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Defensive Risk Premia

Systematic Strategies for the Risk-Off Times

Global Quantitative and Derivatives Strategy

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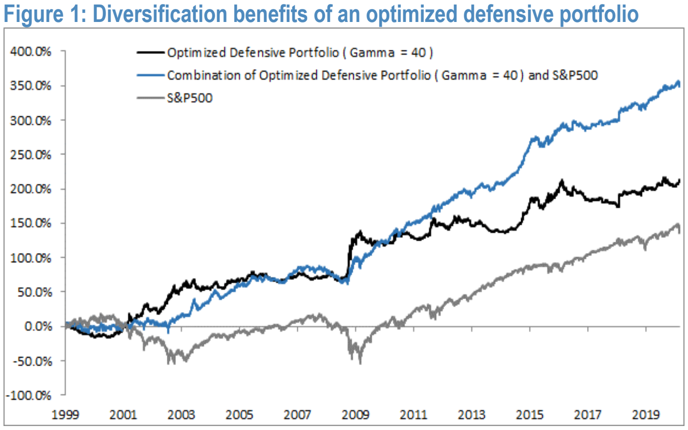
- In the current paper, we focus on risk-premia strategies that are expected to deliver performance when major asset classes and in particular equities incur sell-offs.
- Our proposition relies on diversification among timeframes, profit drivers, asset classes and P&L profiles.
- We put forward three groups of defensive risk premia strategies – core, tactical hedging, and satellite.
- The core defensive strategies typically have low capacity constraints and longer track records. We discuss the profit drivers and empirical performance of asymmetric trend-following, synthetic defensive baskets, mean-reversion, quality and low volatility equity factors.
- A comprehensive flow-based sentiment indicator and a cross-asset volatility-based sentiment indicator are used to determine the right time to place hedges.
- Satellite strategies as intraday momentum and correlation breakout capture bring additional diversification in risk-off times.
- An optimization process that takes into account the higher portfolio moments and the time-series of the hedged asset is implemented to construct a robust portfolio of defensive risk premia strategies.

Figure 1: Diversification benefits of an optimized defensive portfolio



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 1: Performance statistics

	Optimized Defensive Portfolio	S&P500	Combination of Optimized Defensive Portfolio and S&P500
Ann Return	9.7%	6.20%	15.9%
Ann Volatility	14.5%	18.60%	15.7%
Sharpe	0.67	0.33	1.01
Max DD	34.4%	61.40%	24.6%
Skewness	1.03	0.16	0.26
Kurtosis	30.23	12	4.71

Source: J.P. Morgan Quantitative and Derivatives Strategy

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Defensive Risk Premia Portfolios

The Case for Defensive Risk Premia Strategies

Risk premia strategies have been put forward as a diversifying proposition – their returns stream is uncorrelated to that of major asset classes and also the correlation among the component strategies of the risk premia portfolio is low.

While many of the risk premia strategies have remained uncorrelated to each other (see for example our statistical analysis in Quantitative Perspectives on Cross-Asset Risk Premia from 17 January 2020), the correlation of risk premia to equity markets and the implicit long equity exposure has been on the rise (please refer to the empirical analysis in 'Risk premia sensitivity to rates/equities, implications of JPM 2019 FICC outlooks and our latest timing forecasts').

The occurrences of simultaneous sell-offs in both major markets and risk premia strategies have become more frequent and risk premia portfolios have started to exhibit negative skewness (please see our analysis of tail risks in risk premia strategies and portfolios in Quantitative Perspectives on Cross-Asset Risk Premia (from 6 March 2019).

In the current paper, we focus on risk-premia strategies that are expected to deliver performance when major asset classes and in particular equities incur sell-offs. In this respect defensive risk premia portfolios consist of systematic strategies that can diversify and protect both traditional asset classes as well as for mainstream risk premia portfolios.

Defensive Risk Premia Strategies Selection

Our proposition for a defensive risk premia portfolio heavily relies on diversification and consists of a combination of core defensive strategies, tactical hedging, and satellite strategies.

Figure 2: Three groups of defensive risk premia strategies

Source: J.P. Morgan Quantitative and Derivatives Strategy

While detailed description of all strategies can be found further in the body of the paper below, we briefly describe the main features of the various groups of strategies and their components.

Core defensive strategies have low capacity constraints and longer track records that warrant a more sizable allocation. Typically core defensive strategies are strategies that are well-known to investors. Nevertheless, we have made design modifications to some of them in order to enhance the defensive characteristics and we have also put forward some new proposals.

In our case the core defensive strategies consist of asymmetric trend-following, synthetic defensive baskets, single-asset mean-reversion, quality, and low volatility low/short pure equity factors:

- **Asymmetric trend-following** is a modification of our trend-following strategy (Designing Robust Trend-Following System by Tzotchev et al.) with some enhancements aimed at isolating and improving the performance in risk-off times. In particular only one-sided positions that correspond to a risk-off environment are taken: **short** positions in **equities** and **commodities** (except for gold) and **long** positions in **bonds** and **USD**.
- **Synthetic defensive baskets** are a new proposition based on our market-neutral carry strategy (Market-Neutral Carry Strategies). The strategy relies on opportunistic capture of both carry and momentum income opportunities which facilitate the maintenance of a hedging position in the desired direction.
- **Single-asset mean-reversion** has also been a popular strategy and in our analysis we focus on not only the empirical but also the theoretical underpinnings of the strategy's profit drivers in risk-off times.
- The defensive characteristics of **quality** and **low volatility low/short equity factors** have already been discussed in Equity Risk Premia Strategies primer by Kolanovic (2014). For the current application, we use the pure quality and low volatility factors described in The Quest for Pure Equity Factor Exposure and we add an additional defensive tilt to those factors allowing a negative exposure to the market in the optimisation.

