9	-8.6	-8.3	-7.4
24	-18.4	-21.8	-26.5	-26.5	-31.4	-6.9	-7.6	-8.3	-7.8	-7.2	-18.9	-21.0	-24.2	-27.9	-27.1	-8.1	-7.0	-7.4	-8.3	-7.9	-19.2	-19.4	-21.3	-27.8	-26.9	-7.9	-8.2	-7.1	-8.3	-7.8

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Table 58: Performance-Risk of Absolute Momentum Strategies by Rebalancing and Investment Horizons: Equity

Invest Horizon (Months) — Excess Return

Trend Window (Months)	1992-2014 (%): 1	3	6	12	24	2011-2014 (%): 1	3	6	12	24
1	3.3	4.1	3.7	3.8	2.5	3.9	5.2	3.5	3.4	2.6
3	6.4	5.7	5.8	5.4	3.6	9.2	7.0	4.4	4.9	3.2
6	10.4	9.5	9.4	7.5	4.8	8.2	4.7	4.2	5.6	3.9
12	10.6	9.7	8.2	6.1	3.5	5.2	4.7	4.2	3.4	2.9
24	7.8	7.4	6.3	4.6	2.8	7.8	5.9	4.9	3.8	6.7

Invest Horizon (Weeks) — Excess Return

Trend Window (Months)	1992-2014 (%): 1	4	13	26	52	2011-2014 (%): 1	4	13	26	52
1	1.6	1.1	3.8	3.4	3.6	-8.4	-5.1	2.5	2.1	2.2
3	4.8	5.2	5.0	5.0	5.2	2.5	3.3	3.6	2.7	4.0
6	8.4	9.0	8.6	8.8	7.1	3.4	4.2	3.7	4.5	6.0
12	9.8	9.8	9.3	8.1	6.1	1.5	0.9	2.8	3.8	3.4
24	6.1	6.1	6.3	5.6	4.3	2.3	3.1	3.5	3.6	3.4

Invest Horizon (Days) — Excess Return

Trend Window (Months)	1992-2014 (%): 1	5	21	130	261	2011-2014 (%): 1	5	21	130	261
1	0.7	0.5	0.9	3.3	3.6	-9.3	-7.3	-4.7	2.0	2.1
3	3.9	4.8	5.0	5.0	5.2	-1.8	1.7	3.5	2.9	4.0
6	7.7	8.4	9.1	8.9	7.3	3.7	3.3	4.6	4.5	5.9
12	9.9	9.7	10.0	8.2	6.2	2.8	0.5	1.5	3.7	3.4
24	5.3	5.8	6.3	5.7	4.4	-0.2	1.5	3.5	3.9	3.7

Invest Horizon (Months) — Sharpe Ratio

Trend Window (Months)	1992-2014 (%): 1	3	6	12	24	2011-2014 (%): 1	3	6	12	24
1	0.3	0.5	0.6	0.7	0.5	0.4	0.6	0.5	0.7	0.8
3	0.6	0.6	0.6	0.6	0.5	0.8	0.6	0.5	0.7	0.6
6	0.8	0.8	0.8	0.7	0.5	0.7	0.4	0.4	0.6	0.5
12	0.8	0.8	0.6	0.5	0.3	0.4	0.4	0.4	0.3	0.3
24	0.6	0.6	0.5	0.4	0.3	0.6	0.5	0.4	0.4	**1.0**

Invest Horizon (Weeks) — Sharpe Ratio

Trend Window (Months)	1992-2014 (%): 1	4	13	26	52	2011-2014 (%): 1	4	13	26	52
1	0.2	0.2	0.5	0.6	0.7	-0.7	-0.5	0.4	0.4	0.5
3	0.4	0.5	0.5	0.6	0.6	0.3	0.3	0.4	0.3	0.6
6	0.7	0.7	0.7	0.8	0.6	0.3	0.4	0.4	0.5	0.6
12	0.8	0.8	0.7	0.6	0.5	0.2	0.1	0.3	0.4	0.3
24	0.5	0.5	0.5	0.5	0.4	0.3	0.3	0.3	0.3	0.3

Invest Horizon (Days) — Sharpe Ratio

Trend Window (Months)	1992-2014 (%): 1	5	21	130	261	2011-2014 (%): 1	5	21	130	261
1	0.1	0.1	0.1	0.6	0.7	-0.7	-0.6	-0.5	0.4	0.5
3	0.4	0.4	0.5	0.6	0.6	-0.1	0.2	0.4	0.4	0.6
6	0.6	0.7	0.7	0.8	0.7	0.3	0.3	0.4	0.4	0.6
12	0.8	0.8	0.8	0.6	0.5	0.3	0.1	0.2	0.4	0.3
24	0.5	0.5	0.5	0.5	0.4	0.0	0.2	0.3	0.4	0.4

Invest Horizon (Months) — t-Stat

Trend Window (Months)	1992-2014 (%): 1	3	6	12	24	2011-2014 (%): 1	3	6	12	24
1	1.6	2.4	2.7	3.3	2.3	0.7	1.1	0.9	1.3	1.5
3	2.6	2.6	3.0	3.1	2.3	1.4	1.2	0.9	1.3	1.1
6	4.0	3.8	3.8	3.3	2.4	1.2	0.8	0.8	1.1	0.9
12	3.9	3.6	3.1	2.5	1.6	0.8	0.7	0.7	0.6	0.6
24	3.0	2.9	2.5	2.0	1.3	1.2	0.9	0.8	0.7	1.9

Invest Horizon (Weeks) — t-Stat

Trend Window (Months)	1992-2014 (%): 1	4	13	26	52	2011-2014 (%): 1	4	13	26	52
1	0.9	0.7	2.4	2.6	3.1	-1.2	-1.0	0.7	0.7	0.9
3	2.1	2.3	2.4	2.7	3.0	0.5	0.6	0.7	0.6	1.1
6	3.3	3.5	3.4	3.6	3.1	0.6	0.7	0.7	0.8	1.2
12	3.7	3.6	3.4	3.0	2.5	0.3	0.3	0.5	0.7	0.6
24	2.5	2.5	2.5	2.3	1.8	0.5	0.6	0.6	0.6	0.6

Invest Horizon (Days) — t-Stat

Trend Window (Months)	1992-2014 (%): 1	5	21	130	261	2011-2014 (%): 1	5	21	130	261
1	0.6	0.5	0.6	2.6	3.1	-1.4	-1.1	-0.9	0.7	0.9
3	1.8	2.1	2.2	2.7	3.0	-0.2	0.4	0.7	0.7	1.1
6	3.1	3.3	3.5	3.6	3.1	0.6	0.6	0.8	0.8	1.2
12	3.7	3.7	3.7	3.0	2.5	0.5	0.2	0.3	0.6	0.6
24	2.2	2.4	2.5	2.3	1.9	0.1	0.3	0.6	0.6	0.7

Invest Horizon (Months) — Max Drawdown

Trend Window (Months)	1992-2014 (%): 1	3	6	12	24	2011-2014 (%): 1	3	6	12	24
1	-26.3	-20.1	-14.8	-12.1	-23.3	-20.6	-13.4	-10.1	-7.9	-4.4
3	-24.6	-25.4	-19.2	-17.9	-33.1	-13.7	-18.9	-15.1	-10.6	-10.4
6	-28.0	-26.0	-23.3	-25.3	-41.3	-17.1	-22.2	-20.3	-16.0	-15.5
12	-31.6	-31.3	-29.3	-33.6	-51.4	-24.9	-25.7	-22.3	-21.6	-19.2
24	-37.7	-40.1	-47.9	-55.2	-51.1	-24.2	-25.4	-25.5	-21.9	-6.1

Invest Horizon (Weeks) — Max Drawdown

Trend Window (Months)	1992-2014 (%): 1	4	13	26	52	2011-2014 (%): 1	4	13	26	52
1	-40.3	-30.1	-15.5	-13.7	-12.8	-31.3	-22.5	-8.8	-9.2	-7.8
3	-27.0	-23.4	-23.2	-19.2	-15.9	-14.2	-13.5	-19.4	-17.6	-11.7
6	-27.5	-25.2	-27.8	-25.5	-25.0	-20.3	-22.2	-27.3	-22.0	-15.3
12	-38.6	-39.6	-36.7	-31.0	-35.0	-30.9	-33.8	-29.8	-23.0	-21.4
24	-41.5	-43.4	-44.8	-51.1	-55.8	-25.7	-26.1	-25.5	-25.8	-20.7

Invest Horizon (Days) — Max Drawdown

Trend Window (Months)	1992-2014 (%): 1	5	21	130	261	2011-2014 (%): 1	5	21	130	261
1	-40.0	-36.8	-28.8	-12.6	-12.6	-32.8	-27.7	-20.5	-8.8	-7.2
3	-26.9	-24.5	-24.9	-18.6	-16.1	-16.3	-15.3	-13.0	-16.8	-11.2
6	-26.2	-28.5	-24.0	-25.4	-24.9	-20.3	-21.3	-21.9	-22.1	-15.4
12	-36.6	-40.6	-38.5	-31.4	-34.5	-29.3	-33.9	-32.8	-23.2	-21.2
24	-47.9	-44.4	-43.2	-50.7	-55.3	-30.9	-27.5	-25.4	-25.6	-20.5

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Table 59: Performance-Risk of Absolute Momentum Strategies by Rebalancing and Investment Horizons: Bond

Trend Window (Months)	Invest Horizon (Months)					Invest Horizon (Months)					Invest Horizon (Weeks)					Invest Horizon (Weeks)					Invest Horizon (Days)					Invest Horizon (Days)				
	1	3	6	12	24	1	3	6	12	24	1	4	13	26	52	1	4	13	26	52	1	5	21	130	261	1	5	21	130	261
	Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)					Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)					Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)				
1	2.7	3.2	1.4	2.4	1.7	-11.1	-2.7	-0.7	1.4	2.6	-0.4	0.4	2.7	1.4	2.4	-21.6	-10.6	-2.1	0.0	1.3	-7.4	-0.9	0.5	1.4	2.4	-28.2	-18.1	-8.8	0.5	1.7
3	4.7	3.8	2.3	2.7	2.4	-3.2	1.7	3.3	4.3	6.3	3.5	4.1	3.8	2.2	2.9	-11.2	-4.8	0.2	2.1	3.8	-2.1	3.5	4.3	2.2	2.9	-23.0	-11.9	-3.5	2.4	4.0
6	3.2	3.9	3.6	3.2	3.3	-2.6	2.1	1.4	3.5	6.1	2.6	3.8	3.7	3.7	3.5	-4.4	-1.4	-0.1	0.5	3.4	-0.7	2.3	3.8	3.8	3.6	-10.7	-4.0	-0.5	0.7	3.7
12	9.3	7.6	6.6	5.2	4.8	7.9	8.4	9.7	11.3	12.1	8.4	8.2	7.1	6.3	4.9	7.4	7.5	7.4	8.6	10.8	5.7	8.2	8.5	6.5	5.1	2.2	7.0	8.4	9.1	11.1
24	6.4	6.2	5.6	5.5	4.7	9.4	12.4	12.3	13.8	15.0	5.0	6.2	5.8	5.2	5.4	6.0	9.1	11.2	11.0	12.9	3.7	5.3	6.4	5.4	5.6	6.7	7.7	10.1	11.5	13.4
	Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)					Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)					Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)				
1	0.3	0.4	0.2	0.5	0.5	-0.9	-0.3	-0.1	0.4	0.9	0.0	0.1	0.4	0.2	0.5	-1.9	-1.0	-0.3	0.0	0.4	-0.5	0.0	0.1	0.3	0.5	-2.6	-1.8	-0.9	0.1	0.6
3	0.4	0.4	0.3	0.4	0.5	-0.2	0.2	0.5	0.8	**1.1**	0.3	0.4	0.4	0.3	0.4	-0.9	-0.4	0.1	0.4	0.7	-0.1	0.3	0.4	0.3	0.4	-2.0	-1.0	-0.3	0.4	0.7
6	0.3	0.4	0.4	0.4	0.5	-0.2	0.3	0.2	0.5	0.8	0.3	0.4	0.4	0.4	0.4	-0.3	-0.1	0.0	0.1	0.5	0.0	0.2	0.4	0.4	0.4	-0.9	-0.3	0.0	0.1	0.5
12	0.7	0.6	0.6	0.5	0.5	0.7	0.8	0.8	1.0	**1.1**	0.7	0.7	0.6	0.6	0.5	0.7	0.7	0.7	0.7	0.9	0.5	0.7	0.7	0.6	0.5	0.2	0.7	0.8	0.8	0.9
24	0.5	0.5	0.5	0.5	0.5	0.7	0.9	0.9	**1.0**	**1.2**	0.4	0.5	0.5	0.5	0.5	0.5	0.7	0.9	0.8	1.0	0.3	0.5	0.5	0.5	0.5	0.6	0.6	0.8	0.9	**1.0**
	t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)					t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)					t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)				
1	1.3	1.9	1.1	2.5	2.3	-1.7	-0.6	-0.2	0.8	1.6	0.2	0.4	1.7	1.2	2.4	-3.5	-1.9	-0.6	0.0	0.8	-2.5	0.0	0.5	1.2	2.5	-4.9	-3.3	-1.7	0.2	1.0
3	2.0	1.8	1.4	1.9	2.2	-0.4	0.4	1.0	1.4	**2.1**	1.6	1.8	1.9	1.4	2.0	-1.6	-0.7	0.1	0.7	1.3	-0.4	1.6	1.9	1.4	2.1	-3.7	-1.9	-0.5	0.7	1.3
6	1.4	1.8	1.8	1.8	2.2	-0.3	0.5	0.4	0.9	1.6	1.2	1.7	1.7	1.9	2.0	-0.6	-0.1	0.1	0.2	0.9	0.0	1.1	1.7	2.0	2.0	-1.7	-0.6	0.0	0.2	1.0
12	3.5	3.0	2.8	2.4	2.5	1.3	1.4	1.6	1.8	**2.0**	3.2	3.2	2.9	2.7	2.2	1.2	1.3	1.2	1.4	1.7	2.3	3.2	3.3	2.7	2.3	0.4	1.2	1.4	1.5	1.7
24	2.4	2.4	2.2	2.3	2.1	1.3	1.7	1.7	1.9	**2.1**	2.0	2.4	2.3	2.1	2.2	0.9	1.3	1.6	1.5	1.8	1.6	2.1	2.5	2.2	2.3	1.0	1.2	1.5	1.6	1.8
	Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)					Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)					Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)				
1	-52.5	-29.0	-21.4	-16.8	-15.2	-45.9	-29.0	-13.1	-5.7	-5.3	-62.9	-52.2	-29.8	-23.5	-15.3	-60.1	-38.8	-24.8	-8.1	-5.0	-88.5	-62.8	-48.4	-22.8	-15.5	-69.4	-53.5	-36.2	-7.9	-4.4
3	-39.9	-37.5	-30.4	-25.4	-22.0	-39.9	-25.5	-8.7	-6.4	-8.0	-53.4	-39.9	-37.3	-30.9	-25.8	-53.4	-39.9	-26.4	-8.5	-8.0	-70.3	-53.1	-38.8	-30.5	-25.2	-69.7	-53.1	-36.6	-8.1	-7.9
6	-43.9	-35.6	-30.7	-42.8	-27.9	-32.7	-20.0	-12.3	-13.1	-13.6	-53.8	-44.0	-37.0	-32.2	-43.8	-26.9	-24.5	-19.2	-9.8	-11.4	-74.5	-56.8	-47.0	-31.0	-43.6	-41.2	-26.2	-22.0	-9.7	-11.4
12	-28.7	-38.9	-43.6	-49.4	-32.8	-16.2	-19.1	-19.8	-19.3	-17.6	-39.0	-33.7	-39.5	-43.6	-49.9	-15.9	-18.2	-19.9	-20.7	-20.8	-41.1	-32.7	-32.2	-43.8	-49.7	-25.4	-16.1	-16.8	-20.1	-20.2
24	-44.6	-46.6	-46.4	-45.8	-36.3	-24.5	-24.6	-24.9	-23.0	-19.7	-49.2	-47.5	-47.5	-47.0	-45.6	-30.0	-24.3	-25.0	-25.3	-23.3	-52.2	-47.2	-47.4	-46.8	-45.4	-26.8	-26.6	-23.9	-24.8	-22.9

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Table 60: Performance-Risk of Absolute Momentum Strategies by Rebalancing and Investment Horizons: Currency

Trend Window (Months)	Invest Horizon (Months)					Invest Horizon (Months)				
	1	3	6	12	24	1	3	6	12	24
	Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)				
1	2.7	2.6	1.7	1.7	0.7	-3.1	-0.4	-0.6	-0.2	0.2
3	4.2	2.4	2.0	2.4	1.2	-3.5	-1.4	0.7	-0.2	0.2
6	5.0	3.8	3.8	2.9	0.8	-0.1	-0.8	-0.8	-1.3	-0.6
12	5.6	4.6	3.5	2.5	0.3	-1.6	0.0	-0.3	-0.8	-1.2
24	2.6	2.5	1.2	0.1	-1.1	0.0	-1.9	-2.7	-3.3	-1.9
	Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)				
1	0.3	0.4	0.4	0.5	0.2	-0.3	0.0	-0.1	-0.1	0.1
3	0.5	0.3	0.3	0.4	0.2	-0.3	-0.1	0.1	0.0	0.1
6	0.5	0.4	0.5	0.4	0.2	0.0	-0.1	-0.1	-0.2	-0.1
12	0.6	0.5	0.4	0.3	0.1	-0.1	0.0	0.0	-0.1	-0.2
24	0.3	0.3	0.2	0.1	-0.1	0.0	-0.2	-0.3	-0.4	-0.2
	t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)				
1	1.5	2.1	1.8	2.2	1.1	-0.5	-0.1	-0.3	-0.1	0.2
3	2.1	1.5	1.5	2.1	1.2	-0.6	-0.3	0.3	0.0	0.1
6	2.5	2.1	2.2	1.9	0.7	0.1	-0.1	-0.1	-0.3	-0.2
12	2.7	2.4	1.9	1.5	0.4	-0.2	0.1	0.0	-0.1	-0.3
24	1.4	1.4	0.8	0.3	-0.3	0.1	-0.3	-0.5	-0.7	-0.4
	Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)				
1	-27.7	-12.2	-9.0	-9.9	-10.1	-19.9	-12.2	-9.0	-5.7	-5.0
3	-27.2	-20.1	-15.5	-18.8	-24.6	-23.0	-20.1	-11.2	-9.6	-7.2
6	-22.5	-20.3	-22.5	-26.1	-31.8	-22.5	-18.9	-15.9	-14.2	-10.6
12	-23.1	-34.6	-38.5	-31.8	-37.7	-16.9	-14.2	-15.0	-14.8	-15.2
24	-37.7	-36.9	-37.1	-37.3	-42.7	-15.4	-19.4	-19.6	-19.2	-17.2

Trend Window (Months)	Invest Horizon (Weeks)					Invest Horizon (Weeks)				
	1	4	13	26	52	1	4	13	26	52
	Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)				
1	-0.6	1.1	2.1	1.8	1.9	-9.1	-2.4	-0.1	0.2	0.0
3	2.5	3.2	2.9	2.5	2.8	-4.5	-3.3	-1.3	0.1	-0.1
6	3.3	4.4	3.7	3.9	3.1	0.7	1.7	-0.2	-0.4	-0.9
12	6.3	6.1	4.8	3.5	2.5	-0.5	-0.2	0.3	-0.3	-0.9
24	1.9	2.1	2.2	1.1	0.0	0.3	0.0	-1.5	-2.3	-3.1
	Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)				
1	0.0	0.2	0.4	0.4	0.5	-1.0	-0.3	0.0	0.1	0.0
3	0.3	0.4	0.4	0.4	0.5	-0.4	-0.3	-0.1	0.0	0.0
6	0.4	0.5	0.4	0.5	0.4	0.1	0.2	0.0	0.0	-0.1
12	0.6	0.6	0.5	0.4	0.3	0.0	0.0	0.1	0.0	-0.1
24	0.2	0.3	0.3	0.2	0.1	0.1	0.0	-0.1	-0.2	-0.4
	t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)				
1	0.0	0.8	1.7	1.9	2.4	-1.8	-0.5	0.0	0.1	0.0
3	1.4	1.8	1.8	1.9	2.4	-0.8	-0.6	-0.3	0.1	0.0
6	1.8	2.3	2.1	2.3	2.1	0.2	0.4	0.0	0.0	-0.2
12	3.1	3.0	2.5	2.0	1.5	0.0	0.0	0.1	0.0	-0.2
24	1.1	1.2	1.3	0.7	0.2	0.1	0.1	-0.3	-0.4	-0.7
	Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)				
1	-33.6	-26.8	-12.5	-9.4	-10.7	-27.9	-14.7	-10.8	-7.1	-5.2
3	-21.9	-19.7	-18.6	-14.1	-16.5	-19.5	-17.8	-18.6	-11.3	-9.5
6	-24.7	-16.7	-19.7	-21.8	-24.7	-20.0	-15.9	-15.6	-14.5	-13.2
12	-19.5	-22.1	-32.3	-36.7	-30.2	-17.7	-15.1	-14.9	-15.8	-15.3
24	-34.4	-37.4	-36.4	-36.0	-35.2	-13.5	-13.4	-17.6	-19.2	-19.0

Trend Window (Months)	Invest Horizon (Days)					Invest Horizon (Days)				
	1	5	21	130	261	1	5	21	130	261
	Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)				
1	-4.2	-0.9	1.0	1.6	1.8	-13.7	-10.0	-1.4	-0.1	-0.3
3	1.1	3.1	3.6	2.5	2.8	-5.3	-2.6	-2.2	0.3	-0.1
6	2.0	3.6	4.3	3.9	3.0	-3.5	-0.8	1.4	-0.2	-1.1
12	5.1	6.2	6.0	3.6	2.5	-1.3	-1.1	-0.1	-0.3	-0.9
24	1.5	1.7	2.2	1.1	0.0	-0.7	-0.8	-0.2	-2.3	-3.1
	Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)				
1	-0.4	0.0	0.2	0.4	0.5	-1.5	-1.2	-0.2	0.0	-0.1
3	0.2	0.4	0.4	0.4	0.5	-0.5	-0.2	-0.2	0.1	0.0
6	0.2	0.4	0.5	0.5	0.4	-0.3	0.0	0.2	0.0	-0.1
12	0.5	0.6	0.6	0.4	0.3	-0.1	-0.1	0.0	0.0	-0.1
24	0.2	0.2	0.3	0.2	0.1	0.0	-0.1	0.0	-0.2	-0.4
	t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)				
1	-1.8	-0.2	0.8	1.7	2.4	-2.8	-2.2	-0.3	0.0	-0.1
3	0.8	1.7	2.0	1.9	2.4	-1.0	-0.4	-0.4	0.1	0.0
6	1.2	1.9	2.3	2.3	2.0	-0.6	-0.1	0.4	0.0	-0.3
12	2.6	3.1	3.0	2.0	1.6	-0.2	-0.2	0.0	0.0	-0.2
24	1.0	1.0	1.3	0.7	0.2	-0.1	-0.1	0.0	-0.5	-0.7
	Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)				
1	-62.4	-37.2	-25.9	-8.8	-11.3	-39.8	-30.3	-13.3	-7.2	-5.5
3	-29.2	-21.2	-18.0	-14.1	-16.1	-19.2	-16.0	-16.6	-11.1	-9.4
6	-24.4	-22.1	-16.1	-21.9	-25.3	-20.3	-17.2	-15.2	-14.1	-13.6
12	-20.0	-19.1	-22.3	-36.7	-30.4	-16.8	-17.7	-15.4	-15.8	-15.4
24	-37.5	-35.7	-36.6	-35.9	-35.0	-15.7	-16.3	-13.8	-19.3	-19.1

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Table 61: Performance-Risk of Absolute Momentum Strategies by Rebalancing and Investment Horizons: Commodity

Trend Window (Months)	Invest Horizon (Months)					Invest Horizon (Months)					Invest Horizon (Weeks)					Invest Horizon (Weeks)					Invest Horizon (Days)					Invest Horizon (Days)				
	1	3	6	12	24	1	3	6	12	24	1	4	13	26	52	1	4	13	26	52	1	5	21	130	261	1	5	21	130	261
	Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)					Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)					Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)				
1	1.4	2.0	2.1	1.8	0.7	-3.1	-4.0	-0.7	0.3	0.6	0.8	0.2	2.2	2.4	2.1	-7.1	-4.9	-3.5	-0.1	0.7	0.4	0.7	0.7	2.4	2.0	-7.5	-6.5	-3.2	-0.2	0.5
3	4.8	4.9	3.9	2.8	1.2	-7.0	-5.2	-1.0	-0.1	0.4	5.5	5.1	5.2	4.0	2.8	-4.8	-7.2	-4.2	-0.4	0.0	2.9	4.7	4.9	3.9	2.8	-4.2	-4.4	-7.1	-0.6	-0.1
6	4.3	4.1	3.1	2.4	1.3	-5.5	-3.5	-3.2	-0.7	0.4	3.2	3.1	3.7	3.2	2.4	-7.1	-4.9	-3.0	-2.7	-0.6	3.2	3.1	3.1	3.2	2.4	-6.9	-6.5	-4.4	-2.7	-0.6
12	6.4	5.3	3.0	1.6	1.1	0.5	0.3	-0.6	1.5	0.8	6.9	6.3	4.9	2.9	1.6	1.5	0.4	-0.6	-0.8	1.3	5.5	6.2	6.1	2.9	1.6	-0.2	0.4	-0.2	-0.9	1.1
24	1.4	0.8	-0.4	-1.8	-0.8	1.0	1.1	0.3	-0.1	0.0	1.9	1.5	0.7	-0.4	-1.6	-0.8	0.3	0.4	0.2	0.0	2.2	1.9	1.3	-0.4	-1.6	0.6	-0.3	0.1	0.0	-0.1
	Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)					Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)					Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)				
1	0.2	0.3	0.4	0.5	0.2	-0.2	-0.6	-0.1	0.1	0.2	0.1	0.1	0.4	0.5	0.6	-0.6	-0.5	-0.6	0.0	0.2	0.1	0.1	0.1	0.5	0.5	-0.7	-0.6	-0.4	0.0	0.1
3	0.5	0.6	0.5	0.5	0.3	-0.6	-0.6	-0.1	0.0	0.1	0.6	0.6	0.6	0.6	0.5	-0.4	-0.7	-0.5	0.0	0.0	0.3	0.5	0.5	0.5	0.5	-0.3	-0.4	-0.7	-0.1	0.0
6	0.5	0.5	0.4	0.3	0.2	-0.5	-0.4	-0.4	-0.1	0.1	0.4	0.4	0.4	0.4	0.3	-0.7	-0.5	-0.3	-0.3	-0.1	0.4	0.3	0.4	0.4	0.3	-0.7	-0.6	-0.4	-0.3	-0.1
12	0.6	0.6	0.3	0.2	0.2	0.1	0.1	0.0	0.2	0.1	0.7	0.6	0.5	0.3	0.2	0.2	0.1	0.0	0.0	0.2	0.6	0.6	0.6	0.3	0.2	0.0	0.1	0.0	-0.1	0.2
24	0.2	0.1	0.0	-0.1	-0.1	0.2	0.2	0.1	0.0	0.0	0.2	0.2	0.1	0.0	-0.1	0.0	0.1	0.1	0.1	0.0	0.3	0.2	0.2	0.0	-0.1	0.1	0.0	0.1	0.0	0.0
	t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)					t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)					t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)				
1	0.9	1.6	2.0	2.3	1.1	-0.4	-1.2	-0.3	0.2	0.5	0.6	0.3	1.8	2.4	2.6	-1.2	-1.0	-1.0	0.0	0.4	0.4	0.6	0.6	2.3	2.4	-1.3	-1.2	-0.7	-0.1	0.3
3	2.4	2.8	2.5	2.2	1.2	-1.2	-1.1	-0.2	0.0	0.2	2.7	2.6	3.0	2.6	2.2	-0.8	-1.3	-0.9	0.0	0.1	1.5	2.4	2.5	2.5	2.2	-0.6	-0.7	-1.3	-0.1	0.0
6	2.2	2.2	1.8	1.6	1.1	-0.9	-0.7	-0.7	-0.2	0.2	1.7	1.7	2.0	1.9	1.6	-1.2	-0.8	-0.6	-0.6	-0.1	1.7	1.7	1.7	1.9	1.6	-1.2	-1.1	-0.8	-0.6	-0.1
12	3.0	2.6	1.6	1.1	0.9	0.2	0.2	0.0	0.4	0.3	3.2	3.0	2.5	1.6	1.0	0.4	0.2	0.0	-0.1	0.4	2.7	3.0	3.0	1.6	1.0	0.1	0.2	0.1	-0.1	0.3
24	0.9	0.6	0.0	-0.6	-0.3	0.3	0.3	0.1	0.1	0.1	1.1	0.9	0.6	0.0	-0.5	-0.1	0.1	0.2	0.1	0.1	1.2	1.1	0.8	0.0	-0.5	0.2	0.0	0.1	0.1	0.1
	Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)					Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)					Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)				
1	-33.6	-18.3	-11.1	-10.3	-7.8	-18.0	-18.3	-11.1	-6.9	-4.0	-35.2	-30.5	-17.9	-10.7	-12.9	-28.2	-23.0	-17.9	-9.4	-5.8	-37.0	-34.1	-30.9	-10.7	-14.1	-29.8	-26.2	-17.3	-9.2	-6.2
3	-31.4	-27.1	-14.5	-23.9	-13.7	-31.4	-27.1	-14.1	-8.2	-6.5	-22.9	-30.5	-22.9	-16.9	-25.1	-22.9	-30.5	-22.9	-12.3	-7.4	-32.7	-25.6	-29.8	-16.8	-24.7	-21.8	-22.2	-29.8	-12.6	-7.3
6	-29.1	-22.4	-35.3	-31.6	-18.1	-29.1	-22.4	-19.1	-9.4	-7.7	-32.8	-26.0	-24.8	-37.9	-32.9	-30.5	-26.0	-21.4	-18.9	-8.8	-31.1	-29.4	-24.5	-38.4	-33.2	-31.1	-29.4	-24.5	-18.5	-8.7
12	-28.0	-33.5	-40.1	-39.7	-23.2	-23.9	-19.0	-15.8	-12.9	-10.1	-24.9	-27.5	-38.0	-42.5	-41.3	-23.2	-22.9	-18.2	-15.0	-12.5	-21.1	-23.0	-24.9	-42.2	-41.1	-21.1	-20.5	-21.7	-15.2	-12.6
24	-31.1	-35.7	-44.9	-46.2	-36.5	-16.9	-14.7	-13.8	-11.2	-8.2	-28.5	-33.7	-40.1	-47.8	-46.8	-19.8	-17.1	-15.8	-13.5	-11.4	-28.4	-29.6	-34.8	-48.0	-46.9	-18.1	-18.8	-16.8	-13.9	-11.5

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Table 62: Performance-Risk of Relative Momentum Strategies by Rebalancing and Investment Horizons: Cross-Asset

Trend Window (Months)	Invest Horizon (Months) 1	3	6	12	24	Invest Horizon (Months) 1	3	6	12	24
	Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)				
1	5.0	4.8	3.7	3.6	2.2	3.8	2.1	3.0	3.0	1.9
3	6.5	5.2	3.8	3.8	2.0	2.3	1.8	2.0	2.3	1.2
6	6.4	5.2	4.9	4.5	2.8	5.1	2.3	1.6	2.6	1.2
12	8.4	7.1	5.5	4.3	2.4	5.8	3.5	2.7	2.2	0.8
24	5.6	5.0	3.6	2.5	1.3	0.5	-0.2	-1.0	-0.3	2.1
	Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)				
1	0.7	0.9	0.8	1.0	0.7	0.5	0.4	0.7	1.0	0.9
3	0.8	0.7	0.6	0.8	0.5	0.3	0.3	0.4	0.6	0.5
6	0.8	0.7	0.7	0.8	0.5	0.6	0.3	0.3	0.5	0.4
12	1.0	0.9	0.7	0.6	0.4	0.8	0.5	0.4	0.4	0.2
24	0.7	0.7	0.5	0.4	0.2	0.1	0.0	-0.1	0.0	0.6
	t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)				
1	3.1	4.0	3.9	4.6	3.1	0.9	0.7	1.3	1.8	1.7
3	3.7	3.4	3.0	3.6	2.4	0.6	0.5	0.7	1.1	0.9
6	3.7	3.3	3.4	3.6	2.6	1.2	0.6	0.5	1.0	0.7
12	4.9	4.3	3.5	3.1	1.9	1.4	0.9	0.8	0.8	0.4
24	3.5	3.2	2.4	1.8	1.1	0.2	0.0	-0.2	-0.1	1.1
	Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)				
1	-12.8	-9.7	-7.7	-8.9	-14.1	-8.9	-9.7	-4.7	-3.4	-2.0
3	-13.8	-13.8	-14.6	-14.4	-16.6	-13.8	-13.8	-10.3	-6.4	-4.1
6	-14.6	-13.7	-26.0	-18.4	-21.5	-10.6	-13.7	-15.3	-8.4	-6.7
12	-17.4	-17.1	-23.6	-19.9	-29.5	-10.1	-12.7	-12.1	-8.8	-7.5
24	-17.1	-21.1	-26.7	-27.1	-34.0	-12.0	-13.9	-15.3	-10.6	-5.2

Trend Window (Months)	Invest Horizon (Weeks) 1	4	13	26	52	Invest Horizon (Weeks) 1	4	13	26	52
	Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)				
1	0.7	2.8	4.0	3.3	3.4	-8.2	-3.0	-0.1	1.5	1.8
3	4.2	5.3	4.6	3.5	3.6	-1.3	-1.0	0.4	1.0	1.6
6	4.4	5.2	4.7	4.6	4.3	0.9	1.9	1.3	1.3	2.6
12	7.7	7.7	6.7	5.4	4.3	3.2	3.5	3.0	2.9	2.3
24	5.6	5.3	4.8	3.6	2.6	-0.9	-0.9	-1.1	-1.5	-0.4
	Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)				
1	0.1	0.4	0.7	0.8	0.9	-1.0	-0.4	0.0	0.4	0.6
3	0.5	0.7	0.7	0.6	0.7	-0.1	-0.1	0.1	0.2	0.5
6	0.6	0.7	0.7	0.7	0.7	0.1	0.3	0.2	0.2	0.6
12	1.0	1.0	0.9	0.7	0.6	0.4	0.5	0.5	0.5	0.4
24	0.7	0.7	0.7	0.5	0.4	-0.1	-0.1	-0.1	-0.2	0.0
	t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)				
1	0.6	2.0	3.5	3.6	4.3	-1.9	-0.7	0.0	0.7	1.1
3	2.5	3.1	3.1	2.8	3.5	-0.2	-0.1	0.2	0.4	0.8
6	2.6	3.1	3.1	3.2	3.4	0.3	0.5	0.4	0.4	1.0
12	4.5	4.6	4.1	3.5	3.0	0.8	0.9	0.9	0.9	0.8
24	3.5	3.4	3.2	2.4	1.9	-0.2	-0.2	-0.3	-0.4	-0.1
	Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)				
1	-33.4	-16.9	-9.5	-8.1	-8.2	-25.6	-13.4	-9.5	-6.7	-5.7
3	-21.3	-15.1	-15.3	-18.1	-15.6	-14.3	-15.1	-15.3	-10.9	-6.6
6	-16.5	-15.8	-15.8	-28.6	-19.8	-13.4	-13.8	-14.3	-15.0	-8.0
12	-16.2	-15.8	-18.2	-23.6	-21.5	-12.0	-10.8	-12.6	-11.3	-8.8
24	-15.4	-16.2	-21.3	-27.7	-27.2	-14.0	-13.8	-14.1	-15.4	-10.2

Trend Window (Months)	Invest Horizon (Days) 1	5	21	130	261	Invest Horizon (Days) 1	5	21	130	261
	Excess Return 1992-2014 (%)					Excess Return 2011-2014 (%)				
1	-3.4	0.9	3.0	3.4	3.4	-13.3	-7.7	-2.1	1.4	1.6
3	0.8	4.4	5.3	3.5	3.6	-5.9	-1.2	-0.3	1.1	1.7
6	2.1	4.8	5.3	4.6	4.3	-1.4	1.8	2.4	1.3	2.5
12	5.7	7.8	7.9	5.6	4.4	2.7	4.4	4.2	3.0	2.3
24	4.2	5.5	5.3	3.6	2.6	-2.2	-0.7	-0.8	-1.5	-0.4
	Sharpe Ratio 1992-2014 (%)					Sharpe Ratio 2011-2014 (%)				
1	-0.4	0.2	0.5	0.8	0.9	-1.7	-1.0	-0.3	0.4	0.6
3	0.1	0.5	0.7	0.6	0.7	-0.6	-0.1	0.0	0.2	0.5
6	0.3	0.6	0.7	0.7	0.7	-0.1	0.3	0.3	0.2	0.5
12	0.7	1.0	1.0	0.8	0.7	0.4	0.6	0.6	0.5	0.4
24	0.6	0.8	0.7	0.5	0.4	-0.3	-0.1	-0.1	-0.2	0.0
	t-Stat 1992-2014 (%)					t-Stat 2011-2014 (%)				
1	-1.8	0.8	2.2	3.7	4.3	-3.2	-1.9	-0.5	0.7	1.0
3	0.7	2.6	3.1	2.8	3.4	-1.2	-0.2	0.0	0.4	0.8
6	1.4	2.9	3.2	3.3	3.4	-0.2	0.5	0.6	0.4	1.0
12	3.5	4.6	4.7	3.6	3.1	0.7	1.1	1.1	0.9	0.8
24	2.7	3.6	3.4	2.5	1.9	-0.6	-0.1	-0.2	-0.4	-0.1
	Max Drawdown 1992-2014 (%)					Max Drawdown 2011-2014 (%)				
1	-61.2	-32.8	-13.3	-8.1	-8.5	-38.7	-24.5	-13.1	-6.2	-5.4
3	-32.7	-20.1	-13.9	-18.0	-15.9	-26.4	-15.2	-13.9	-10.9	-6.5
6	-24.4	-15.6	-14.8	-28.7	-19.9	-15.6	-12.4	-13.0	-14.8	-7.9
12	-19.6	-15.3	-14.3	-23.9	-21.2	-10.5	-10.1	-9.7	-11.1	-8.8
24	-18.2	-16.1	-16.3	-27.3	-26.9	-17.9	-14.2	-13.5	-15.2	-10.1

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Transaction Cost Analysis

In this Appendix, we apply various transaction cost assumptions and examine their impact on the performance of different Absolute Momentum strategies by varying trend signal window size, rebalance frequency as well as investment horizons. For example, Table 63 below summarizes key return/risk analytics (return, draw-down, Sharpe ratio, etc) for multi-asset Time Series strategies based on past 1-year return, with monthly, weekly, and daily rebalancing frequencies as well as one-month, one-week and one-day investment horizons. See Chapter 2 for more analysis.