The **tactical hedging** approach aspires at determining the right time to place hedges and their optimal size. We rely on a systematic signal that should provide us with an early warning. We position for a risk-off environment depending on the strength of the signal by taking **short** positions in **equities**, **oil** and **credit** (buying credit protection) and **long** positions in **bonds**, **USD**, **gold** and **volatility**. For the current application the tactical hedging approach itself consists of two indicators:

- **A comprehensive flow-based sentiment indicator:** A comprehensive sentiment indicator has been designed to measure the sentiment in the equity markets and has been proposed by Das et al. in Asia Portfolio Strategy: Utilising Sentiment for Better Positioning. The aggregated indicator includes technical inputs, flow, volatility, positioning, and sentiment surveys.
- **A volatility-based sentiment indicator:** the indicator has originally been constructed to time the investments in short FX volatility strategies (Ravagli, L. and Duran-Vara, J.; Timing FX Short-Vol Strategies: A systematic Approach). The majority of the inputs are volatility related and for the current application we have used the global components of the indicator plus the 1M realized volatility of the underlying.

The **satellite defensive strategies** are more recent innovative systematic strategies that display strong risk-off characteristics but typically may face capacity constraints. We have put forward two satellite defensive strategies:

- **Intraday momentum**: we discuss the rationale for the existence of intraday momentum (see Kolanovic et al. Market Impact of Derivatives Hedging-Daily Patterns and Ravagli et al. Optimal Option Delta-Hedging) and present the recent academic backing. The intraday momentum strategy is constructed to explicitly profit in highly volatility regimes and in times of continuous selling throughout the day.
- **Correlation break-out capture:** the strategy aims to capture the transition to new volatility/correlation regime (higher volatility, higher correlation among risk assets) during sell-offs. A systematic strategy is constructed that profits in risk-off times and has contained losses when markets normalize.

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The table below summarizes the key characteristics of the proposed strategies:

Figure 3: Defensive strategies description

	Defensive Strategy	Profit Driver in a Risk-Off Scenario	Advantages	Disadvantages	Time-frame	Convexity
Core/High Capacity Strategies	Asymmetric Trend-Following	Behavioural reasons – over/under-reaction, herding	Provides convexity during extended risk-off periods	- No protection against abrupt shifts to a risk-on environment - Losses in a mean-reverting market	Multiple periods: Monthly/ Yearly	Convex
	Mean-reversion	-Increase in the negative autocorrelation during risk-off times -Higher volatility increases P&L	A great compliment to trend-following around reversal points	- Relies on persistent negative autocorrelation - A strong trend can make the strategy unprofitable	Weekly/ Bi-Weekly	Concave
	Synthetic Defensive Baskets	Positive exposure to the risk-off factors by design	Ability to mitigate the negative carry of buying protection	Creation of the synthetic baskets is not always feasible	Multiple periods: Monthly/ Yearly	Somewhat convex
	Defensive Equity Factors	The stocks with low volatility and solid balance sheets outperform in risk-off	-Substantive academic research backing - Broad universe of stocks	The strong performance of those factors raises crowding concerns	Weekly/ Monthly	
Tactical Hedging	Volatility-Based Sentiment Indicator	Clustering of volatility regimes, volatility spill-overs among assets	Easy and simple to implement	A high number of false alarms especially in downward volatility regime	Daily/ Weekly	
	Comprehensive Sentiment Indicator	Leading information contained in various sources	Broad range of inputs	-Decay of the forecasting power of some the inputs	Daily/ Weekly	
Satellite Strategies	Correlation Break-Out Capture	Correlation structure changes with the shift to a risk-off environment	- Solid macro underpinning - Highly reactive in the initial stages of the risk-off period	We have to rely on predefined pairs and expect the same type of correlation patterns to extend forward	<week	
	Intraday Momentum	-Short gamma by market makers leads to intraday price momentum -Intraday momentum and mean-reversion coexists	Highly reactive strategy relying on market and macro rationale	Some of drivers might not always be present	Intraday	Convex

Source: J.P. Morgan Quantitative and Derivatives Strategy

The Benefits of a Diversified Portfolio of Defensive Risk Premia Strategies

Before delving into the actual empirical backtests results, we would like to elaborate on the need of having a truly diversified set of defensive risk premia strategies so that a robust performance in a risk-off environment can be expected with a high degree of certainty.

In our implementation, we are aiming for diversification in four dimensions:

- **Timeframes**: diversification across timeframes allows reactivity at different timescales and respite versus abrupt and protruded sell-offs.
- **Profit drivers**: it is important to benefit from a diverse set of profit drivers ranging from behavioral (like in the case of trend-following) to structural (as in the case of intraday momentum).
- **Asset classes**: we implement strategies consistently across different asset classes. Risk-off environment developments are evident in different asset classes and sometimes a particular asset class can exhibit early signs of stress before contagion reaches the rest of the asset classes.
- **P&L profile**: both strategies with convex and concave profile are present. For apparent reasons convex ones are preferable but concave ones can bring diversification – for example, mean-reversion can offset the losses in trend-following when the market transitions from a risk-off to a risk on environment.