Table 63: Performance-Risk analytics of Cross Asset Absolute Momentum Strategies based on past 1-year return: 1992-2014

Rebalance Freq	Invest Horizon	One-Way Cost (bps)	Ann. Return	Ann. Volatility	Max Drawdown	MaxDDur (in years)	Sharpe Ratio	Hit Rate	Return Skewness	Return Kurtosis
Monthly	*One Month*	No Cost	9.0	7.0	-12.4	2.1	1.27	55.8	-0.3	2.1
		5	8.8	7.0	-12.5	2.1	1.24	55.8	-0.3	2.1
		10	**8.6**	**7.0**	**-12.6**	**2.1**	**1.21**	**55.6**	**-0.3**	**2.1**
		20	8.1	7.0	-12.9	2.1	1.16	55.4	-0.3	2.1
		50	6.8	7.0	-13.6	2.7	0.98	54.9	-0.3	2.0
Weekly	*One Month*	No Cost	8.6	7.0	-12.7	2.0	1.22	55.8	-0.3	2.6
		5	8.4	7.0	-12.8	2.0	1.19	55.6	-0.3	2.6
		10	**8.1**	**7.0**	**-12.9**	**2.1**	**1.16**	**55.5**	**-0.3**	**2.6**
		20	7.7	7.0	-13.2	2.1	1.09	55.3	-0.3	2.6
		50	6.3	7.0	-13.8	2.8	0.91	54.5	-0.3	2.6
Daily	*One Month*	No Cost	8.6	7.0	-12.8	2.0	1.22	55.5	-0.4	2.6
		5	8.4	7.0	-12.9	2.0	1.19	55.4	-0.4	2.6
		10	**8.1**	**7.0**	**-13.0**	**2.0**	**1.16**	**55.3**	**-0.4**	**2.6**
		20	7.7	7.0	-13.2	2.2	1.10	55.1	-0.4	2.6
		50	6.3	7.0	-13.8	2.8	0.91	54.5	-0.4	2.6
Weekly	*One Week*	No Cost	9.2	6.9	-12.3	1.8	1.30	55.6	-0.3	2.6
		5	8.8	6.9	-12.3	1.8	1.25	55.4	-0.3	2.6
		10	**8.3**	**6.9**	**-12.3**	**1.9**	**1.19**	**55.2**	**-0.3**	**2.6**
		20	7.5	7.0	-12.6	2.5	1.07	54.7	-0.3	2.6
		50	5.0	7.0	-14.2	3.1	0.73	53.6	-0.3	2.5
Daily	*One Week*	No Cost	8.9	6.9	-12.6	1.9	1.27	55.7	-0.3	2.6
		5	8.5	6.9	-12.6	1.9	1.21	55.4	-0.3	2.6
		10	**8.0**	**6.9**	**-12.7**	**2.0**	**1.15**	**55.3**	**-0.3**	**2.6**
		20	7.2	6.9	-12.7	2.7	1.03	54.9	-0.3	2.6
		50	4.6	6.9	-14.8	3.1	0.68	53.7	-0.3	2.6
Daily	*One Day*	No Cost	8.9	6.9	-13.1	1.9	1.26	55.5	-0.3	2.6
		5	7.9	6.9	-13.2	2.2	1.14	55.1	-0.3	2.6
		10	**7.0**	**6.9**	**-13.3**	**2.6**	**1.01**	**54.7**	**-0.3**	**2.6**
		20	5.1	6.9	-14.8	3.1	0.76	53.9	-0.3	2.5
		50	-0.2	7.0	-36.2	8.0	0.00	51.7	-0.3	2.4

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 64: Performance-Risk analytics of Cross Asset Absolute Momentum Strategies based on past 3-month return: 1992-2014

Rebalance Freq	Invest Horizon	One-Way Cost (bps)	Ann. Return	Ann. Volatility	Max Drawdown	MaxDDur (in years)	Sharpe Ratio	Hit Rate	Return Skewness	Return Kurtosis
Monthly	*One Month*	No Cost	6.4	7.1	-16.4	2.7	0.94	54.3	-0.1	3.9
		5	6.0	7.1	-18.4	2.7	0.87	54.0	-0.1	4.0
		10	**5.5**	**7.1**	**-20.3**	**2.7**	**0.81**	**53.8**	**-0.1**	**4.0**
		20	4.6	7.1	-24.0	2.7	0.67	53.5	-0.1	4.0
		50	1.7	7.2	-34.2	2.7	0.28	52.8	-0.3	4.5
Weekly	*One Month*	No Cost	5.8	6.8	-16.0	2.7	0.88	54.6	-0.1	5.9
		5	5.3	6.8	-18.0	2.7	0.81	54.3	-0.1	5.9
		10	**4.8**	**6.8**	**-20.0**	**2.7**	**0.74**	**54.1**	**-0.1**	**5.9**
		20	3.9	6.8	-23.8	2.7	0.60	53.3	-0.1	5.9
		50	1.0	6.9	-34.2	2.7	0.18	51.8	-0.1	5.7
Daily	*One Month*	No Cost	5.8	6.8	-14.5	2.7	0.88	55.0	-0.1	6.3
		5	5.3	6.8	-16.5	2.7	0.81	54.7	-0.1	6.3
		10	**4.8**	**6.8**	**-18.5**	**2.7**	**0.74**	**54.3**	**-0.1**	**6.3**
		20	3.9	6.8	-22.4	2.7	0.60	53.8	-0.1	6.3
		50	1.0	6.8	-32.8	2.7	0.18	51.9	-0.1	6.3
Weekly	*One Week*	No Cost	6.4	7.1	-14.2	2.7	0.93	53.6	-0.1	4.4
		5	5.4	7.1	-19.0	2.7	0.79	53.0	-0.1	4.4
		10	**4.5**	**7.1**	**-23.5**	**2.7**	**0.66**	**52.4**	**-0.1**	**4.4**
		20	2.6	7.2	-31.9	2.7	0.39	51.7	-0.1	4.3
		50	-3.2	7.4	-59.9	15.6	-0.39	49.6	-0.3	4.7
Daily	*One Week*	No Cost	6.4	7.0	-13.7	2.7	0.94	53.9	-0.2	4.8
		5	5.4	7.0	-18.6	2.7	0.81	53.4	-0.2	4.8
		10	**4.4**	**7.0**	**-23.1**	**2.7**	**0.67**	**52.9**	**-0.1**	**4.8**
		20	2.5	7.0	-31.5	2.7	0.39	52.1	-0.1	4.7
		50	-3.2	7.0	-59.6	15.6	-0.43	48.9	-0.1	4.6
Daily	*One Day*	No Cost	6.1	7.0	-14.8	2.7	0.90	54.0	-0.1	4.4
		5	4.0	7.0	-24.7	2.7	0.60	52.7	-0.1	4.4
		10	**1.9**	**7.1**	**-33.5**	**4.1**	**0.30**	**51.5**	**-0.1**	**4.4**
		20	-2.4	7.1	-52.5	15.6	-0.30	49.6	-0.1	4.2
		50	-14.0	7.4	-96.6	22.4	-2.00	44.3	-0.1	3.9

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Table 65: Performance-Risk analytics of Cross Asset Absolute Momentum Strategies based on past 1-month return: 1992-2014

Rebalance Freq	Invest Horizon	One-Way Cost (bps)	Ann. Return	Ann. Volatility	Max Drawdown	MaxDDur (in years)	Sharpe Ratio	Hit Rate	Return Skewness	Return Kurtosis
Monthly	*One Month*	No Cost	4.9	6.7	-14.9	2.7	0.74	52.5	-0.1	3.1
		5	4.0	6.7	-18.7	2.7	0.61	52.1	-0.1	3.1
		10	**3.1**	**6.7**	**-22.6**	**5.4**	**0.48**	**51.7**	**-0.1**	**3.1**
		20	1.3	6.8	-32.1	5.4	0.22	51.2	-0.1	3.1
		50	-3.8	7.2	-65.0	16.8	-0.51	50.2	-0.4	4.0
Weekly	*One Month*	No Cost	2.9	6.0	-17.0	5.4	0.51	51.3	0.1	6.7
		5	2.0	6.0	-22.2	5.4	0.36	50.7	0.1	6.7
		10	**1.1**	**6.0**	**-27.2**	**5.4**	**0.21**	**50.1**	**0.1**	**6.7**
		20	-0.7	6.0	-37.5	15.6	-0.09	49.2	0.1	6.6
		50	-6.0	6.2	-76.7	21.8	-0.97	46.7	0.1	5.9
Daily	*One Month*	No Cost	2.9	5.8	-13.5	5.4	0.52	51.8	0.1	7.0
		5	2.0	5.8	-18.4	5.4	0.37	51.3	0.1	7.0
		10	**1.1**	**5.8**	**-23.5**	**5.4**	**0.22**	**50.8**	**0.1**	**7.0**
		20	-0.7	5.8	-38.0	15.6	-0.09	49.6	0.1	7.0
		50	-5.9	5.9	-76.2	21.8	-1.01	46.3	0.1	6.9
Weekly	*One Week*	No Cost	4.2	7.0	-25.1	5.0	0.62	52.7	0.0	4.3
		5	2.5	7.0	-33.4	5.0	0.39	51.7	0.0	4.3
		10	**0.8**	**7.1**	**-40.7**	**5.0**	**0.15**	**50.9**	**0.0**	**4.2**
		20	-2.5	7.1	-54.3	15.6	-0.31	49.7	0.0	4.1
		50	-11.7	7.7	-93.9	22.4	-1.59	46.8	-0.3	3.9
Daily	*One Week*	No Cost	3.7	6.7	-22.4	5.4	0.57	53.2	-0.1	5.0
		5	2.0	6.7	-31.1	5.4	0.33	52.4	0.0	5.0
		10	**0.3**	**6.7**	**-38.8**	**5.4**	**0.08**	**51.2**	**0.0**	**5.0**
		20	-3.0	6.7	-57.9	15.6	-0.42	49.3	0.0	4.9
		50	-12.1	6.7	-94.6	21.8	-1.89	44.3	0.0	4.7
Daily	*One Day*	No Cost	4.8	7.0	-17.6	5.4	0.71	53.0	-0.1	4.7
		5	1.2	7.0	-35.3	5.4	0.21	51.1	0.0	4.7
		10	**-2.3**	**7.0**	**-51.3**	**15.6**	**-0.29**	**49.1**	**0.0**	**4.6**
		20	-8.9	7.0	-87.6	22.4	-1.28	45.9	0.0	4.4
		50	-26.2	7.5	-99.9	22.4	-4.01	38.2	-0.1	3.8

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 66: Performance-Risk analytics of Cross Asset Absolute Momentum Strategies based on past 1-day return: 1992-2014

Rebalance Freq	Invest Horizon	One-Way Cost (bps)	Ann. Return	Ann. Volatility	Max Drawdown	MaxDDur (in years)	Sharpe Ratio	Hit Rate	Return Skewness	Return Kurtosis
Monthly	*One Month*	No Cost	0.4	6.1	-28.8	12.9	0.09	51.3	0.0	4.1
		5	-0.5	6.1	-31.3	13.7	-0.06	50.7	0.0	4.1
		10	**-1.4**	**6.2**	**-35.9**	**21.0**	**-0.20**	**50.2**	**0.0**	**4.0**
		20	-3.2	6.2	-54.7	21.1	-0.48	49.5	0.0	3.9
		50	-8.2	6.7	-85.8	21.8	-1.25	48.8	-0.3	3.5
Weekly	*One Month*	No Cost	1.3	3.1	-12.1	4.4	0.42	51.3	0.0	5.0
		5	0.3	3.1	-16.8	6.5	0.11	49.8	0.1	5.0
		10	**-0.7**	**3.1**	**-24.3**	**15.6**	**-0.20**	**49.0**	**0.1**	**4.9**
		20	-2.6	3.2	-45.7	21.7	-0.81	47.2	0.1	4.7
		50	-8.1	3.4	-85.0	22.3	-2.47	43.7	-0.1	3.7
Daily	*One Month*	No Cost	0.7	1.5	-5.8	5.6	0.49	52.8	-0.1	9.5
		5	-0.2	1.5	-11.4	10.0	-0.11	50.3	-0.1	9.5
		10	**-1.1**	**1.5**	**-23.7**	**16.8**	**-0.72**	**47.8**	**-0.1**	**9.5**
		20	-2.9	1.5	-48.5	21.8	-1.92	43.1	-0.1	9.4
		50	-8.2	1.6	-85.0	22.3	-5.46	31.4	0.0	8.9
Weekly	*One Week*	No Cost	0.7	6.4	-19.0	7.9	0.13	50.1	0.1	4.6
		5	-3.1	6.4	-52.6	21.7	-0.46	47.5	0.1	4.5
		10	**-6.7**	**6.5**	**-79.2**	**22.4**	**-1.04**	**45.7**	**0.1**	**4.3**
		20	-13.6	6.7	-96.2	22.4	-2.13	43.7	0.0	3.6
		50	-31.3	8.4	-100.0	22.4	-4.44	41.3	-0.6	2.5
Daily	*One Week*	No Cost	-1.3	2.8	-26.4	21.6	-0.43	48.0	0.4	12.6
		5	-5.0	2.8	-68.2	22.4	-1.78	43.2	0.4	12.6
		10	**-8.5**	**2.9**	**-86.5**	**22.4**	**-3.12**	**38.3**	**0.4**	**12.5**
		20	-15.3	2.9	-97.6	22.4	-5.75	30.7	0.4	12.1
		50	-32.7	3.1	-100.0	22.4	-12.81	16.4	0.3	9.3
Daily	*One Day*	No Cost	-2.7	6.1	-54.1	18.0	-0.42	48.6	0.1	4.2
		5	-19.6	6.1	-99.2	22.4	-3.56	38.5	0.2	4.2
		10	**-33.6**	**6.1**	**-100.0**	**22.4**	**-6.62**	**30.1**	**0.2**	**4.0**
		20	-54.7	6.5	-100.0	22.4	-12.19	18.3	0.1	3.4
		50	-85.7	8.4	-100.0	22.4	-22.90	5.7	-0.3	2.3

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Performance of Alternative Trend Signals

In this Appendix, we introduce popular choices of alternative trend signals such as moving averages, moving average crossovers, MACD, RSI, etc and study their impacts on Trend-Following strategy performance. For each strategy, we summarize annualized compound return, Sharpe ratio, maximum drawdown and hit rate during 1992-2014 (the full sample period) as well as during 2011-2014. Explanations of signal acronyms are summarized on page 37 of Chapter 2.

Asset Class	Trend Signal	1992-2014				2011-2014				Corr/w
		Return	Sharpe	MaxDD	Hit Rate	Return	Sharpe	MaxDD	Hit Rate	Ret(261)
TSM - Equities	**Ret(130)**	10.7	0.84	-28.0	53.6	9.1	0.69	-17.1	52.9	**75.5**
	Ret(261)	**10.9**	**0.82**	**-31.6**	**53.5**	**6.2**	**0.47**	**-24.9**	**52.1**	
	MA(200)	11.2	0.88	-24.7	54.1	8.9	0.67	-17.0	53.0	**76.9**
	MA(100)	7.6	0.61	-22.3	52.7	7.5	0.57	-17.2	53.9	57.2
	MA(50)	5.0	0.41	-28.1	51.3	7.5	0.60	-16.4	52.8	41.6
	X-Over(5, 200)	11.1	0.86	-25.2	54.2	8.8	0.67	-15.4	54.5	**77.6**
	X-Over(50, 200)	11.2	0.87	-28.1	53.8	7.3	0.54	-21.5	53.1	**80.4**
	X-Over(5, 100)	8.1	0.65	-20.5	52.7	6.4	0.51	-16.3	52.8	**58.3**
	X-Over(10, 200)	10.3	0.79	-34.2	54.1	8.3	0.62	-18.6	53.7	**78.1**
	Up2Down(261)	6.2	0.54	-34.4	53.6	1.7	0.13	-27.0	53.0	57.3
	Up2Down(130)	6.2	0.58	-30.2	53.3	4.9	0.42	-18.1	52.8	**44.0**
	Up2Down(65)	4.6	0.47	-22.0	52.3	5.0	0.51	-12.3	52.6	32.5
	MACD	0.0	0.00	-52.0	49.7	-2.7	-0.24	-25.4	50.3	-4.6
	RSI(14)	3.6	0.39	-28.6	52.6	1.6	0.18	-14.5	52.0	22.9
	RSI(20)	3.9	0.42	-19.5	54.7	2.0	0.24	-13.2	53.0	33.3
	RSI(50)	3.0	0.45	-14.0	62.5	1.3	0.24	-8.1	63.6	50.3
TSM - Bonds	Ret(130)	4.0	0.31	-43.9	51.9	-2.0	-0.17	-32.7	50.1	73.4
	Ret(261)	**9.8**	**0.75**	**-28.7**	**53.4**	**8.2**	**0.71**	**-16.2**	**53.8**	
	MA(200)	7.2	0.55	-36.3	52.3	0.4	0.04	-33.1	50.7	78.1
	MA(100)	5.0	0.38	-44.3	51.4	-7.8	-0.62	-44.3	50.1	56.6
	MA(50)	3.4	0.26	-49.4	50.9	-9.5	-0.77	-47.4	49.6	47.3
	X-Over(5, 200)	7.2	0.56	-41.8	52.2	1.7	0.14	-31.9	50.0	77.9
	X-Over(50, 200)	6.5	0.49	-39.8	52.3	2.1	0.17	-28.8	51.5	75.9
	X-Over(5, 100)	6.1	0.47	-42.7	51.9	-5.3	-0.44	-42.7	50.2	57.8
	X-Over(10, 200)	7.0	0.53	-39.6	52.4	-0.9	-0.08	-34.3	49.8	78.3
	Up2Down(261)	8.9	0.69	-42.9	52.5	10.0	0.95	-13.6	53.6	**64.6**
	Up2Down(130)	7.1	0.57	-44.6	52.2	7.9	0.75	-17.2	52.9	57.8
	Up2Down(65)	4.8	0.41	-49.7	51.2	5.5	0.56	-17.7	51.7	52.0
	MACD	-2.8	-0.22	-65.4	48.6	-12.0	-1.02	-35.9	46.7	-1.7
	RSI(14)	2.4	0.22	-44.4	51.9	-11.4	-1.16	-39.5	49.1	30.6
	RSI(20)	1.1	0.11	-49.2	53.5	-8.3	-0.89	-37.0	53.7	37.0
	RSI(50)	1.7	0.20	-37.5	64.1	-3.7	-0.53	-26.3	62.5	51.2

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Asset Class	Trend Signal	1992-2014				2011-2014				Corr/w
		Return	Sharpe	MaxDD	Hit Rate	Return	Sharpe	MaxDD	Hit Rate	Ret(261)
TSM - Currencies	**Ret(130)**	5.4	0.53	-22.5	53.1	0.3	0.03	-22.5	52.4	**73.2**
	Ret(261)	**6.0**	**0.58**	**-23.1**	**53.9**	**-1.3**	**-0.14**	**-16.9**	**53.0**	
	MA(200)	5.5	0.53	-29.2	53.2	-3.0	-0.30	-29.2	51.0	**73.4**
	MA(100)	4.4	0.43	-26.8	52.7	-3.0	-0.30	-26.8	50.2	55.7
	MA(50)	3.1	0.31	-32.3	51.8	-4.1	-0.43	-22.7	48.7	42.1
	X-Over(5, 200)	5.6	0.54	-27.4	53.3	-0.6	-0.06	-27.4	51.7	**73.0**
	X-Over(50, 200)	5.4	0.53	-19.3	52.8	0.4	0.05	-18.1	51.1	**75.9**
	X-Over(5, 100)	4.8	0.46	-26.3	52.7	0.1	0.01	-26.3	52.2	**56.8**
	X-Over(10, 200)	6.4	0.62	-22.3	53.4	1.8	0.19	-22.3	51.5	**74.3**
	Up2Down(261)	1.8	0.21	-24.4	50.6	0.5	0.06	-12.7	51.2	36.5
	Up2Down(130)	0.9	0.11	-26.4	49.8	-0.2	-0.03	-13.0	50.4	23.4
	Up2Down(65)	1.3	0.15	-27.2	50.1	-0.3	-0.04	-19.3	49.6	21.8
	MACD	-0.4	-0.05	-49.0	50.3	-3.9	-0.41	-22.6	49.9	-2.8
	RSI(14)	1.4	0.18	-33.8	51.3	-4.4	-0.55	-21.6	51.1	29.6
	RSI(20)	1.7	0.23	-27.3	51.8	-0.3	-0.04	-12.8	53.5	34.0
	RSI(50)	1.1	0.17	-18.4	59.0	-1.4	-0.26	-13.9	56.2	50.0
TSM - Commodities	Ret(130)	4.8	0.46	-29.1	53.2	-5.0	-0.48	-29.1	49.1	68.4
	Ret(261)	**6.8**	**0.63**	**-28.0**	**54.2**	**1.2**	**0.11**	**-23.9**	**52.4**	
	MA(200)	5.1	0.48	-32.8	53.5	-6.7	-0.63	-32.8	50.6	71.0
	MA(100)	4.5	0.43	-30.9	52.7	-6.3	-0.61	-30.9	50.8	55.7
	MA(50)	1.4	0.13	-44.9	51.9	-1.8	-0.17	-18.7	52.1	44.1
	X-Over(5, 200)	5.3	0.50	-25.3	53.3	-3.7	-0.35	-25.3	51.5	71.1
	X-Over(50, 200)	6.0	0.58	-29.1	53.2	-5.1	-0.51	-29.1	50.9	**69.9**
	X-Over(5, 100)	5.0	0.48	-26.9	53.0	-4.8	-0.45	-25.5	50.6	56.2
	X-Over(10, 200)	4.8	0.45	-28.4	52.9	-5.1	-0.48	-28.4	50.9	71.6
	Up2Down(261)	2.6	0.26	-36.2	52.3	-1.2	-0.13	-19.6	52.5	37.5
	Up2Down(130)	3.1	0.32	-30.1	52.9	-5.7	-0.62	-27.5	49.3	34.9
	Up2Down(65)	3.3	0.36	-28.7	52.6	-3.9	-0.43	-21.7	50.2	34.0
	MACD	1.0	0.10	-49.7	51.3	-7.7	-0.78	-29.8	50.1	10.7
	RSI(14)	1.2	0.15	-28.1	52.5	-4.5	-0.54	-21.1	51.5	38.8
	RSI(20)	2.2	0.28	-22.6	52.6	-1.4	-0.16	-13.6	50.2	39.4
	RSI(50)	1.2	0.20	-20.9	56.9	-0.9	-0.12	-12.9	58.9	51.9

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Asset Class	Trend Signal	1992-2014				2011-2014				Corr/w
		Return	Sharpe	MaxDD	Hit Rate	Return	Sharpe	MaxDD	Hit Rate	Ret(261)
CSM - Multi Asset	Ret(130)	6.6	0.78	-14.6	53.5	5.3	0.62	-10.6	52.4	78.9
	Ret(261)	**8.4**	**1.04**	**-17.4**	**54.7**	**5.9**	**0.78**	**-10.1**	**53.0**	
	MA(200)	7.4	0.86	-15.7	54.2	3.8	0.44	-14.4	52.6	80.4
	MA(100)	6.6	0.78	-14.0	53.5	3.0	0.34	-13.5	52.7	66.5
	MA(50)	5.3	0.65	-14.6	52.7	3.0	0.37	-8.7	53.0	54.5
	X-Over(5, 200)	7.4	0.87	-15.2	54.0	5.2	0.61	-12.7	53.6	80.8
	X-Over(50, 200)	6.7	0.80	-14.7	54.1	3.7	0.44	-12.8	52.4	82.9
	X-Over(5, 100)	7.0	0.83	-13.0	53.5	3.8	0.44	-12.2	53.6	67.6
	X-Over(10, 200)	7.3	0.85	-14.5	54.2	5.5	0.63	-12.1	53.3	80.7
	Up2Down(261)	-1.3	-0.21	-45.6	47.7	-0.3	-0.06	-12.1	49.6	-47.0
	Up2Down(130)	-1.6	-0.26	-43.1	48.6	-2.7	-0.45	-16.3	49.7	-42.8
	Up2Down(65)	-1.5	-0.24	-43.4	49.4	-0.9	-0.14	-14.1	52.2	-35.7
	MACD	1.7	0.32	-18.7	51.2	2.0	0.41	-8.2	51.6	19.9
	RSI(14)	5.3	0.66	-16.8	52.6	0.2	0.03	-16.6	53.0	40.7
	RSI(20)	5.5	0.65	-18.0	52.6	0.0	0.00	-18.0	51.8	45.5
	RSI(50)	6.4	0.70	-19.1	53.4	0.9	0.09	-19.1	51.7	55.0
	Ret2Vol(130)	7.0	0.78	-15.1	53.5	5.5	0.62	-10.7	53.5	72.4
	Ret2Vol(261)	8.6	0.99	-14.6	55.1	6.7	0.87	-9.6	55.3	**88.4**
	Regression	9.6	0.70	-27.2	52.8	12.4	0.85	-13.7	53.9	**29.8**
	InvVol(261)	5.2	0.65	-24.2	52.4	5.1	0.63	-12.7	53.3	**15.5**

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Stop-Loss Trigger and Short-Term Reversion Sensitivities

This Appendix summarizes performance/risk metrics for prototype 12-month Absolute Momentum strategies incorporating different assumptions of stop-loss triggers on the long and short portfolios. See the section Stop-Loss and Volatility Signals for analysis.

Table 67: Performance/Risk statistics of 12-month Absolute Momentum models with an assumption of 3% stop loss on long positions with 1-month block-out

	3% Stop Loss on Short Positions				5% Stop Loss on Short Positions				7% Stop Loss on Short Positions				10% Stop Loss on Short Positions				No Stop Loss on Short Positions			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	5.6	4.8	2.7	4.7	5.5	5.4	3.6	5.3	5.0	5.3	3.5	5.4	4.9	5.2	3.7	5.3	4.9	5.2	4.0	5.0
CAGR (%)	5.4	4.5	2.5	4.5	5.1	5.0	3.4	5.1	4.6	4.9	3.3	5.2	4.5	4.8	3.4	5.0	4.5	4.8	3.7	4.7
STDev (%)	8.9	9.0	6.6	7.3	9.5	9.4	7.3	7.8	9.7	9.8	7.7	8.2	9.9	9.9	8.0	8.5	10.0	10.0	8.3	8.7
MaxDD (%)	-20.2	-27.6	-21.8	-12.9	-20.4	-27.3	-27.1	-14.0	-26.0	-28.5	-28.4	-14.6	-26.8	-29.9	-28.4	-17.2	-26.9	-30.3	-25.0	-16.3
MaxDDur (in yrs)	3.4	7.5	9.5	2.6	5.2	7.4	9.5	3.4	5.2	8.2	9.5	2.5	5.2	5.2	9.5	2.5	5.2	5.2	8.1	2.7
***t*-Statistic**	**3.0**	**2.5**	**1.9**	**3.0**	**2.7**	**2.7**	**2.3**	**3.2**	**2.4**	**2.6**	**2.2**	**3.1**	**2.3**	**2.5**	**2.2**	**3.0**	**2.3**	**2.5**	**2.3**	**2.7**
Sharpe Ratio	**0.63**	**0.53**	**0.41**	**0.64**	**0.58**	**0.57**	**0.49**	**0.68**	**0.51**	**0.54**	**0.46**	**0.66**	**0.49**	**0.52**	**0.46**	**0.62**	**0.49**	**0.52**	**0.48**	**0.57**
Hit Rate (%)	55.3	55.7	53.4	54.4	54.4	55.0	53.4	54.1	54.1	54.9	53.0	54.3	53.8	54.8	53.1	54.0	53.7	54.7	53.0	54.2
Skewness	-0.08	-0.04	-0.15	-0.25	-0.18	-0.05	-0.22	-0.19	-0.21	-0.06	-0.28	-0.14	-0.18	-0.07	-0.32	-0.11	-0.13	-0.09	-0.32	-0.13
Kurtosis	9.13	6.33	5.73	4.44	8.21	5.17	4.86	4.24	7.52	4.65	4.43	3.95	6.77	4.53	3.57	3.81	6.76	4.50	4.22	3.53

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 68: Performance/Risk statistics of 12-month Absolute Momentum models with an assumption of 5% stop loss on long positions with 1-month block-out

	3% Stop Loss on Short Positions				5% Stop Loss on Short Positions				7% Stop Loss on Short Positions				10% Stop Loss on Short Positions				No Stop Loss on Short Positions			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	7.1	6.7	3.3	4.4	7.0	7.1	4.0	5.2	6.5	7.2	4.0	5.2	6.3	7.2	4.2	5.2	6.3	7.3	4.3	4.9
CAGR (%)	6.8	6.4	3.1	4.2	6.7	6.8	3.8	4.9	6.1	6.9	3.7	4.9	5.9	6.8	3.8	4.9	5.8	6.9	3.9	4.6
STDev (%)	9.9	10.2	7.4	8.0	10.4	10.5	7.9	8.5	10.6	10.8	8.4	8.8	10.8	10.9	8.7	9.1	10.8	11.0	9.0	9.3
MaxDD (%)	-24.4	-31.7	-20.6	-14.3	-25.3	-26.3	-24.7	-13.7	-29.8	-27.6	-25.7	-16.6	-31.3	-28.2	-25.2	-19.6	-31.4	-28.7	-23.6	-18.3
MaxDDur (in yrs)	3.3	3.5	9.5	3.1	4.4	3.5	9.5	2.7	5.2	3.5	9.5	2.5	5.2	3.5	9.5	3.1	5.2	3.5	9.5	3.1
***t*-Statistic**	**3.4**	**3.1**	**2.1**	**2.6**	**3.2**	**3.2**	**2.4**	**2.9**	**2.9**	**3.2**	**2.3**	**2.8**	**2.8**	**3.1**	**2.3**	**2.7**	**2.7**	**3.1**	**2.2**	**2.5**
Sharpe Ratio	**0.72**	**0.66**	**0.45**	**0.55**	**0.68**	**0.68**	**0.51**	**0.61**	**0.61**	**0.67**	**0.48**	**0.59**	**0.58**	**0.66**	**0.48**	**0.57**	**0.58**	**0.66**	**0.47**	**0.52**
Hit Rate (%)	54.9	54.5	52.8	53.7	53.9	54.0	53.2	54.1	53.5	53.9	53.3	54.1	53.4	53.9	53.4	54.0	53.5	53.7	53.1	53.8
Skewness	-0.12	-0.09	-0.11	-0.44	-0.19	-0.09	-0.20	-0.33	-0.22	-0.10	-0.27	-0.29	-0.19	-0.11	-0.32	-0.27	-0.20	-0.11	-0.28	-0.27
Kurtosis	6.85	4.76	5.55	4.71	6.41	4.08	4.76	4.28	5.76	3.63	4.50	4.07	5.45	3.59	3.69	3.80	5.23	3.64	4.38	3.53

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 69: Performance/Risk statistics of 12-month Absolute Momentum models with an assumption of 7% stop loss on long positions with 1-month block-out

	3% Stop Loss on Short Positions				5% Stop Loss on Short Positions				7% Stop Loss on Short Positions				10% Stop Loss on Short Positions				No Stop Loss on Short Positions			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	7.8	7.9	5.0	5.8	7.8	8.3	5.6	6.4	7.3	8.5	5.6	6.5	7.1	8.4	5.7	6.4	7.1	8.6	6.0	6.1
CAGR (%)	7.5	7.6	4.8	5.6	7.4	8.0	5.4	6.2	6.9	8.1	5.3	6.2	6.6	8.1	5.4	6.1	6.7	8.2	5.7	5.8
STDev (%)	10.7	11.0	8.1	8.6	11.1	11.3	8.6	9.0	11.3	11.5	9.0	9.4	11.5	11.6	9.3	9.6	11.5	11.7	9.6	9.9
MaxDD (%)	-25.2	-33.4	-17.3	-15.5	-27.6	-28.5	-16.9	-15.1	-32.9	-25.8	-19.0	-18.4	-33.8	-25.0	-20.9	-21.4	-33.8	-25.0	-19.9	-20.3
MaxDDur (in yrs)	5.6	5.5	3.8	3.1	5.2	5.4	6.6	2.8	5.2	5.5	8.2	3.1	5.2	5.4	9.5	3.1	5.2	5.4	5.2	3.1
***t*-Statistic**	**3.5**	**3.4**	**2.9**	**3.2**	**3.3**	**3.5**	**3.1**	**3.4**	**3.0**	**3.5**	**2.9**	**3.3**	**2.9**	**3.4**	**2.9**	**3.2**	**2.9**	**3.5**	**2.9**	**2.9**
Sharpe Ratio	**0.73**	**0.72**	**0.62**	**0.67**	**0.70**	**0.74**	**0.66**	**0.71**	**0.64**	**0.73**	**0.62**	**0.69**	**0.62**	**0.73**	**0.62**	**0.67**	**0.62**	**0.73**	**0.62**	**0.62**
Hit Rate (%)	54.5	53.6	53.0	54.1	54.0	53.4	53.6	54.1	53.6	53.3	53.5	54.1	53.5	53.4	53.8	54.0	53.5	53.3	53.7	54.0
Skewness	-0.30	-0.18	-0.09	-0.33	-0.35	-0.17	-0.20	-0.26	-0.34	-0.18	-0.26	-0.22	-0.34	-0.18	-0.31	-0.21	-0.31	-0.18	-0.29	-0.22
Kurtosis	5.64	3.88	5.48	3.84	5.26	3.37	3.94	3.60	4.85	3.03	3.72	3.29	4.51	2.98	3.17	3.04	4.42	3.01	3.75	2.82

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 70: Performance/Risk statistics of 12-month Absolute Momentum models with an assumption of 10% stop loss on long positions with 1-month block-out

	3% Stop Loss on Short Positions				5% Stop Loss on Short Positions				7% Stop Loss on Short Positions				10% Stop Loss on Short Positions				No Stop Loss on Short Positions			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	9.8	8.7	5.4	5.9	9.7	9.1	6.0	6.6	9.2	9.3	5.9	6.6	9.0	9.3	6.1	6.5	9.1	9.4	6.3	6.2
CAGR (%)	9.5	8.3	5.1	5.7	9.4	8.7	5.8	6.4	8.8	9.0	5.7	6.3	8.6	8.9	5.8	6.2	8.7	9.0	5.9	5.8
STDev (%)	11.7	11.6	8.4	9.0	12.1	11.9	8.8	9.4	12.3	12.2	9.2	9.7	12.4	12.3	9.6	10.0	12.5	12.3	9.9	10.2
MaxDD (%)	-27.0	-33.5	-16.3	-22.0	-29.4	-28.3	-16.8	-21.9	-34.3	-26.2	-18.3	-22.9	-35.3	-25.9	-20.7	-25.9	-35.3	-25.8	-19.7	-26.2
MaxDDur (in yrs)	5.2	6.9	3.8	5.9	5.2	5.5	3.3	5.9	5.2	6.5	6.6	5.9	5.2	5.5	6.1	5.9	5.2	5.5	3.3	5.9
***t*-Statistic**	**3.9**	**3.5**	**3.0**	**3.1**	**3.8**	**3.6**	**3.2**	**3.3**	**3.6**	**3.6**	**3.0**	**3.2**	**3.4**	**3.6**	**3.0**	**3.1**	**3.5**	**3.6**	**3.0**	**2.9**
Sharpe Ratio	**0.83**	**0.74**	**0.64**	**0.66**	**0.80**	**0.76**	**0.68**	**0.70**	**0.75**	**0.77**	**0.64**	**0.68**	**0.73**	**0.75**	**0.63**	**0.65**	**0.73**	**0.76**	**0.63**	**0.60**
Hit Rate (%)	54.4	53.6	52.9	53.9	53.6	53.5	53.2	53.9	53.3	53.4	53.3	53.8	53.1	53.5	53.8	54.0	53.1	53.3	53.9	53.7
Skewness	-0.38	-0.18	-0.18	-0.37	-0.41	-0.18	-0.24	-0.30	-0.40	-0.19	-0.29	-0.26	-0.40	-0.19	-0.33	-0.25	-0.38	-0.18	-0.33	-0.27
Kurtosis	5.01	3.14	3.57	3.60	4.66	2.73	2.73	3.23	4.34	2.44	2.66	2.98	4.09	2.40	2.39	2.70	4.01	2.41	2.65	2.51