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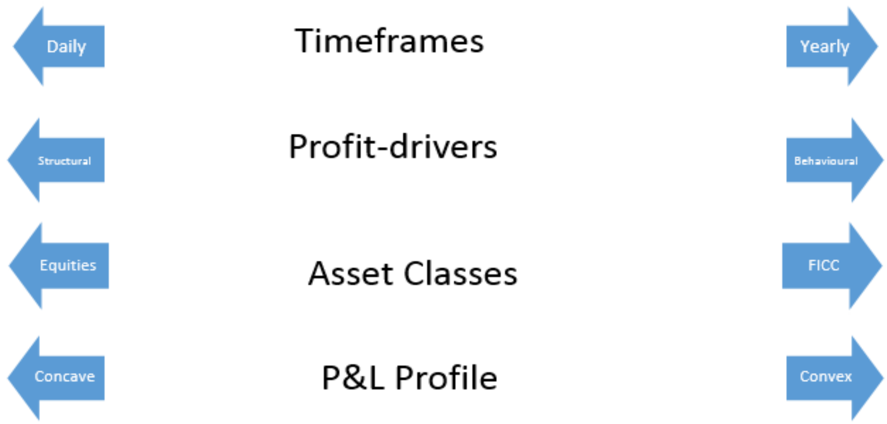
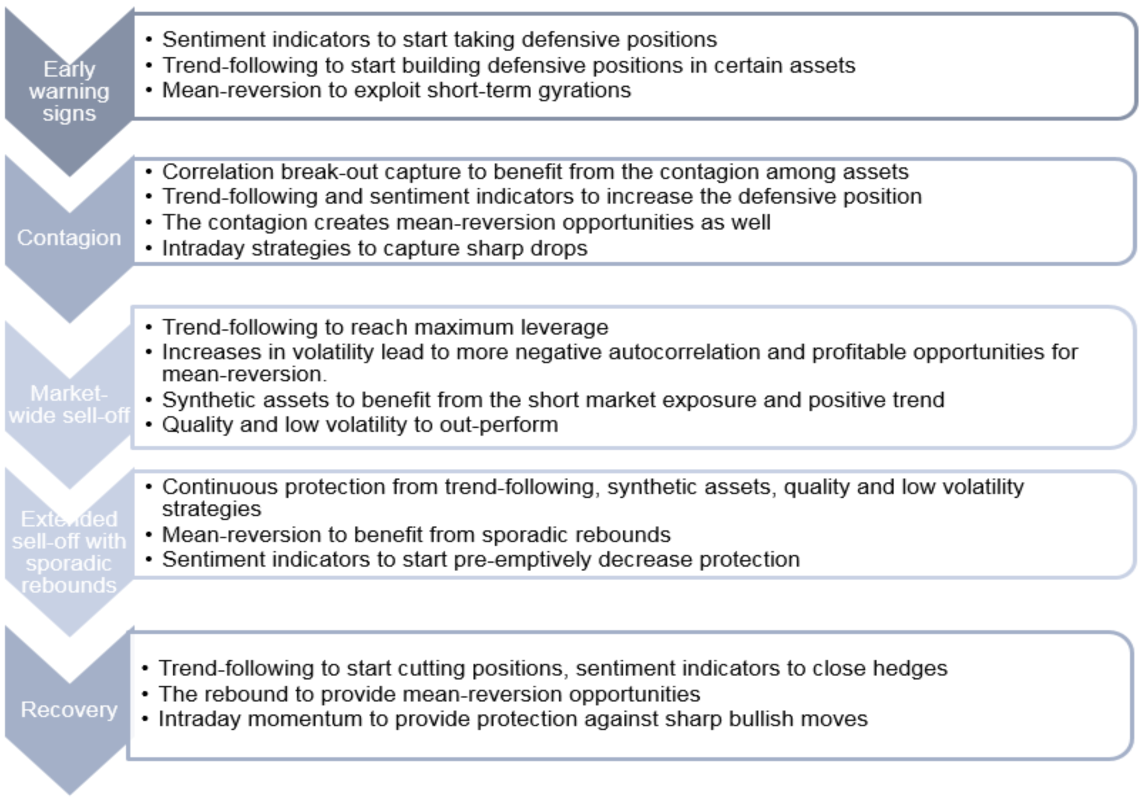
Figure 4: Diversification dimensions for defensive risk premia portfolios



Source: J.P. Morgan Quantitative and Derivatives Strategy

The broad diversification allows a risk-off oriented risk-premia portfolio to benefit at different stages of a crisis. Naturally, there is no guarantee that a portfolio of defensive risk premia strategies will provide protection for every sell-off and that the extent of the protection will be sufficient. Nevertheless, the broad diversification largely mitigates and eliminates such a problem.

Figure 5: Aiming for protection at every stage of the crisis



Source: J.P. Morgan Quantitative and Derivatives Strategy

Portfolio Construction for Risk-Off Times

In our opinion the portfolio construction approach for a defensive risk premia portfolio should incorporate at least three specific elements:

- Taking into account the higher moments (like skewness and kurtosis) in the optimisation process.
- Account for the specific features of the asset (or the portfolio) for which we are seeing protection.
- The results of the optimization process shall be easily implementable in real-life.

First, it is well-known that many of the disadvantageous statistical properties of standard markets (like negative skewness and outsized kurtosis) are linked to the sizable negative returns during periods of sell-offs and rising risk aversion.

We make use of a portfolio optimization approach that takes into account the higher moments of the portfolio return (like skewness and kurtosis) in addition to the mean and the variance. The methodology relies on the optimization of **CRRA** (constant relative risk aversion) utility function and has been introduced in Optimal Portfolio Construction – Beyond Risk Parity by Cheng et al. Another recent application can be found in From Relative Value Signals to Optimal Portfolio Weights.