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Table 71: Performance/Risk statistics of 12-month Absolute Momentum models without stop loss on long positions with 1-month block-out

	3% Stop Loss on Short Positions				5% Stop Loss on Short Positions				7% Stop Loss on Short Positions				10% Stop Loss on Short Positions				No Stop Loss on Short Positions			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	11.5	9.1	5.2	6.6	11.3	9.4	5.8	7.2	10.9	9.7	5.7	7.1	10.7	9.7	5.8	7.0	10.9	9.8	6.0	6.7
CAGR (%)	11.2	8.7	4.9	6.3	11.0	9.0	5.5	6.9	10.6	9.3	5.4	6.8	10.3	9.2	5.4	6.7	10.6	9.3	5.6	6.3
STDev (%)	12.7	12.4	8.8	9.6	13.1	12.6	9.3	9.9	13.2	12.9	9.6	10.2	13.4	13.0	10.0	10.4	13.4	13.1	10.3	10.7
MaxDD (%)	-23.9	-34.7	-17.6	-22.5	-25.0	-30.1	-21.0	-24.0	-30.4	-27.2	-21.3	-24.1	-31.9	-28.2	-24.3	-27.5	-31.6	-28.7	-23.1	-28.0
MaxDDur (in yrs)	2.4	6.9	3.8	5.9	4.2	6.4	3.2	5.9	4.8	6.4	3.3	5.9	4.9	5.5	6.1	5.9	4.9	5.5	6.1	5.9
***t*-Statistic**	**4.3**	**3.5**	**2.8**	**3.2**	**4.1**	**3.5**	**3.0**	**3.4**	**3.9**	**3.6**	**2.8**	**3.3**	**3.8**	**3.5**	**2.7**	**3.2**	**3.9**	**3.5**	**2.7**	**3.0**
Sharpe Ratio	**0.90**	**0.73**	**0.59**	**0.69**	**0.87**	**0.75**	**0.62**	**0.72**	**0.83**	**0.75**	**0.59**	**0.69**	**0.80**	**0.74**	**0.58**	**0.67**	**0.82**	**0.75**	**0.58**	**0.63**
Hit Rate (%)	54.6	53.7	53.0	54.1	54.0	53.5	53.2	54.2	53.7	53.5	53.3	54.1	53.5	53.5	53.8	54.3	53.5	53.4	53.9	54.2
Skewness	-0.29	-0.24	-0.16	-0.38	-0.32	-0.24	-0.23	-0.32	-0.32	-0.24	-0.26	-0.29	-0.32	-0.24	-0.32	-0.28	-0.30	-0.24	-0.31	-0.28
Kurtosis	4.35	3.37	3.73	3.63	3.87	2.96	2.87	3.29	3.61	2.71	2.70	2.97	3.41	2.61	2.38	2.70	3.29	2.60	2.77	2.50

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 72: Performance/Risk statistics of 12-month Absolute Momentum models with an assumption of 3% stop loss on long positions without 1-month block-out

	3% Stop Loss on Short Positions				5% Stop Loss on Short Positions				7% Stop Loss on Short Positions				10% Stop Loss on Short Positions				No Stop Loss on Short Positions			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	7.1	4.5	2.6	5.8	6.8	4.9	3.1	6.2	6.9	5.4	3.4	6.4	7.1	5.3	3.6	5.9	7.3	5.3	3.8	5.6
CAGR (%)	6.7	3.9	2.2	5.5	6.3	4.3	2.7	6.0	6.5	4.8	3.0	6.2	6.7	4.7	3.2	5.7	6.9	4.8	3.4	5.3
STDev (%)	10.9	11.0	8.3	8.8	11.1	11.2	8.7	9.1	11.2	11.3	9.0	9.3	11.3	11.4	9.1	9.4	11.3	11.3	9.2	9.5
MaxDD (%)	-23.5	-37.4	-22.0	-16.9	-27.0	-34.0	-24.0	-17.1	-28.9	-33.4	-22.9	-19.5	-28.6	-32.9	-24.6	-19.8	-28.6	-31.7	-23.1	-19.4
MaxDDur (in yrs)	5.2	11.0	10.3	2.7	5.2	11.0	10.3	2.7	5.2	11.0	10.3	2.5	5.2	11.0	10.3	3.1	5.2	9.1	10.3	2.7
***t*-Statistic**	**3.1**	**1.9**	**1.5**	**3.1**	**2.9**	**2.1**	**1.7**	**3.3**	**2.9**	**2.2**	**1.8**	**3.3**	**3.0**	**2.2**	**1.9**	**3.0**	**3.1**	**2.2**	**1.9**	**2.8**
Sharpe Ratio	**0.65**	**0.41**	**0.31**	**0.66**	**0.61**	**0.43**	**0.35**	**0.69**	**0.62**	**0.47**	**0.38**	**0.69**	**0.63**	**0.46**	**0.40**	**0.63**	**0.64**	**0.47**	**0.41**	**0.59**
Hit Rate (%)	53.5	53.5	52.2	54.0	53.4	53.3	52.3	54.3	53.3	53.3	52.6	54.4	53.2	53.4	52.7	54.5	53.2	53.3	52.9	54.3
Skewness	-0.18	-0.23	-0.09	-0.22	-0.23	-0.25	-0.13	-0.22	-0.23	-0.25	-0.20	-0.14	-0.21	-0.25	-0.22	-0.12	-0.19	-0.25	-0.24	-0.13
Kurtosis	5.58	4.35	5.63	3.09	5.29	3.95	4.89	2.84	5.18	3.69	4.71	2.82	4.94	3.65	4.47	2.81	4.90	3.64	4.44	2.75

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 73: Performance/Risk statistics of 12-month Absolute Momentum models with an assumption of 5% stop loss on long positions without 1-month block-out

	3% Stop Loss on Short Positions				5% Stop Loss on Short Positions				7% Stop Loss on Short Positions				10% Stop Loss on Short Positions				No Stop Loss on Short Positions			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	7.6	6.2	3.0	5.8	7.3	6.6	3.6	6.2	7.5	7.1	3.9	6.4	7.6	7.0	4.1	5.9	7.8	7.1	4.2	5.5
CAGR (%)	7.2	5.7	2.7	5.5	6.8	6.1	3.2	5.9	7.0	6.6	3.5	6.1	7.1	6.5	3.7	5.6	7.3	6.5	3.8	5.2
STDev (%)	11.6	11.9	8.8	9.3	11.8	12.1	9.3	9.6	11.9	12.1	9.5	9.8	12.0	12.2	9.6	9.9	12.0	12.2	9.7	10.0
MaxDD (%)	-31.0	-36.0	-23.2	-18.8	-33.3	-28.9	-27.4	-20.1	-35.1	-28.0	-26.6	-23.5	-34.9	-28.2	-28.0	-24.0	-35.0	-29.0	-27.0	-23.6
MaxDDur (in yrs)	5.6	5.0	10.3	3.1	5.6	7.0	10.3	3.1	5.2	7.0	10.3	3.1	5.2	7.0	10.3	3.1	5.2	6.9	10.3	3.1
***t*-Statistic**	**3.1**	**2.5**	**1.6**	**2.9**	**2.9**	**2.6**	**1.8**	**3.1**	**3.0**	**2.8**	**1.9**	**3.1**	**3.0**	**2.7**	**2.0**	**2.8**	**3.1**	**2.8**	**2.1**	**2.6**
Sharpe Ratio	**0.65**	**0.52**	**0.34**	**0.62**	**0.61**	**0.55**	**0.39**	**0.65**	**0.63**	**0.59**	**0.41**	**0.65**	**0.63**	**0.58**	**0.42**	**0.60**	**0.65**	**0.58**	**0.44**	**0.55**
Hit Rate (%)	53.2	53.2	52.5	53.8	53.2	53.1	52.9	54.2	53.2	53.1	53.0	54.3	53.2	53.0	53.1	54.3	53.2	53.0	53.2	54.1
Skewness	-0.24	-0.19	-0.13	-0.31	-0.28	-0.21	-0.17	-0.31	-0.28	-0.21	-0.24	-0.24	-0.27	-0.21	-0.26	-0.23	-0.26	-0.21	-0.28	-0.24
Kurtosis	4.61	3.81	4.91	3.35	4.34	3.50	4.38	3.04	4.23	3.30	4.33	3.03	4.12	3.27	4.12	2.95	4.06	3.28	4.05	2.88

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 74: Performance/Risk statistics of 12-month Absolute Momentum models with an assumption of 7% stop loss on long positions without 1-month block-out

	3% Stop Loss on Short Positions				5% Stop Loss on Short Positions				7% Stop Loss on Short Positions				10% Stop Loss on Short Positions				No Stop Loss on Short Positions			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	8.1	7.4	4.7	6.1	7.7	7.8	5.2	6.5	7.8	8.4	5.5	6.7	7.9	8.2	5.7	6.2	8.2	8.3	5.8	5.9
CAGR (%)	7.6	6.9	4.4	5.7	7.2	7.3	4.9	6.2	7.3	7.9	5.2	6.4	7.4	7.7	5.3	5.9	7.7	7.8	5.5	5.5
STDev (%)	12.3	12.3	9.2	9.6	12.4	12.4	9.6	9.9	12.5	12.5	9.8	10.1	12.5	12.5	9.9	10.2	12.6	12.5	10.0	10.3
MaxDD (%)	-32.0	-36.1	-21.1	-21.9	-34.2	-29.1	-19.2	-24.2	-36.1	-28.3	-20.0	-25.9	-36.1	-27.8	-19.9	-27.3	-36.1	-26.7	-20.2	-27.4
MaxDDur (in yrs)	5.6	6.9	3.9	5.9	5.2	6.9	3.3	5.9	5.2	6.9	2.9	5.9	5.2	6.9	5.6	5.9	5.2	5.5	5.6	5.9
***t*-Statistic**	**3.1**	**2.9**	**2.4**	**3.0**	**2.9**	**3.0**	**2.6**	**3.1**	**3.0**	**3.2**	**2.7**	**3.1**	**3.0**	**3.1**	**2.7**	**2.9**	**3.1**	**3.1**	**2.8**	**2.7**
Sharpe Ratio	**0.66**	**0.60**	**0.51**	**0.63**	**0.62**	**0.63**	**0.54**	**0.66**	**0.63**	**0.67**	**0.56**	**0.66**	**0.63**	**0.66**	**0.57**	**0.61**	**0.65**	**0.66**	**0.58**	**0.57**
Hit Rate (%)	53.1	53.2	53.1	54.0	53.2	53.2	53.5	54.4	53.1	53.2	53.7	54.4	53.2	53.1	53.7	54.3	53.2	53.1	53.9	54.2
Skewness	-0.31	-0.22	-0.15	-0.31	-0.35	-0.23	-0.19	-0.31	-0.35	-0.24	-0.26	-0.25	-0.34	-0.24	-0.28	-0.24	-0.32	-0.24	-0.29	-0.25
Kurtosis	4.92	3.45	4.42	2.97	4.61	3.19	3.96	2.73	4.44	3.01	3.91	2.61	4.38	2.99	3.73	2.54	4.35	3.00	3.69	2.47

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 75: Performance/Risk statistics of 12-month Absolute Momentum models with an assumption of 10% stop loss on long positions without 1-month block-out

	3% Stop Loss on Short Positions				5% Stop Loss on Short Positions				7% Stop Loss on Short Positions				10% Stop Loss on Short Positions				No Stop Loss on Short Positions			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	9.3	7.9	4.8	6.4	8.8	8.4	5.4	6.9	9.0	8.9	5.7	7.1	9.2	8.8	5.9	6.6	9.4	8.8	6.0	6.3
CAGR (%)	8.8	7.4	4.5	6.1	8.3	7.8	5.0	6.6	8.5	8.4	5.3	6.8	8.7	8.3	5.5	6.3	8.9	8.3	5.6	5.9
STDev (%)	12.7	12.6	9.3	9.9	12.9	12.7	9.7	10.1	13.0	12.8	9.9	10.3	13.0	12.8	10.1	10.4	13.0	12.8	10.2	10.5
MaxDD (%)	-33.1	-37.2	-19.3	-24.4	-35.5	-30.3	-19.1	-26.5	-37.1	-29.0	-19.8	-27.7	-37.1	-28.5	-20.7	-29.1	-37.0	-27.4	-21.0	-29.0
MaxDDur (in yrs)	5.6	7.0	3.8	5.9	5.6	6.9	3.3	5.9	5.2	6.9	2.8	5.9	5.2	6.5	5.6	5.9	5.2	5.5	5.6	5.9
***t*-Statistic**	**3.4**	**3.0**	**2.5**	**3.1**	**3.2**	**3.1**	**2.6**	**3.2**	**3.3**	**3.3**	**2.7**	**3.3**	**3.3**	**3.2**	**2.7**	**3.0**	**3.4**	**3.3**	**2.8**	**2.8**
Sharpe Ratio	**0.73**	**0.63**	**0.52**	**0.65**	**0.69**	**0.66**	**0.55**	**0.68**	**0.70**	**0.69**	**0.57**	**0.69**	**0.70**	**0.68**	**0.58**	**0.64**	**0.72**	**0.69**	**0.59**	**0.60**
Hit Rate (%)	53.2	53.2	53.0	54.0	53.2	53.1	53.5	54.3	53.1	53.1	53.6	54.3	53.1	53.0	53.7	54.3	53.2	53.0	53.9	54.1
Skewness	-0.36	-0.22	-0.17	-0.35	-0.39	-0.24	-0.20	-0.35	-0.39	-0.24	-0.26	-0.28	-0.39	-0.24	-0.28	-0.27	-0.37	-0.24	-0.30	-0.29
Kurtosis	4.16	3.07	3.91	2.96	3.90	2.83	3.49	2.72	3.81	2.67	3.45	2.64	3.72	2.65	3.33	2.51	3.69	2.65	3.29	2.44

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 76: Performance/Risk statistics of 12-month Absolute Momentum models without stop loss on long positions without 1-month block-out

	3% Stop Loss on Short Positions				5% Stop Loss on Short Positions				7% Stop Loss on Short Positions				10% Stop Loss on Short Positions				No Stop Loss on Short Positions			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	10.7	8.9	4.8	6.9	10.3	9.3	5.3	7.4	10.5	9.8	5.6	7.6	10.6	9.7	5.8	7.1	10.9	9.8	6.0	6.7
CAGR (%)	10.4	8.4	4.5	6.6	9.9	8.8	4.9	7.1	10.1	9.4	5.3	7.3	10.2	9.3	5.4	6.8	10.6	9.3	5.6	6.3
STDev (%)	13.1	12.9	9.4	10.1	13.3	13.0	9.8	10.3	13.3	13.1	10.0	10.5	13.4	13.1	10.2	10.6	13.4	13.1	10.3	10.7
MaxDD (%)	-26.3	-37.4	-19.2	-24.6	-29.6	-30.5	-20.1	-25.4	-31.8	-28.4	-20.5	-26.4	-31.9	-29.1	-22.5	-28.0	-31.6	-28.7	-23.1	-28.0
MaxDDur (in yrs)	4.5	6.9	3.8	5.9	4.7	6.4	3.3	5.9	4.9	6.4	3.3	5.9	4.9	5.5	6.1	5.9	4.9	5.5	6.1	5.9
***t*-Statistic**	**3.9**	**3.3**	**2.4**	**3.2**	**3.7**	**3.4**	**2.6**	**3.4**	**3.7**	**3.6**	**2.7**	**3.4**	**3.8**	**3.5**	**2.7**	**3.2**	**3.9**	**3.5**	**2.7**	**3.0**
Sharpe Ratio	**0.82**	**0.69**	**0.51**	**0.69**	**0.78**	**0.72**	**0.54**	**0.71**	**0.79**	**0.75**	**0.56**	**0.72**	**0.79**	**0.74**	**0.57**	**0.67**	**0.82**	**0.75**	**0.58**	**0.63**
Hit Rate (%)	53.5	53.5	53.2	54.1	53.6	53.4	53.6	54.4	53.4	53.5	53.6	54.4	53.4	53.4	53.7	54.4	53.5	53.4	53.9	54.2
Skewness	-0.28	-0.22	-0.20	-0.34	-0.32	-0.23	-0.23	-0.34	-0.32	-0.24	-0.28	-0.28	-0.31	-0.23	-0.31	-0.28	-0.30	-0.24	-0.31	-0.28
Kurtosis	3.83	2.97	2.98	3.07	3.55	2.75	2.71	2.84	3.46	2.61	2.70	2.71	3.37	2.59	2.67	2.59	3.29	2.60	2.77	2.50

Source: J.P. Morgan Quantitative and Derivatives Strategy.

The Appendix below summarizes performance/risk metrics for prototype Absolute Momentum strategies incorporating different short-term reversion window sizes. See the section Incorporating Value/Reversion Factors for more analysis.