Second, the optimization of the defensive portfolio should not be a stand-alone process and performed in isolation. It is important that the inherent characteristics of the market that the defensive risk premia portfolio will provide protection for are taken into account during the portfolio construction process. In our optimization approach, we take into account the moments of the combined portfolio (asset to be hedged plus overlay defensive risk portfolio) to arrive at our recommendation. Optimizing the defensive risk premia portfolio on a stand-alone basis can be shown to lead to suboptimal results.

Last but not the least the portfolio recommendations shall be implementable in the real-life environment. We have already discussed that some of the strategies have lower capacity constraints than some of the rest. During the optimization process we impose particular constraints so that the core, tactical hedging and satellite strategies receive allocations that can be implemented in a real-life setting.

Core Defensive Risk Premia Strategies

We refer to core defensive risk premia strategies as the risk strategies that have limited capacity constraints. While many of those strategies have been on the investors radar for some time and are to some extent well-established in our opinion many aspects of their diversifying properties with respect to risk-off environments have not been fully analyzed.

Asymmetric Trend-Following

Investment Rationale

In Designing Robust Trend-Following System by Tzotchev et al. we have theoretically and empirically demonstrated that a trend-following strategy based on a signal emulating the delta of a straddle exhibits convexity with respect to the Sharpe ratio of the underlying asset and hence can be profitable in both bullish and bearish markets.

Below, we focus on a trend-following system that aims to profit solely from bearish markets and hence not to take positions during bullish markets. Therefore, we keep open positions when the system detects a bearish market and we do not have positions when the system detects a bullish market. The bearish/bullish decision is based on the trend-following signal of the underlying.

In particular for defensive purposes we only take the following one-sided positions:

- Short positions in equity futures
- Long positions in fixed income futures

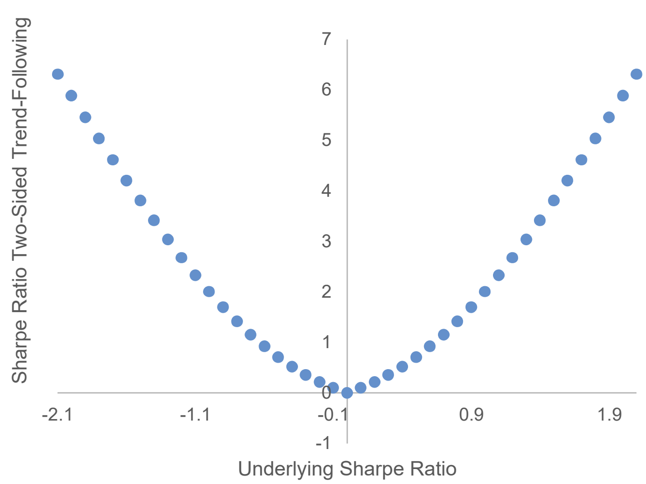
- Long positions in USD via forwards (no positions in USDJPY and USDCHF are taken)
- Short positions in commodities futures with the exception of gold in which we keep the long positions.

We apply the same trend-following signal methodology as described in Designing Robust Trend-Following System by Tzotchev et al. In particular we use the 'delta-of-a-straddle' trend-following signal that we have shown to be justified by standard statistical tests for positive/negative mean based on t-statistics. If $\overline{R_{t,T}}$ denotes the average return over period T, $\widehat{\sigma_t}$ is the estimated volatility at time t then $tstat_{t,T} = \frac{\sqrt{T}\,\overline{R_{t,T}}}{\widehat{\sigma_t}}$. Then the standard signal at time t with a lookback period of T is $S_{t,T} = 2 * N(tstat_{t,T}) - 1$. Depending on the direction we want to trade the final signal is a transformed raw signal[1]:

- $\text{AsymmS}_{t,T} = \text{Max}(S_{t,T}, 0)$ if only long positions are to be taken
- $\text{AsymmS}_{t,T} = \text{Min}(S_{t,T}, 0)$ if only short positions are to be taken

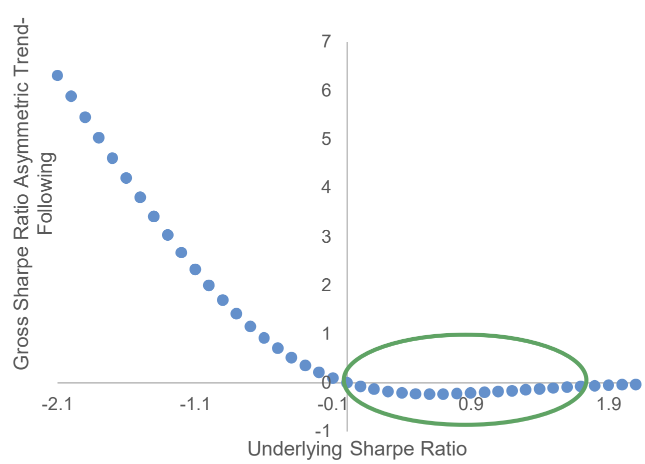
In the Appendix, we have demonstrated that such a rule also results in a convex P&L profile. The profile of the asymmetric (one-sided) trend-following system is compared to that of the traditional (two-sided) one in the graphs below:

Figure 6: P&L Profile Two-Sided Trend-Following with Lookback=1 Year



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 7: P&L Profile Asymmetric Trend-Following Trading Short Positions in the Underlying with Lookback=1 Year



Source: J.P. Morgan Quantitative and Derivatives Strategy

Note that the one-sided trend-following system will incur some limited losses when the actual trend in the underlying is in the opposite direction of the one the system takes. The bigger trend in the opposite direction, the more limited will be the loss as the false signals will be fewer.

Furthermore, the asymmetric trend-following will outperform the double-sided in terms of Sharpe ratio when the underlying asset trend is in the direction of the position the one-sided system takes and it is not very sizable. As shown in the Appendix, the volatility of the one-sided trend-following system is smaller that of the two-sided by approximately 40%[2]. Furthermore, we expect average nominal P&L of the one-sided system to be bigger that than of the two-sided when the direction is the

[1] Note that an alternative is to directly take positons that correspond to the delta of the put when only short positions are taken and that correspond to the delta of the call when long positions are taken. For consistency with our previous research work we have focused on the delta-of-the-straddle signal.

[2] The result holds for the case when the asset's return process is a random walk without a drift.

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right one - the one-sided system will have a zero P&L for the false signals as no position is taken while the double-sided one will on average incur a loss. Therefore, the asymmetric trend-following system will dominate the two-sided in terms of Sharpe ratio. The stronger is trend on the desired side, the more similar will be the one-sided and the two-sided strategies.

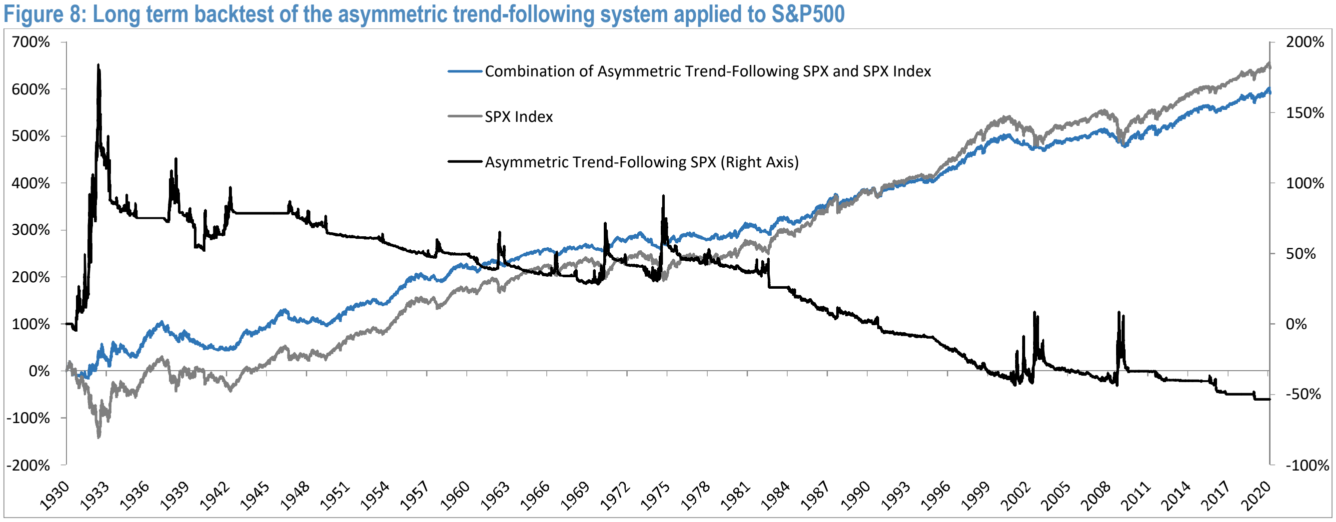
Note that we diversify among several lookback periods – 32 days, 64 days, 126 days, 1 year and 2 years – based on the theoretical results in Designing Robust Trend-Following System and we use the same futures and FX forwards universe.

A Long-Term Illustration: S&500 Asymmetric Trend-Following Backtest

We would like first to start with a simple illustration of the benefits of the asymmetric trend-following system over a long span of time. We consider a long-term backtest of the asymmetric trend-following model applied to S&P500 since the beginning of 1930.

Note that in this case we do not have an explicit volatility target for the asymmetric trend-following system as we typically do in the case of the standard trend-following systems. As we have only one underlying and the goal is to offset the adverse price moves we always take positions that equal two times the signal. As the average expected signal when the system takes position is -0.5 the average expected position of the trend-following system will -1, i.e. on average we will be neutralizing the long S&P500 position whenever the asymmetric trend-following system takes position[3].

Figure 8: Long term backtest of the asymmetric trend-following system applied to S&P500



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 2: Performance statistics

	Asymmetric Trend-Following SPX	SPX Index	Combination of Asymmetric Trend-Following SPX and SPX Index
Ann Return	-0.6%	7.2%	6.6%
Ann Volatility	15.8%	18.3%	13.2%
Sharpe	-0.04	0.39	0.50
Max DD	95.8%	83.0%	48.9%
Skewness	-2.08	-0.02	-0.78
Kurtosis	89.18	16.75	19.05

Source: J.P. Morgan Quantitative and Derivatives Strategy

[3] In the Appendix it is demonstrated that the average signal of the asymmetric trend-following system is -0.5 when the asset return process is a random walk without a drift and only short positions are taken.

On a stand-alone basis the asymmetric trend-following strategy delivers close to flat return over 90 years after costs which in itself can be considered an achievement given upward move in S&P500 over the same period[4]. The biggest diversification benefit can be seen in the years of the Great Depression though these results should also be considered in light of the much bigger volatility over this period.

Furthermore, the combined portfolio has much better performance characteristics in comparison to a stand-alone S&P position. The volatility and the drawdown have been decreased and the Sharpe ratio has been improved.

The strong diversification effect is also evident if we analyze the performance of the asymmetric trend-following system during the NBER recession periods – the average return of the asymmetric trend-following system fully offsets the average S&P500 loss during those periods.