Table 77: Performance/Risk Statistics of Absolute Momentum Models with Short-term Reversion (Days Skipped): 12-Month and 9-Month Trends

	12M Trend Skipping 5-Days				12M Trend Skipping 10-Days				12M Trend Skipping 15-Days				12M Trend Skipping 21-Days			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	11.4	9.1	6.2	6.7	11.3	8.3	5.8	6.7	11.2	8.6	6.3	7.7	10.6	7.9	5.5	8.0
CAGR (%)	11.1	8.5	5.8	6.4	11.0	7.7	5.4	6.3	10.8	8.1	5.9	7.4	10.2	7.3	5.1	7.7
STDev (%)	13.5	13.1	10.3	10.7	13.3	13.2	10.3	10.7	13.6	13.2	10.4	10.6	13.5	13.1	10.2	10.5
MaxDD (%)	-32.6	-33.3	-27.4	-32.6	-30.7	-35.3	-24.0	-26.7	-33.3	-35.0	-23.5	-25.0	-34.8	-35.7	-31.4	-29.7
MaxDDur (in yrs)	4.9	7.0	6.1	5.9	4.9	7.2	6.1	5.9	5.2	7.0	5.9	5.4	5.2	7.0	6.1	5.9
t-Statistic	**4.0**	**3.3**	**2.9**	**3.0**	**4.0**	**3.0**	**2.7**	**2.9**	**3.9**	**3.1**	**2.9**	**3.4**	**3.7**	**2.9**	**2.6**	**3.6**
Sharpe Ratio	**0.85**	**0.69**	**0.60**	**0.63**	**0.85**	**0.63**	**0.56**	**0.62**	**0.83**	**0.66**	**0.61**	**0.73**	**0.79**	**0.61**	**0.54**	**0.76**
Hit Rate (%)	53.8	53.1	54.3	54.5	53.7	52.7	53.6	53.8	53.8	52.9	53.6	54.1	53.7	52.9	53.4	53.7
Skewness	-0.34	-0.23	-0.36	-0.27	-0.30	-0.23	-0.31	-0.26	-0.36	-0.22	-0.34	-0.23	-0.34	-0.26	-0.39	-0.25
Kurtosis	3.42	2.65	2.53	2.73	3.37	2.63	2.78	2.68	3.66	2.57	3.36	2.52	3.69	2.74	2.72	2.70

	9M Trend Skipping 5-Days				9M Trend Skipping 10-Days				9M Trend Skipping 15-Days				9M Trend Skipping 21-Days			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	11.4	7.4	6.6	2.4	11.7	6.4	6.4	3.2	11.3	6.2	5.2	2.5	10.5	6.1	3.9	3.1
CAGR (%)	11.2	6.8	6.3	1.9	11.5	5.6	6.0	2.7	11.0	5.5	4.7	1.9	10.2	5.4	3.5	2.6
STDev (%)	13.1	13.2	10.2	10.7	13.1	13.1	10.3	10.5	13.2	13.1	10.4	10.4	13.1	13.0	10.3	10.5
MaxDD (%)	-25.8	-32.8	-19.1	-41.9	-24.9	-31.7	-20.0	-37.7	-26.4	-33.4	-21.6	-37.0	-33.6	-35.7	-33.3	-41.0
MaxDDur (in yrs)	4.2	4.1	3.4	5.9	4.2	4.1	3.4	4.9	4.2	4.0	10.3	5.9	4.9	4.1	10.3	5.9
t-Statistic	**4.1**	**2.7**	**3.1**	**1.1**	**4.2**	**2.3**	**2.9**	**1.4**	**4.1**	**2.3**	**2.4**	**1.1**	**3.8**	**2.2**	**1.8**	**1.4**
Sharpe Ratio	**0.88**	**0.56**	**0.65**	**0.23**	**0.90**	**0.48**	**0.62**	**0.30**	**0.86**	**0.48**	**0.50**	**0.24**	**0.80**	**0.47**	**0.38**	**0.30**
Hit Rate (%)	54.2	52.5	53.4	52.8	53.8	52.4	53.0	52.9	54.1	52.3	52.5	52.7	53.6	52.2	52.4	52.7
Skewness	-0.31	-0.16	-0.36	-0.31	-0.28	-0.20	-0.21	-0.31	-0.31	-0.22	-0.27	-0.29	-0.32	-0.21	-0.36	-0.27
Kurtosis	3.64	2.45	2.40	2.76	3.79	2.64	3.12	2.69	3.70	2.68	3.04	2.69	3.64	2.64	2.64	2.74

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Table 78: Performance/Risk Statistics of Absolute Momentum Models with Short-term Reversion (Days Skipped): 6-Month and 3-Month Trends

	6M Trend Skipping 5-Days				6M Trend Skipping 10-Days				6M Trend Skipping 15-Days				6M Trend Skipping 21-Days			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	10.8	3.4	3.8	4.6	10.1	3.4	4.7	4.8	9.9	3.6	4.6	4.4	8.7	2.8	4.3	4.6
CAGR (%)	10.4	2.6	3.4	4.2	9.6	2.6	4.3	4.3	9.5	2.8	4.2	3.9	8.2	2.0	3.9	4.2
STDev (%)	13.0	12.9	9.9	10.4	13.1	13.0	9.9	10.4	12.9	13.1	10.0	10.3	12.8	13.3	10.0	10.2
MaxDD (%)	-29.4	-48.8	-20.7	-26.8	-30.7	-47.7	-19.6	-23.9	-29.5	-45.6	-22.3	-24.0	-30.5	-48.4	-21.5	-22.6
MaxDDur (in yrs)	3.2	11.0	4.0	3.1	3.1	11.0	5.0	2.7	3.1	11.0	5.0	2.8	3.5	11.0	5.0	3.1
***t*-Statistic**	**3.9**	**1.3**	**1.8**	**2.1**	**3.6**	**1.2**	**2.3**	**2.2**	**3.6**	**1.3**	**2.2**	**2.0**	**3.2**	**1.0**	**2.1**	**2.1**
Sharpe Ratio	**0.83**	**0.27**	**0.38**	**0.44**	**0.77**	**0.26**	**0.48**	**0.46**	**0.77**	**0.27**	**0.46**	**0.42**	**0.68**	**0.21**	**0.43**	**0.45**
Hit Rate (%)	53.8	52.2	52.4	53.5	53.5	52.1	52.9	52.8	53.8	51.9	52.5	53.0	53.2	51.6	52.9	53.0
Skewness	-0.31	-0.21	-0.28	-0.28	-0.24	-0.20	-0.29	-0.19	-0.35	-0.23	-0.29	-0.22	-0.38	-0.19	-0.31	-0.22
Kurtosis	3.32	2.35	1.89	2.58	3.95	2.22	1.95	2.58	3.14	2.37	2.09	2.34	3.05	2.75	1.79	2.37

	3M Trend Skipping 5-Days				3M Trend Skipping 10-Days				3M Trend Skipping 15-Days				3M Trend Skipping 21-Days			
	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty	Equity	Bond	Curncy	Comdty
Ann. Ex Ret (%)	6.6	4.8	5.2	4.7	6.7	2.7	3.7	4.0	6.5	2.2	3.8	3.7	6.4	1.3	2.3	4.0
CAGR (%)	6.0	4.0	4.8	4.2	6.0	1.9	3.3	3.5	5.9	1.4	3.4	3.2	5.8	0.5	1.9	3.6
STDev (%)	12.8	13.0	10.3	10.5	12.8	13.2	10.1	10.3	12.4	13.2	9.9	10.2	12.5	13.1	9.8	9.9
MaxDD (%)	-24.9	-42.5	-29.2	-28.8	-24.4	-50.2	-29.9	-30.5	-26.9	-44.9	-28.0	-27.2	-33.5	-44.3	-26.9	-27.4
MaxDDur (in yrs)	5.6	7.3	2.8	4.4	3.4	8.1	4.6	2.4	5.4	7.2	5.1	4.2	5.9	8.2	7.9	4.0
***t*-Statistic**	**2.5**	**1.7**	**2.4**	**2.1**	**2.5**	**1.0**	**1.7**	**1.8**	**2.5**	**0.8**	**1.8**	**1.7**	**2.4**	**0.5**	**1.1**	**1.9**
Sharpe Ratio	**0.52**	**0.36**	**0.51**	**0.45**	**0.52**	**0.21**	**0.37**	**0.38**	**0.52**	**0.17**	**0.39**	**0.36**	**0.51**	**0.10**	**0.24**	**0.41**
Hit Rate (%)	52.5	51.4	52.8	53.1	52.7	50.8	53.1	52.7	52.8	50.8	52.4	52.9	52.2	50.8	51.9	53.0
Skewness	-0.09	-0.06	-0.17	-0.20	-0.07	-0.13	-0.23	-0.17	-0.17	-0.18	-0.33	-0.14	-0.20	-0.21	-0.28	-0.13
Kurtosis	3.92	2.39	3.30	2.42	3.79	2.55	3.35	2.28	3.64	2.50	2.62	2.26	3.14	2.27	2.26	2.56

Source: J.P. Morgan Quantitative and Derivatives Strategy.

Table 79: Performance/Risk Statistics of Cross Asset Relative Momentum Models with Short-term Reversion (Days Skipped)

	12M Cross Asset Relative Momentum				
	No Skip	5-Day	10-Day	15-Day	21-Day
Ann. Ex Ret (%)	8.4	8.7	8.6	8.6	8.1
CAGR (%)	8.4	8.8	8.7	8.6	8.1
STDev (%)	8.1	8.1	8.0	8.0	7.9
MaxDD (%)	-17.4	-14.8	-13.1	-13.4	-14.4
MaxDDur (in yrs)	4.2	4.1	4.2	3.9	4.8
***t*-Statistic**	**4.9**	**5.1**	**5.1**	**5.1**	**4.8**
Sharpe Ratio	**1.03**	**1.08**	**1.08**	**1.07**	**1.02**
Hit Rate (%)	54.7	55.0	55.1	55.3	55.2
Skewness	-0.35	-0.31	-0.35	-0.37	-0.36
Kurtosis	2.41	2.33	2.37	2.41	2.34

	9M Cross Asset Relative Momentum				
	No Skip	5-Day	10-Day	15-Day	21-Day
Ann. Ex Ret (%)	7.2	6.9	6.3	5.9	5.7
CAGR (%)	7.1	6.8	6.2	5.8	5.5
STDev (%)	8.2	8.0	8.1	7.9	7.8
MaxDD (%)	-14.9	-14.9	-14.0	-14.6	-16.1
MaxDDur (in yrs)	5.3	4.8	4.7	5.4	5.9
***t*-Statistic**	**4.2**	**4.0**	**3.7**	**3.5**	**3.4**
Sharpe Ratio	**0.88**	**0.86**	**0.78**	**0.75**	**0.72**
Hit Rate (%)	54.2	54.5	54.2	54.5	54.2
Skewness	-0.31	-0.37	-0.36	-0.35	-0.38
Kurtosis	2.65	2.40	2.92	2.37	2.15

	6M Cross Asset Relative Momentum				
	No Skip	5-Day	10-Day	15-Day	21-Day
Ann. Ex Ret (%)	6.6	6.5	6.1	5.7	5.5
CAGR (%)	6.4	6.4	5.9	5.5	5.3
STDev (%)	8.4	8.4	8.3	8.2	7.9
MaxDD (%)	-14.6	-16.7	-17.1	-16.6	-16.7
MaxDDur (in yrs)	2.6	2.6	2.6	2.1	2.3
***t*-Statistic**	**3.7**	**3.7**	**3.5**	**3.3**	**3.3**
Sharpe Ratio	**0.78**	**0.78**	**0.73**	**0.69**	**0.69**
Hit Rate (%)	53.5	54.0	53.5	53.7	53.9
Skewness	-0.27	-0.31	-0.27	-0.31	-0.31
Kurtosis	2.24	1.90	2.29	2.24	1.71

	3M Cross Asset Relative Momentum				
	No Skip	5-Day	10-Day	15-Day	21-Day
Ann. Ex Ret (%)	6.6	6.7	5.9	4.6	3.9
CAGR (%)	6.5	6.5	5.7	4.3	3.6
STDev (%)	8.6	8.5	8.4	8.3	8.0
MaxDD (%)	-13.8	-13.5	-16.1	-14.1	-16.6
MaxDDur (in yrs)	2.7	2.7	2.7	2.7	4.1
***t*-Statistic**	**3.7**	**3.7**	**3.3**	**2.6**	**2.3**
Sharpe Ratio	**0.78**	**0.78**	**0.70**	**0.55**	**0.48**
Hit Rate (%)	53.1	53.8	53.4	52.5	53.0
Skewness	-0.16	-0.15	-0.14	-0.17	-0.20
Kurtosis	2.68	2.60	2.68	3.02	2.24

Source: J.P. Morgan Quantitative and Derivatives Strategy.

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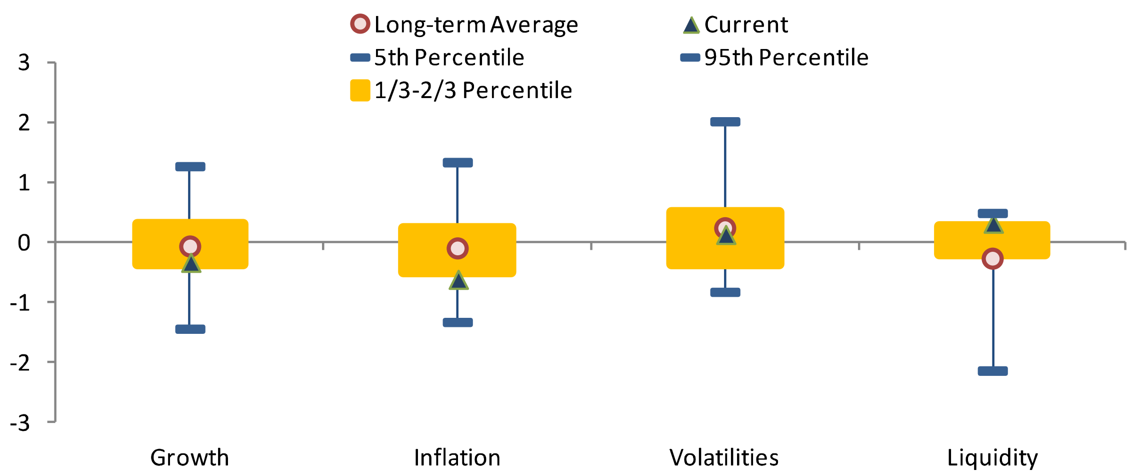
Macro and Market Regimes

To develop a better understanding of Momentum Risk Factors, we studied properties of each factor under different macro-economic and market-technical regimes. In particular, we examined factor performance in different regimes of **Growth** (YoY change of OECD CLI, a leading indicator of global economic growth), **Inflation (**OECD global consumer price inflation indicator), **Volatility** (VIX Index), **Funding Liquidity** (TED Spread, defined as the difference between 3-month Treasury Bill rate and 3-month US$ Libor rate, measures broad US$ funding risk).

Figure 118 below shows the historical distribution of the five regime indicators[133] - Growth, Inflation, Volatility, Funding Liquidity during 1992-2014, using monthly data.

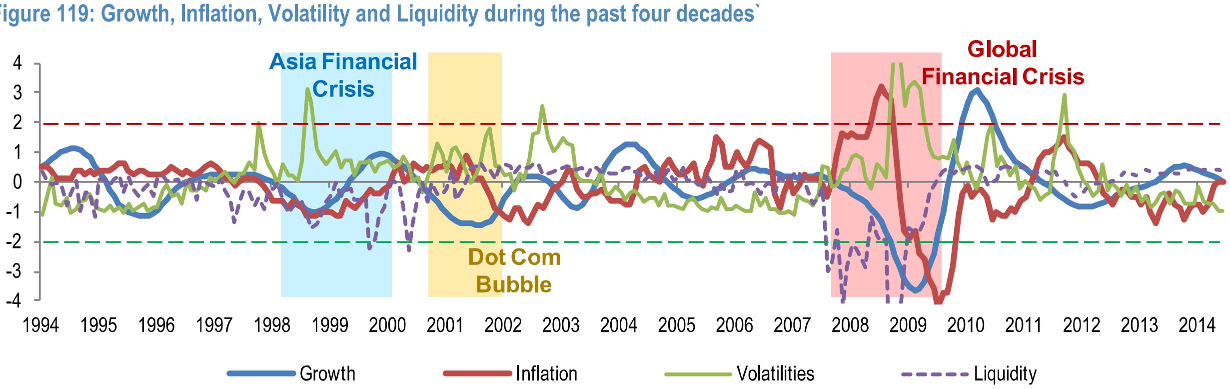
Figure 118: Historical profile of macro economic and market regime factors during 1994-2014



Source: J.P. Morgan Quantitative and Derivatives Strategy, Bloomberg, OECD. ` Regime factors are standardized to unit variance and zero median. `` Current values (green triangles) for Growth, Inflation, Volatilities and Funding Liquidity factors are based Dec 2014 readings.

We note that Volatility has a tendency to spike (positive skewness), and the liquidity measure has a tendency to drop (negative skewness). On the other hand, during the past two decades (1992-2014), Growth and Inflation displayed relatively even distribution on both tails. Figure 119 shows the history of these measures over the past 20 years. Notable features include Growth/Inflation cycles during 2007-08 crisis, high Volatility during market crises of 1997-1998 and 2008-2009. Figure 119 shows that we are currently in a mid Growth, mid Inflation, low Volatility, and high Liquidity regime.

Figure 119: Growth, Inflation, Volatility and Liquidity during the past four decades`



Source: J.P. Morgan Quantitative and Derivatives Strategy. ` Regime factors are standardized to unit variance and zeros median.

[133] These indicators were standardized "in-sample" to have unit variance and zeros median.

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The four macro and market technical regime indicators discussed are not independent of one another. Table 80 below shows the correlation of these regime indicators over the past 20 years, as well as during three crisis periods. For instance, Volatility was negatively correlated with all the other factors, and the negative correlation was most pronounced during crisis periods. Liquidity was significantly negatively correlated with inflation, partly reflecting the secular decline in inflation and improvements in systemic banking credibility and so on.

Table 80: Correlation matrix of Growth, Inflation, Volatility and Liquidity Indicators (lower triangular statistics are the all-sample pair-wise correlation, upper triangular are the correlation statistics during crisis periods`)

	Growth	Inflation	Volatilities	Liquidity
Growth		38	-83	28
Inflation	4		-39	-22
Volatilities	-39	-21		-54
Liquidity	38	-28	-47	
Full Sample Ave	1	-15	-36	-12
Crisis Average	-9	-17	-46	-18
During GFC	-5	-8	-59	-16

Source: J.P. Morgan Quantitative and Derivatives Strategy.
` Lower triangular statistics are the all-sample pair-wise correlation and upper triangular are the correlation statistics during crisis periods.
`` Crisis periods we include for the correlation calculations are Jul 1997 - Aug 1998 (Asian Financial Crisis, Russian Default and LTCM), Jan 2000 – Sep 2001 (Tech Bubble), and June 2007 - Feb 2009 (Global Financial Crisis or GFC).

Performance-Risk Analytics

Similar to our primer on Cross Asset Systematic Strategies, we define the performance and risk metrics we reported in our analysis of Momentum Risk Factor styles.