Table 3: Performance of the Asymmetric Trend-Following Strategy and S&P500 during NBER recession periods

Start Date	End Date	Asymmetric Trend Following	S&P500
August 1929	March 1933	111.45%	-97.18%
May 1937	June 1938	3.99%	-26.89%
February 1945	October 1945	0.00%	19.93%
November 1948	October 1949	-5.03%	-2.89%
July 1953	May 1954	-4.21%	19.06%
August 1957	April 1958	3.10%	-9.78%
April 1960	February 1961	-7.42%	13.69%
December 1969	November 1970	17.33%	-6.97%
November 1973	March 1975	21.26%	-21.71%
January 1980	July 1980	-1.90%	13.20%
July 1981	November 1982	-11.41%	5.39%
July 1990	March 1991	-6.03%	5.88%
March 2001	November 2001	2.05%	-6.67%
December 2007	June 2009	6.65%	-35.30%
Average		9.27%	-9.30%

Source: J.P. Morgan Quantitative and Derivatives Strategy

Empirical Results for Equity Futures

Below we apply the asymmetric trend-following system to the same set of equity futures as in our standard trend-following system. In this case the volatility target of the asymmetric trend-following system is equal the volatility of S&P500 calculated on the days when the asymmetric trend-following system has open positons.

[4] Note that costs have been taken into account when the performance of the asymmetric trend-following system has been calculated. No costs have been assumed for holding S&P500 and no netting of costs has been considered.

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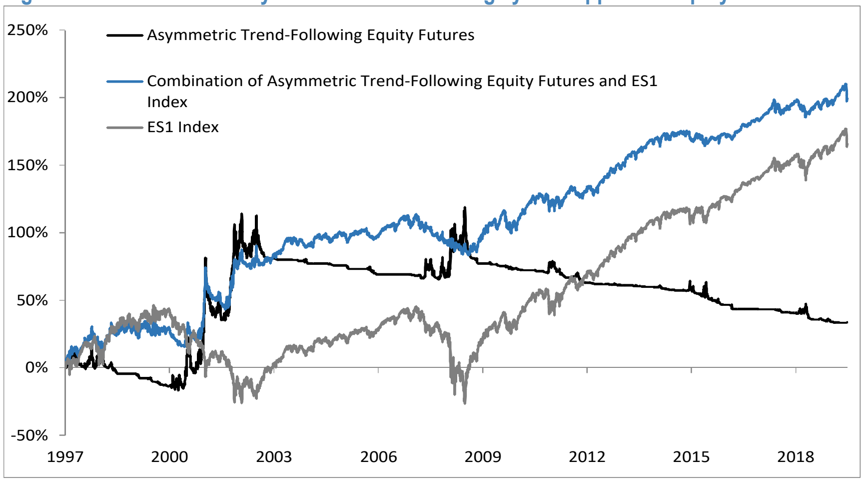
Figure 9: Backtest of the asymmetric trend-following system applied to equity futures



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 4: Performance statistics

	Asymmetric Trend-Following Equity Futures	ES1 Index	Combination of Asymmetric Trend-Following Equity Futures and ES1 Index
Ann Return	1.4%	7.1%	8.5%
Ann Volatility	17.9%	18.8%	16.2%
Sharpe	0.08	0.38	0.52
Max DD	61.9%	61.4%	28.3%
Skewness	-0.52	0.07	-0.11
Kurtosis	23.59	11.47	8.11

Source: J.P. Morgan Quantitative and Derivatives Strategy

Similarly to the long-term backtest the asymmetric trend-following system applied to equity futures delivers close to flat return since 1997. Nevertheless the diversification benefit is quite evident and the overall Sharpe ratio and drawdown have been significantly improved.

An implicit benefit of the asymmetric trend-following system in comparison to the standard two-sided one is that it avoids the losses linked to sharp reversals from bullish to bearish markets. As the system does not keep long positions it does not incur a negative P&L when the markets reverse after a long bullish run which are often realized as intensive sell-offs.

Empirical Results for Fixed Income Futures

We analyze separately the diversification properties of the asymmetric trend-following system with respect to S&P500 – taking long positions in fixed income futures in the asymmetric trend-following system – and to a long fixed income portfolio – taking short positions in fixed income futures in the asymmetric trend-following system and providing protection versus an increase in rates.

The volatility target of the asymmetric trend-following system is set equal the volatility of S&P500 or the volatility of the fixed income benchmark on the days the trend-following system has open positons.

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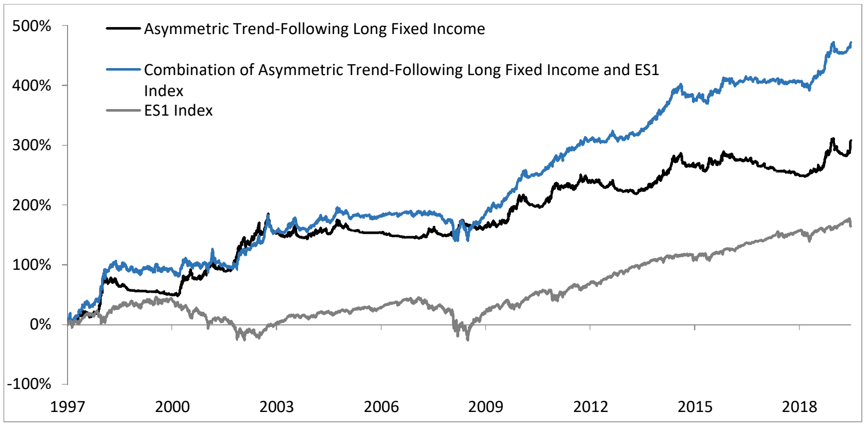
Figure 10: Backtest of the asymmetric trend-following system applied to fixed-income futures – diversification results with S&P500