For a time series observation of total returns $\boldsymbol{R} = (r_1, \ldots, r_T)'$ with N observations per annum and the corresponding time series of risk-free rates $\boldsymbol{R_f}$, $\boldsymbol{R_e} = \boldsymbol{R} - \boldsymbol{R_f} = (r_1^e, \ldots, r_T^e)'$ is the excess return. In addition, $\boldsymbol{S_R} = (S_1, \ldots, S_T)^T$ with $S_t = \prod_{i=1}^{t}(1 + r_i)$ is the net asset value (NAV) for the return series $\boldsymbol{R}$. We define the following performance-risk metrics:

1) **Annualized average return (Average):**

$$\boldsymbol{\mu_R} = \frac{N}{T}\sum_{i=1}^{T} r_i$$

2) **Annualized compounded return (CAGR):**

$$\boldsymbol{g_R} = \left[\prod_{i=1}^{T}(1 + r_i)\right]^{\frac{N}{T}} - 1 = (S_T)^{\frac{N}{T}} - 1$$

3) **Annualized standard deviation (StDev):**

$$\boldsymbol{\sigma_R} = \sqrt{N\frac{\sum_{i=1}^{T}(r_i - \bar{r})^2}{T - 1}}$$

where $\bar{r} = \frac{1}{T}\sum_{i=1}^{T} r_i = \boldsymbol{\mu_R}/N$ is the arithmetic average of the returns.

4) **Annualized downside deviation (DownDev):**

$$\boldsymbol{D\sigma_R}(R_{\text{Target}}) = \sqrt{N\frac{\sum_{i=1}^{T}\left[\min\left(r_i - R_{\text{Target}}, 0\right)\right]^2}{T}}$$

where $R_{\textbf{Target}}$ is so-called target return (or Minimum Acceptable Return to evaluate the relative performance). The downside deviation is also called the "loss standard deviation".

5) **Annualized upside deviation (UpDev)** or "Gain standard deviation":

$$\boldsymbol{U\sigma_R}(R_{\text{Target}}) = \sqrt{N\frac{\sum_{i=1}^{T}\left[\max\left(r_i - R_{\text{Target}}, 0\right)\right]^2}{T}}$$

6) **Annualized Covariance (CoVar)** between $\boldsymbol{R}$ and another return series $\boldsymbol{X}$:

$$\mathbf{CoVar}_{\boldsymbol{R},\boldsymbol{X}} = \frac{N}{T - 1}\sum_{i=1}^{T}(r_i - \bar{r})(x_i - \bar{x})$$

7) **Correlation (Correl)** between $\boldsymbol{R}$ and another return series $\boldsymbol{X}$:

$$\mathbf{Correl}_{\boldsymbol{R},\boldsymbol{X}} = \frac{\mathbf{CoVar}_{\boldsymbol{R},\boldsymbol{X}}}{\boldsymbol{\sigma_R}\boldsymbol{\sigma_X}}$$

Covariance and correlation could be calculated either in total returns or excess returns.

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8) **Skewness (Skew)** measures the symmetry of a distribution:

$$\mathbf{Skew}_{\boldsymbol{R}} = \frac{T}{(T-1)(T-2)} \sum_{i=1}^{T} \left(\frac{r_i - \bar{r}}{\boldsymbol{s_R}} \right)^3$$

where $\boldsymbol{s_R} = \boldsymbol{\sigma_R}/\sqrt{\boldsymbol{N}}$ is the (un-annualized) standard deviation of the returns.

9) **Kurtosis (Kurt)** characterizes the relative richness of the tail of a distribution compared with a normal distribution:

$$\mathbf{Kurt}_{\boldsymbol{R}} = \frac{T(T+1)}{(T-1)(T-2)(T-3)} \sum_{i=1}^{T} \left(\frac{r_i - \bar{r}}{\boldsymbol{s_R}} \right)^4 - \frac{3(T-1)^2}{(T-2)(T-3)}$$

10) **Drawdown (DD)** measures the current percentage loss of NAV from the previous high water mark (HWM) within a specific time window:

$$\mathbf{DD}_{\boldsymbol{R}}(t_1, t_2) = \frac{S_{t_2}}{\mathrm{HWM}(t_1, t_2)} - 1, \text{where } \mathrm{HWM}(t_1, t_2) = \max_{t_1 \le t \le t_2} S_t$$

11) **Maximum Drawdown (MaxDD)** measures the maximum peak to trough percentage change of the NAV during a specific period:

$$\mathbf{MaxDD}_{\boldsymbol{R}}(t_1, t_2) = -\max_{t_1 \le t \le t_2} |\mathbf{DD}_{\boldsymbol{R}}(t_1, t)|$$

As the absolute value of maximum drawdown is higher for longer periods, a reasonable window (e.g. past three years) is usually applied to the calculation so as not to disadvantage managers with longer track records.

12) **Drawdown Duration (DDur)** measures the time in years from the last HWM:

$$\mathbf{DDur}_{\boldsymbol{R}}(t_1, t_2) = \frac{t_2 - \tau}{N}, \text{for } t_1 \le \tau \le t_2 \text{ such that } S_\tau = \mathrm{HWM}(t_1, t_2)$$

13) **Maximum Drawdown Duration (MaxDDur)** measures the maximum amount of time in years to reach previous HWM:

$$\mathbf{MaxDDur}_{\boldsymbol{R}}(t_1, t_2) = \max_{t_1 \le t \le t_2} \mathbf{DDur}_{\boldsymbol{R}}(t_1, t)$$

14) **Sharpe Ratio (SR)**:

$$\mathrm{SR}_{\boldsymbol{R_e}} = \frac{\boldsymbol{\mu_{R_e}}}{\boldsymbol{\sigma_{R_e}}}$$

When the benchmark used for the calculation of excess return is not a risk-free asset, this is often called **Information Ratio**.

15) **Adjusted Sharpe Ratio (ASR)**:

$$\mathrm{ASR}_{\boldsymbol{R_e}} = \mathrm{SR}_{\boldsymbol{R_e}} \times \left[1 + \frac{\mathbf{Skew}_{\boldsymbol{R_e}}}{6} \mathrm{SR}_{\boldsymbol{R_e}} - \frac{\mathbf{Kurt}_{\boldsymbol{R_e}}}{24} \left(\mathrm{SR}_{\boldsymbol{R_e}} \right)^2 \right]$$

The adjusted Sharpe Ratio was proposed as an alternative to the standard Sharpe ratio when related performance is not normally distributed. The measure is derived from a Taylor series expansion of an exponential utility function.

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16) Sortino Ratio (Sortino):

$$\text{Sortino}_{\boldsymbol{R_e}} = \frac{\boldsymbol{\mu_{R_e}}}{\boldsymbol{D\sigma_{R_e}}(R_{\text{Target}})}$$

where the target return R_{Target} is usually set to be 0 for an excess return series.

17) Calmar Ratio (Calmar):

$$\text{Calmar}_{\boldsymbol{R_e}} = -\frac{\boldsymbol{\mu_{R_e}}}{\mathbf{MaxDD}_{\boldsymbol{R_e}}(\text{Past 3 years})}$$

18) Pain Ratio (PainRatio):

$$\text{PainRatio}_{\boldsymbol{R_e}} = \frac{\boldsymbol{\mu_{R_e}}}{\mathbf{PainIdx}_{\boldsymbol{R_e}}}$$

19) Reward to VaR Ratio (VaRatio):

$$\text{VaRatio}_{\boldsymbol{R_e}} = -\frac{\boldsymbol{\mu_{R_e}}}{N \times \mathbf{VaR}_{\boldsymbol{R_e}}(\delta)}$$

20) Reward to CVaR Ratio (CVaRatio):

$$\text{CVaRatio}_{\boldsymbol{R_e}} = -\frac{\boldsymbol{\mu_{R_e}}}{N \times \mathbf{CVaR}_{\boldsymbol{R_e}}(\delta)}$$

21) Hit Rate measures the percentage of non-negative returns relative to a certain benchmark:

$$\text{Hit}_{\boldsymbol{R_e}} = \frac{\sum_{i=1}^{T} 1\{r_i^e \geq 0\}}{T}$$

22) Gain to Pain Ratio (GPR) measures the sum of positive returns to sum of negative returns:

$$\mathbf{GPR}_{\mathbf{R_e}} = -\frac{\sum_{\mathbf{i=1}}^{\mathbf{T}} \mathbf{max}(\mathbf{r_i^e}, \mathbf{0})}{\sum_{\mathbf{i=1}}^{\mathbf{T}} \mathbf{min}(\mathbf{r_i^e}, \mathbf{0})}$$

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Review of Portfolio Construction Methods

The goal of a **portfolio optimization process** is to create the best possible portfolio for a particular investment objective, given some assumptions for future asset performance. The optimization objective can be to achieve a portfolio with the lowest possible risk, highest Sharpe ratio, smallest tracking error relative to a benchmark, or other objectives specified by an investor. In order to obtain asset weights that will result in an optimal portfolio, an investor often needs to make assumptions on the future asset returns, volatilities and correlation between assets. These assumptions (forecast) are input into an optimizer (e.g. a computer code) or may already be built into a commercial model (e.g. such as MSCI Barra).

The optimal portfolio construction is a straightforward mathematical procedure (e.g. see mean-variance optimization method later in this section). However, the forecasts for asset returns, volatilities and correlations are often not accurate, and an expected optimal mathematical solution may not turn out to be a portfolio with the desired properties after the fact. Given that asset returns are not easy to forecast, an investor may choose to limit themselves to forecasting volatility and correlations. The rationale behind forecasting volatility and correlations (and not returns) is that these measures tend to exhibit properties of persistence and mean reversion, and their average levels should (in principle) be easier to estimate. To avoid forecasting asset returns, an investor can use simplifying assumptions such as equal expected returns, equal asset Sharpe ratios, etc.

An investor's objective is often expressed via a utility function ("utility" effectively quantifies an investor's level of satisfaction/happiness with an economic outcome). A utility function quantifies the trade-off between the desired attributes of a portfolio such as high return, and undesirable properties such as high volatility and tail risk. An example of such a utility function is given below.

$$\text{Investor's Utility} = \text{Expected Return} - (\text{Risk Aversion}) \times \text{Variance}$$

To increase the investor's utility, one would need to find asset weights with the best 'trade-off' between high expected return, at low contribution to portfolio volatility. The parameter that determines the 'trade-off' between the return and risk parts of the utility function is called 'Risk aversion'. Levy and Markowitz (1979) showed that using a simple utility function such as the one above provides optimal solutions for a very broad set of utility functions, i.e. different types of investors (mathematically, the simple utility function above can be viewed as a second order approximation for any standard utility function). A portfolio constructed by optimizing this utility function would also have the highest possible Sharpe ratio (provided returns, volatility and correlations are accurately forecast).

Mean-Variance Optimization (MVO), Market Portfolio and Fixed Weight Allocation

MVO was first proposed by Markowitz (1952). The goal of the method is to produce a portfolio with the highest Sharpe ratio. Specifically, the method solves the portfolio optimization problem by maximizing a simple utility function aiming for higher returns and lower risk. As a result, Mean Variance Optimization will result in an optimal portfolio with a maximum Sharpe ratio. Specifically, an MVO tries to maximize

$$\text{Expected Portfolio Return} - \frac{\lambda}{2} \times \text{Expected Portfolio Variance}$$

A risk aversion factor (λ, positive value) is used to balance the risk-return tradeoff. The larger the risk aversion factor (λ) is, the higher penalty investor puts on "risk" (i.e. the more risk averse the investor). When λ is equal to 0, an MVO will put 100% weight in the best performing asset without regard to portfolio risk. On the other hand, when risk aversion factor is very large, MVO will not be concerned with returns, and will simply minimize portfolio risk – resulting in a portfolio with lowest possible volatility (also called the Global Minimum Variance (GMV) portfolio).

MVO is at the center of many traditional asset allocation approaches such as capitalization based allocations (Market Portfolio), and fixed weight investing (e.g. 60 bond / 40 equity portfolio). The Capital Asset Pricing Model (CAPM) introduced separately by Jack Treynor, William Sharpe and John Lintner suggests that the market portfolio is the optimal choice for investors seeking to maximize Sharpe ratio, and an asset's expected returns are proportional to the asset's beta to the market and the market's returns. Under a set of assumptions, the CAPM implies that the market portfolio is mean-variance optimal portfolio and that all investors should hold a proportion of the market portfolio as it has the highest Sharpe ratio (the "Two Fund Theorem" suggests investors should allocate between market portfolio and risk free asset). Currently, most equity investors are benchmarked to capitalization weighted indices – thus implementing a form of the MVO approach. Major equity benchmarks such as MSCI World, S&P 500, or MSCI Europe represent global and regional market portfolios and are thus approximately MVO optimal.

During 1950s-1960s when the Markowitz portfolio theory and CAPM were introduced, a 60% stock / 40% bond mix roughly represented the market capitalization weights of the universe of investable US assets. The simple bond/stock allocation prescription indirectly follows MVO. In fact, from a domestic US investor's point of view, the "market weight" of Treasury bonds in a Stock-Treasury bond portfolio actually stood in the 20%-40% range over the past five decades.

Global Minimum Variance (GMV)

Given the potential drawbacks of MVO related to the sensitivity to return forecasts (model inputs), many investors decided to turn to purely risk-based portfolio methods. Focus on risk based models further increased over recent years, as the global financial crisis shifted investor attention to preventing large losses.

Global Minimum Variance (GMV) is a special case of MVO where an investor has very high risk aversion. In this case "risk avoidance" takes priority to "return maximization" and the optimization tries to find the weights that will result in a portfolio with the lowest possible volatility. As we will show in the mathematical box below, the GMV approach is also equivalent to a special case of an MVO in which the investor simply assumes that the expected returns for all assets are equal. Thus GMV may be an optimal approach for investors that are either highly risk averse, or don't have any differentiating view on the performance of individual assets. An equal return assumption also implies that higher volatility assets have lower Sharpe ratios. While this may contrast with assumptions of efficient markets, there is some recent historical evidence that Sharpe ratios may indeed be lower for higher volatility assets (Volatility anomaly).

Since GMV only depends on the estimated covariance matrix of returns, statistical methods such as multivariate GARCH are usually employed to improve the stability of covariance matrix estimates. Other methods can be used as well such as using option implied volatilities to forecast future realized volatility.

Despite the oversimplifying assumptions of GMV, the performance of this method has often been better than e.g. an Equal Weight approach. This partly reflects the market performance over the past several years, which was heavily influenced by risky asset draw-downs in 2008 and 2011. Additionally, a more pronounced 'Volatility anomaly' would have benefited GMV due to its assumption of equal returns. At the end of this chapter we will test the performance of risk models applied to realistic portfolios of traditional and alternative factors. While GMV outperformed EW and occasionally other models, its performance over the long time periods was inferior to Risk Budgeting models. The GMV outperformed during times of market stress, due to its disproportionate focus on minimizing risk (as opposed to a more balanced approach between risk and returns).

Most-Diversified Portfolio (MDP)

Another popular method based entirely on forecasted risk (i.e. does not require return forecasts) is the Most Diversified Portfolio (MDP). MDP maximizes a measure called the 'diversification ratio'. Diversification ratio is defined as the ratio of the weighted average asset volatility to overall portfolio volatility. In other words, the portfolio diversification is high when the relatively high volatility of component assets results in overall low portfolio volatility through the offsetting effect of correlations. The simplest example is a portfolio of stocks and bonds. If stocks rally, and bonds crash, both assets exhibit a large move (high asset volatility). However, stock gains may offset bond losses, leading to constant portfolio value (low portfolio volatility). The mathematical box below provides a more precise definition of the diversification ratio.

Although MDP was formally introduced by Choueifaty and Coignard (2008), the concept of maximizing diversification is hardly new. In fact, MDP is just a special case of MVO in which an investor assumes that the Sharpe ratios for all the assets are equal. In fact, if we assume the Sharpe ratios of all assets are equal, the diversification ratio is simply proportional to portfolio Sharpe ratio. In this case, maximizing the Sharpe ratio via MVO is the same as finding the most diversified portfolio.

For uncorrelated assets, MDP gives a simple prescription of weighting the assets inversely to their individual volatility (see mathematical box below). In this specific case (uncorrelated assets), MDP becomes equivalent to another risk-based method called 'Equal Marginal Volatility'.

As we will show later in the chapter, the MDP approach often outperformed the simplest Equal Weight method. On average, MDP performed similar to GMV as both models focused on lowering the portfolio volatility. These models outperformed during risky times (e.g. had lower draw-downs), but they underperformed Risk Budgeting based models such as Risk Parity and Equal Marginal Volatility over full market cycles.

Diversification ratio is related to another theoretical concept called the "number of degrees of freedom" that MDP tries to maximize. This number represents the effective number of independent Risk Factors (independent assets) in the portfolio risk. For instance, if all the assets are perfectly independent, the number of degrees of freedom is simply equal to the number of assets in the portfolio. In the presence of correlations, the "effective" number of independent Risk Factors will generally be different from the number of assets depending on the average level of correlation.

Risk Budgeting (RB)

Traditional portfolio allocation methods based on MVO use expected returns, volatilities and correlations as in input to derive optimal portfolio weights. An alternative approach is to start with 'risk budgets' for each of the assets and then solve for portfolio weights. For instance, an investor can require that commodities add to 10% of total portfolio risk, Equities 50%, and so on. Such risk budgets should add to 100%. Risk budgets can be based on the investor's specific view on future performance of assets, or some general principles such as to assign equal risk budget to major asset classes or factor styles.

Risk budgeting can be used to avoid allocating too much risk to one asset or a group of correlated assets. An often quoted argument in support for risk budgeting is the traditional 60% Equity, 40% Bond allocation; it was argued that such a portfolio has 90% of risk in Equities and only 10% in Bonds, and is therefore prone to equities tail risk. A portfolio with more balanced risk budgets would select a lower allocation to equities and higher allocation to bonds.

The contribution of each asset to portfolio risk is determined by asset's volatility as well as its correlation to other assets in the portfolio. Adding an uncorrelated asset will increase the volatility of the portfolio only in proportion to the asset's weight and volatility, while adding a highly correlated asset will increase portfolio volatility largely through the correlations with other risky assets.

Detailed derivation of Risk Budget weights and optimal conditions are provided in mathematical box below. The most important result is that in the Risk Budget approach, asset weights are equal to the risk budget, divided by the beta of the asset with respect to the portfolio. So Risk Budgeting methods rely on the quality of the forecast of the asset's beta to the portfolio. In practice, optimal weights cannot be determined by independently estimating asset betas. Weights are determined in an iterative numerical procedure (e.g. increasing the weight of an asset also changes the betas/weights of all other assets). If an investor believes that realized (ex-post) return contributions of each asset will be in line with the pre-determined risk budget profile, the risk budgeted portfolio will also have the Maximal Sharpe Ratio.