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 5: Performance statistics

	Asymmetric Trend-Following Long Fixed Income	ES1 Index	Combination of Asymmetric Trend-Following Long Fixed Income and ES1 Index
Ann Return	13.3%	7.1%	20.3%
Ann Volatility	18.8%	18.9%	22.2%
Sharpe	0.71	0.37	0.92
Max DD	36.7%	61.4%	49.1%
Skewness	-0.04	0.07	0.05
Kurtosis	7.73	11.34	6.39

Source: J.P. Morgan Quantitative and Derivatives Strategy

Naturally a long-only fixed income trend-following system has been quite profitable over the last 20 years and the major driver behind the profitability of the long-only fixed income trend-following system has been the relentless downward move in rates over the last decade. Despite the strong performance of asymmetric trend-following system on a stand-alone basis, the overall Sharpe ratio increases further if the asymmetric trend-following system and S&P are combined in the same portfolio. While the S&P500 drawdown in 2008 has not been fully eliminated it has been substantially decreased.

Next, we turn to the second type of analysis that uses a short-only trend-following system in fixed income to protect a long only fixed income portfolio against a rise in rates[5]. Neutralizing the upward moves in rates via a trend-following system has been challenging due to the transitory nature of such moves, especially post the GFC. While the overall performance characteristics have not been improved when a combined portfolio is constructed there have been visible diversification benefits in 2005-06 and 2017-18 periods.

[5] In this case the benchmark consists of vol-weighted combination of the component returns that is subsequently geared to the average volatility of the underlyings.

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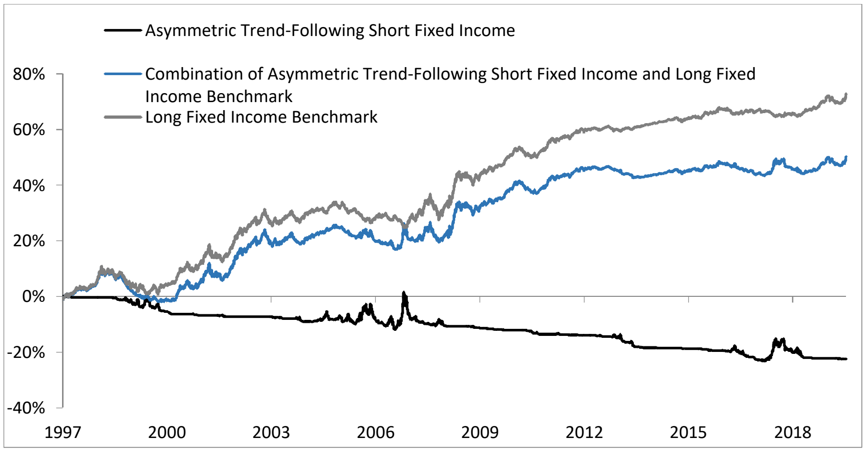
Figure 11: Backtest of the asymmetric trend-following system applied to fixed-income futures – diversification results with a long fixed income benchmark



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 6: Performance statistics

	Asymmetric Trend-Following Short Fixed Income	Long Fixed Income Benchmark	Combination of Asymmetric Trend-Following Short Fixed Income and Long Fixed Income Benchmark
Ann Return	-1.0%	3.1%	2.2%
Ann Volatility	2.9%	3.6%	3.7%
Sharpe	-0.33	0.86	0.58
Max DD	22.1%	9.8%	11.8%
Skewness	-0.67	-0.11	-0.20
Kurtosis	29.62	4.45	6.34

Source: J.P. Morgan Quantitative and Derivatives Strategy

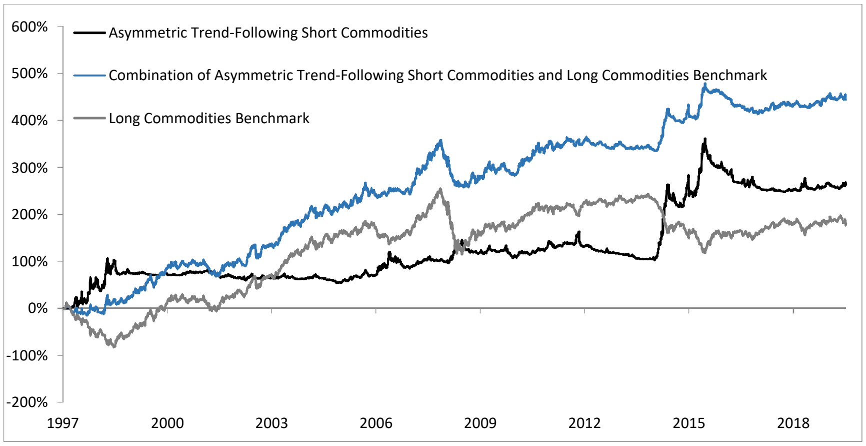
Empirical Results for Commodities Futures

Commodities have been the natural ground for pursuing trend-following strategies for several decades. For defensive purposes the asymmetric trend-following strategy in commodities only takes short positions in commodities futures except for gold where long positions are allowed[6].

The asymmetric trend-following system provides a noticeable diversification and helps avoid the commodities sell-offs in 2008 and 2014. The combined Sharpe ratio is substantially bigger than any of the components and the drawdown has been much better contained. Nevertheless, the drawdown in 2008 has been decreased but not fully eliminated.

[6] Similarly, the commodity benchmark consists of long only positions in all commodities futures except for gold in which the benchmark's positions is long.