As we will show at the end of this Chapter, when applied on realistic portfolios of traditional and alternative Risk Factors, Risk Budgeting models outperformed Equal Weight allocation and MVO-based approaches (MVO, GMV and MDP) over the past 40 years. Risk budgeting models such as Equal Marginal Volatility and Risk Parity struck a good balance between minimizing risk and maximizing returns, while maintaining relatively stable asset weights (unlike MVO that had high asset turnover). Part of the success of risk budgeting methods was in their reliance on more stable volatility and correlation estimates. Additionally, Risk Budgeting models were able to reduce draw-downs through balanced allocation of risk across portfolio components (typically higher weights in low volatility assets such as bonds).

Risk Parity (RP)

A special case of the Risk Budgeting approach is to assign equal risk budgets to all assets in the portfolio. This approach is also called Equal Risk Contribution, or Risk Parity. During recent years, Risk Parity (RP) methods drew a lot of interest because of their strong performance when applied to multi-asset portfolios. Given the relative higher marginal volatility of stocks, commodities and credit, these models had on average higher allocation to Treasuries. The strong performance of US Treasuries over the past few decades has helped these models to outperform most other asset allocation approaches. The most recent underperformance of Treasuries due to expected Fed tapering, as well as an increase in bond-equity correlations caused Risk Parity portfolios to underperform many other approaches. More detailed analysis of recent underperformance of Risk Parity can be found in the report The Risks of Risk Parity.

As we show in mathematical box below, the total risk contribution of an asset to a portfolio is equal to the corresponding portfolio weight times its beta with the portfolio (the "beta" component incorporates the correlation of an asset to the portfolio). If an investor assumes the return contribution of each asset is equal, then the Risk Parity portfolio has the highest Sharpe ratio. When all the pair-wise correlations of assets are zero, the Risk Parity portfolio allocates weights just based on assets' volatility. This special case is called Equal Marginal Volatility approach (EMV) and is briefly discussed below.

Equal Marginal Volatility (EMV)

Equal Marginal Volatility (EMV) assigns portfolio weights based on to the expected volatilities of individual assets. It underweights assets with higher volatility and overweights those with lower volatility – so as to achieve an equal marginal volatility contribution for all assets. However, the EMV approach ignores the contribution to portfolio volatility coming from asset correlations. In that regards, EMV is a special case of the Most Diversified Portfolio (MDP) when the average level of correlation is zero, and a special case of Risk Parity when all the correlations are zero.

The weight of an asset in the EMV approach is just the inverse of expected asset volatility. Investors often use recent historical volatility to estimate EMV (and more generally RP) weights. However, one can use option implied volatilities that often have better predictive power than recent realized volatility. Similarly, investors can use option implied betas to calculate weights in any Risk Budgeting approach.

Black-Litterman (BL)

The Black-Litterman (BL) framework was proposed by Fischer Black and Robert Litterman in 1990 to address the challenges of using MVO when there are no reliable return estimates. BL uses proper statistical methods to combine information implied by the market (market portfolio) and investors' views on expected returns. Combining market information and the investor's view results in return and covariance estimates that are then fed into a standard MVO process. The idea is that these estimates will lead to more robust (stable) MVO weights.

The first step of applying the BL framework involves reverse engineering the expected returns from current market portfolio weights (reverse solving MVO for market weights, to obtain 'market implied' asset returns). This step establishes the so called 'market prior' distribution of the expected returns. In addition, investor views on absolute and relative performance of the assets are specified to form an 'active portfolio'. The 'market prior' expected returns and specific investor views are combined in a Bayesian (conditional probability) framework to produce the so-called 'posterior distribution' of portfolio returns. Without investor views, BL is simply reduced to a CAPM market portfolio.

With investor views, the optimal portfolio (the posterior) under the BL framework reflects a combination of market portfolio ('market prior') and a portfolio reflecting optimal application of the investor's views. The investor also needs to set a parameter representing the relative weighting between the 'market prior' and 'investor views'. The BL approach often results in more stable asset weights (as compared to traditional MVO) because the 'posterior' expected returns are anchored to a common 'market prior' returns. Additionally, while the 'market prior' is usually specified as a normal distribution around expected CAPM returns, the BL framework allows for other choices of a 'market prior' distribution.

Comparison of Portfolio Construction Models

Table 81 below shows the main objectives of different risk methods as well as conditions under which each of these methods leads to an optimal portfolio.

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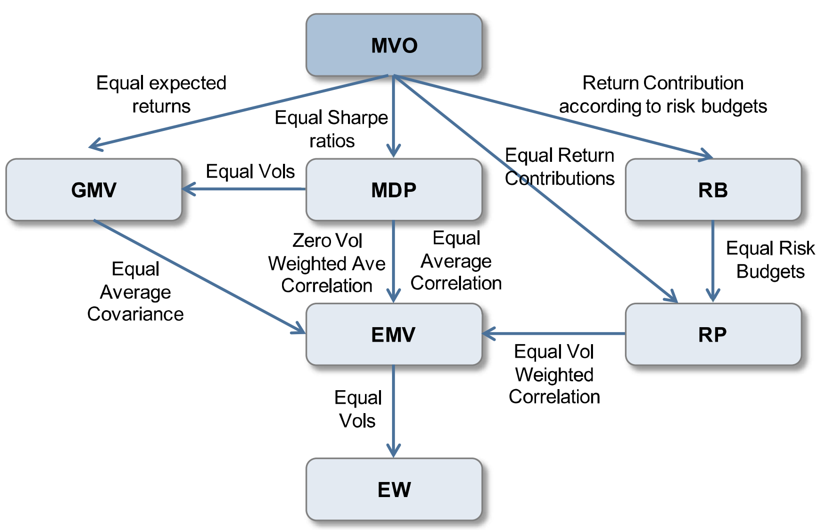
Table 81: Portfolio Construction Methodologies, Their Objectives and Conditions for Optimality

Asset Allocation Method	Objective	Conditions for Portfolio to be Mean Variance Optimal
Market weight (MW)	To Obtain Market Portfolio	Efficient market conditions as in CAPM
Equal weight (EW)	Each Asset has Equal weight	Expected return for the asset is proportional to the sum of the corresponding row of the covariance matrix
Fixed weight (FW)	Specific weights for each of Asset	Expected return for the asset is proportional to the weighted average of the corresponding row of the covariance matrix
Mean-Variance Optimization (MVO)	Achieve Maximum Portfolio Sharpe ratio	Ex Ante always. Ex Post if asset return and covariance forecasts were accurate
Black-Litterman (BL)	Achieve Maximum Sharpe ratio after incorporating expected return views	Posterior expected return is proportional to posterior beta
Global Minimum Variance (GMV)	To Obtain Minimum variance	Equal expected returns for all Assets
Most-Diversified Portfolio (MDP)	To Obtain Maximum diversification ratio	Equal Sharpe ratios for all Assets
Equal Marginal Volatility (EMV)	Each Asset has Equal Marginal Volatility	Expected return for the Asset is proportional to the correlation weighted marginal volatility
Risk Parity (RP)	Equal total risk contribution for each Asset	Equal total return contribution from each Asset
Generic Risk Budgeting (RB)	Specific total risk contribution for each Asset	Total return contribution from each Asset is the same with the corresponding total risk contribution

Source: J.P. Morgan Quantitative and Derivatives Strategy.

As shown in Figure 120 below, each portfolio method discussed is an implementation of MVO under certain assumptions. Working from the bottom of the diagram, EW is an EMV if we assume equal asset volatilities; EMV is an MDP if we assume zero average correlation; and finally MDP is an MVO if we assume equal marginal Sharpe ratios. GMV is an MDP if the asset volatilities are the same, and it is MVO if the expected returns are the same. The condition for the equivalence of MDP and RB is more complicated: it is achieved when the portfolio weight is proportional to the ratio of risk budget to marginal volatility. RP becomes EMV for zero correlation or equal volatility weighted correlations. RP also becomes general RB for non-equal risk budgets, and it becomes MVO for equal return contributions from each asset.

Figure 120: Theoretical Links between Various Portfolio Construction Methods



Source: J.P. Morgan Quantitative and Derivatives Strategy.

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Glossary

In this appendix we only show glossary of terms related to Momentum Investing. For a full glossary of terms related to Risk Factors see appendix of our Cross Asset Systematic Strategies primer.

Advance-Decline Line
The advance–decline line is a plot of the cumulative sum of the daily difference between the number of issues advancing and the number of issues declining. Each day's number of declining issues is subtracted from the number of advancing issues. The net difference is added to a running sum if the difference is positive or subtracted from the running sum if the difference is negative.

Autocorrelation
A mathematical representation of the degree of similarity between a given time series and a lagged version of itself over successive time intervals.

Average true range (ATR)
The average true range is an N-day exponential moving average of the true range values, where the true range is the largest of the most recent period's high minus the most recent period's low, the absolute value of the most recent period's high minus the previous close and the absolute value of the most recent period's low minus the previous close.

Bollinger Bands
A band plotted two standard deviations away from a simple moving average, developed by famous technical trader John Bollinger. The closer the prices move to the upper band, the more overbought the market, and the closer the prices move to the lower band, the more oversold the market.

Channel
A price channel contains prices (or short-term moving averages) throughout a trend band.

Commodity Futures Trading Commission (CFTC)
The U.S. Commodity Futures Trading Commission (CFTC) is an independent agency of the US government created in 1974, which regulates futures and option markets.

Commodity Channel Index (CCI)
The Commodity channel index (CCI) is calculated as the difference between the typical price of a commodity and its simple moving average, divided by the mean absolute deviation of the typical price.

Commodity Trading Advisor (CTA)
An individual or firm who provides individualized advice regarding the buying and selling of futures contracts or options on futures, or certain foreign exchange contracts. The Commodity Trading Advisor (CTA) registration is required by the National Futures Association, the self-regulatory organization for the industry in the US.

Confirmation Bias
Confirmation bias is a cognitive bias whereby one tends to notice and look for information that confirms one's existing beliefs, whilst ignoring anything that contradicts those beliefs. It is a type of selective thinking behavior rooted in investor psychology that contributes to the Momentum effect.

Crossover
Crossovers are used in technical analysis to aid in forecasting the future movements in the price of a security/index. In most technical analysis models, a crossover is a signal to either buy or sell.

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Donchian Channel
Donchian Channel is a Trend-following Channel breakout system developed by Richard Donchian. It is based on the following basic rules: When price closes above the Donchian Channel, buy long and cover short positions; When price closes below the Donchian Channel, sell short and liquidate long positions.

Earnings Growth or Earnings Momentum
Earning Growth or Earnings Momentum is a Risk Factor signal used to rank stocks based on the increase in their reported or consensus forward Earnings per Share, usually on a YoY basis. For stock analysts' consensus EPS, investors typically consider FY1 or FY2 estimates and 1 month or 3 months spans of time to calculate respective Earnings Growth factors.

Equal Marginal Volatility (EMV)
Equal Marginal Volatility (or Volatility Parity) is a portfolio allocation technique that weights each asset according the inverse of its volatility.

Enhanced Price Momentum
Enhanced Price Momentum is defined as three month daily return volatility adjusted 12 month Price Momentum, while taking a reversal view on the last month. Mathematically it can be expressed as

$$\text{Enhance Price Momentum}_i(t) = \frac{\frac{Price_i(t-1) - Price_i(t-12)}{Price_i(t-12)} - \frac{Price_i(t) - Price_i(t-1)}{Price_i(t-1)}}{\sigma(t, t-3)_i}$$

Exponential moving average (EMA or EWMA)
An exponential moving average (EMA), also known as an exponentially weighted moving average (EWMA), is a type of infinite impulse response filter that applies weighting factors which decrease exponentially.

Head and shoulders
A technical analysis term used to describe a chart formation in which a stock's price, which rises to a peak and subsequently declines and then, the price rises above the former peak and again declines, and finally, rises again, but not to the second peak, and declines once more.

Kalman Filters
Kalman filtering, also known as linear quadratic estimation (LQE), is an algorithm that uses a series of measurements observed over time, containing noise (random variations) and other inaccuracies, and produces estimates of unknown variables that tend to be more precise than those based on a single measurement alone.

Keltner Channel
Keltner channel is a technical analysis indicator showing a central moving average line plus channel lines at a distance above and below.

Managed Futures
An alternative investment strategy in which portfolio managers (usually in a Commodity Trading Advisor) use futures contracts as part of their overall investment strategy. Managed futures provide portfolio diversification among various types of investment styles and asset classes. See also Commodity Trading Advisors (CTA).

Mean-Variance Optimization (MVO)
MVO solves one-period portfolio optimization by using only the first two moments of the underlying return series. It achieves minimum variance given a certain expected return target.

Mean reversion
The tendency of a certain metric (price, yield, portfolio etc) to revert to its short-term or long-term fair value determined by technical or fundamental variables. It can work in either absolute or relative terms. Mean reversion belongs to the Value style in systematic strategy terms.

Momentum
The tendency of a trend to continue or the best (worst) performance assets to continue to outperform (underperform). See also ‘Price Momentum’.

Moving Average Convergence Divergence (MACD)
A Trend-Following Momentum indicator that shows the relationship between two moving averages of prices. The MACD is calculated by subtracting the 26-day exponential moving average (EMA) from the 12-day EMA. A nine-day EMA of the MACD, called the "signal line", is then plotted on top of the MACD, functioning as a trigger for buy and sell signals.

On-Balance Volume
Developed by Joseph Granville in the 1960s, it is a Momentum indicator that uses volume flow to predict price changes.

Pitchfork Channel
Pitchfork Channel is a Trend-following Channel breakout system developed by Alan Andrews. The system contains three lines: The median trend line in the center with two parallel equidistant trend lines on either side. These lines are drawn by selecting three points, usually based on reaction highs or lows during a certain historical time horizon.

Price Momentum
Price Momentum can be defined as the rate at which prices increase or decrease over a period of time. It is generally calculated by their total return over the previous months. Price Momentum is generally used to determine price movement and trend lines, and can be used in combination with other technical indicators as a buy/sell indicator.

Rebalance Period
The rebalance period or investment horizon is the interval between portfolio rebalancing. It defines in the backtest the points in time where historical investment decisions were made and the composition of the portfolio was updated. For most backtests, 1 month is the commonly accepted rebalance period as a good compromise between reactivity of the portfolio and turnover of the portfolio.

Relative Strength Index (RSI)
A technical Momentum indicator that compares the magnitude of recent gains to recent losses in an attempt to determine overbought and oversold conditions of an asset. It is calculated using the following formula: $RSI = 100 - 100/(1 + RS)$, where RS = Average of x days' up closes / Average of x days' down closes. Generally an RSI of 70 or higher indicates overbought asset and an RSI of sub 30 indicates an oversold asset.

Seasonality
We calculate this by using total return versus local country MSCI index, and the hit-rate represents the percentage of times the stock has outperformed in the specified month. Stocks which outperformed/ underperformed in a particular period of the year, tend to continue doing so in future years.

Stop Loss
A stop loss strategy is a portfolio risk management technique that is fully invested in a risky portfolio but unwinds this investment and switches to 100% allocation to the risk-free asset when the portfolio value touches a designated floor level.

Technical Analysis
A method of evaluating securities by analyzing statistics generated by market activity, such as past prices and volume. Technical analysts do not attempt to measure a security's intrinsic value, but instead use charts and other tools to identify patterns that can suggest future activity

Trend-Following
Trend-Following is an investment strategy based on the technical analysis of market prices, rather than on the fundamental strengths of the companies. In financial markets, traders and investors using a Trend-Following strategy believe that prices tend to move upwards or downwards over time. They try and take advantage of these market trends by observing the current

direction and using this to decide whether to buy or sell. See Also Technical Analysis.

Williams %R
Williams %R, or just %R, is a technical analysis oscillator showing the current closing price in relation to the high and low of the past N days (for a given N).

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Risks of Common Option Strategies

Risks to Strategies: Not all option strategies are suitable for investors; certain strategies may expose investors to significant potential losses. We have summarized the risks of selected derivative strategies. For additional risk information, please call your sales representative for a copy of "Characteristics and Risks of Standardized Options." We advise investors to consult their tax advisors and legal counsel about the tax implications of these strategies. Please also refer to option risk disclosure documents.

Put Sale. Investors who sell put options will own the underlying stock if the stock price falls below the strike price of the put option. Investors, therefore, will be exposed to any decline in the stock price below the strike potentially to zero, and they will not participate in any stock appreciation if the option expires unexercised.

Call Sale. Investors who sell uncovered call options have exposure on the upside that is theoretically unlimited.

Call Overwrite or Buywrite. Investors who sell call options against a long position in the underlying stock give up any appreciation in the stock price above the strike price of the call option, and they remain exposed to the downside of the underlying stock in the return for the receipt of the option premium.

Booster. In a sell-off, the maximum realised downside potential of a double-up booster is the net premium paid. In a rally, option losses are potentially unlimited as the investor is net short a call. When overlaid onto a long stock position, upside losses are capped (as for a covered call), but downside losses are not.

Collar. Locks in the amount that can be realized at maturity to a range defined by the put and call strike. If the collar is not costless, investors risk losing 100% of the premium paid. Since investors are selling a call option, they give up any stock appreciation above the strike price of the call option.

Call Purchase. Options are a decaying asset, and investors risk losing 100% of the premium paid if the stock is below the strike price of the call option.

Put Purchase. Options are a decaying asset, and investors risk losing 100% of the premium paid if the stock is above the strike price of the put option.

Straddle or Strangle. The seller of a straddle or strangle is exposed to stock increases above the call strike and stock price declines below the put strike. Since exposure on the upside is theoretically unlimited, investors who also own the stock would have limited losses should the stock rally. Covered writers are exposed to declines in the long stock position as well as any additional shares put to them should the stock decline below the strike price of the put option. Having sold a covered call option, the investor gives up all appreciation in the stock above the strike price of the call option.

Put Spread. The buyer of a put spread risks losing 100% of the premium paid. The buyer of higher ratio put spread has unlimited downside below the lower strike (down to zero), dependent on the number of lower struck puts sold. The maximum gain is limited to the spread between the two put strikes, when the underlying is at the lower strike. Investors who own the underlying stock will have downside protection between the higher strike put and the lower strike put. However, should the stock price fall below the strike price of the lower strike put, investors regain exposure to the underlying stock, and this exposure is multiplied by the number of puts sold.

Call Spread. The buyer risks losing 100% of the premium paid. The gain is limited to the spread between the two strike prices. The seller of a call spread risks losing an amount equal to the spread between the two call strikes less the net premium received. By selling a covered call spread, the investor remains exposed to the downside of the stock and gives up the spread between the two call strikes should the stock rally.

Butterfly Spread. A butterfly spread consists of two spreads established simultaneously. One a bull spread and the other a bear spread. The resulting position is neutral, that is, the investor will profit if the underlying is stable. Butterfly spreads are established at a net debit. The maximum profit will occur at the middle strike price, the maximum loss is the net debit.

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