Figure 12: Backtest of the asymmetric trend-following system applied to commodities futures – diversification results with a long commodities benchmark



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 7: Performance statistics

	Asymmetric Trend-Following Short Commodities	Long Commodities Benchmark	Combination of Asymmetric Trend-Following Short Commodities and Long Commodities Benchmark
Ann Return	11.4%	7.8%	19.3%
Ann Volatility	29.4%	30.1%	29.8%
Sharpe	0.39	0.26	0.65
Max DD	71.0%	84.1%	66.0%
Skewness	-0.39	0.03	-0.20
Kurtosis	26.25	3.44	4.99

Source: J.P. Morgan Quantitative and Derivatives Strategy

Empirical Results for Currencies

The asymmetric trend-following system takes long USD via FX forwards to provide protection against rising dollar – dollar appreciation usually happens in risk-off times. In this case the benchmark consist of short USD positions in the G10 currencies and JPY and CHF have been excluded from the tradable universe.

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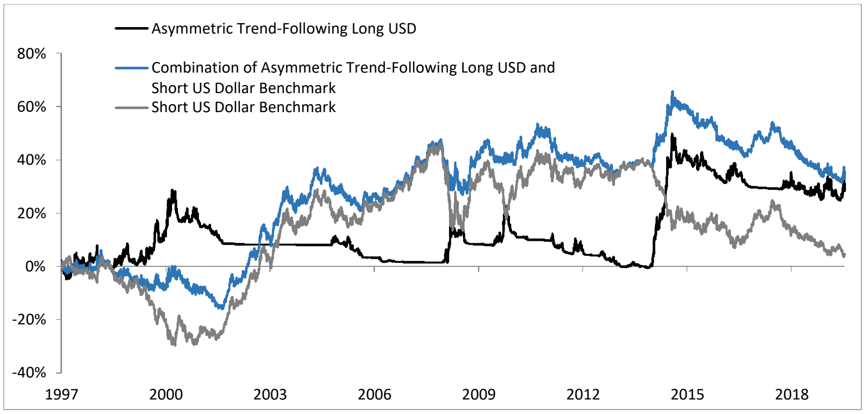
Figure 13: Backtest of the asymmetric trend-following system applied to FX forwards futures – diversification results with a short USD benchmark



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 8: Performance statistics

	Asymmetric Trend-Following Long USD	Short US Dollar Benchmark	Combination of Asymmetric Trend-Following Long USD and Short US Dollar Benchmark
Ann Return	1.2%	0.2%	1.4%
Ann Volatility	7.8%	9.5%	12.4%
Sharpe	0.15	0.02	0.11
Max DD	26.9%	38.7%	31.6%
Skewness	-0.20	0.06	-0.08
Kurtosis	12.75	2.27	3.45

Source: J.P. Morgan Quantitative and Derivatives Strategy

Similarly to the case of commodities the FX asymmetric trend-following system provides attractive diversification benefits during the GFC and in 2014. Recent performance has been more challenging but nevertheless there is an overall improvement in the Sharpe ratio and the drawdown by volatility statistics.

Empirical Results for the Cross-Asset Asymmetric Trend-Following System

In the following we examine the performance of the cross-asset asymmetric trend-following system and its diversification and hedging properties with respect to a long S&P position. The system takes simultaneously defensive positions across asset classes. Similarly to the individual asset class cases discussed above the system takes short positions in equities and commodities (except for gold) and long positons in fixed income and USD.

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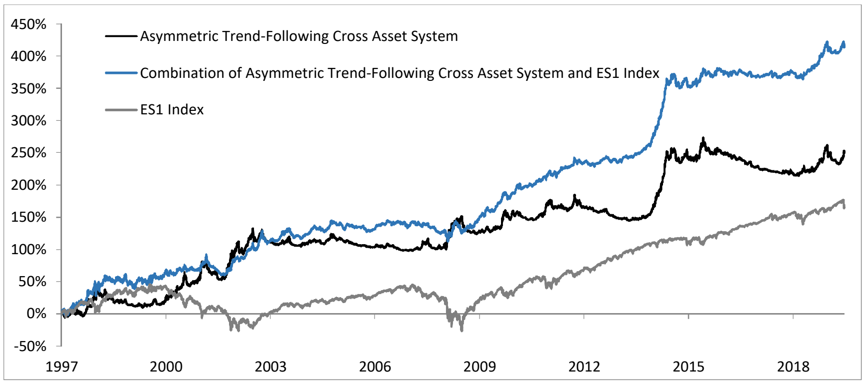
Figure 14: Backtest of the asymmetric cross-asset trend-following system – diversification results with a long S&P500 position



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 9: Performance statistics

	Asymmetric Trend-Following Cross Asset System	ES1 Index	Combination of Asymmetric Trend-Following Cross Asset System and ES1 Index
Ann Return	10.7%	7.1%	17.7%
Ann Volatility	19.3%	18.8%	19.7%
Sharpe	0.55	0.38	0.90
Max DD	46.4%	61.4%	30.6%
Skewness	-0.30	0.07	-0.28
Kurtosis	8.12	11.51	5.58

Source: J.P. Morgan Quantitative and Derivatives Strategy

The volatility target of the asymmetric trend-following system is set to volatility of S&P on the days the system has open positions and the risk budgets are separated equally among asset classes. Since 1997 the asymmetric trend-following system has outperformed S&P and delivered a better Sharpe ratio. The combination between the cross-asset asymmetric trend-following system and S&P demonstrates the strong diversification between two. Note that since 2015 the asymmetric trend-following strategy has displayed weaker performance mainly driven by the FX and commodity components. An investor who is predominantly concerned with the equities market might decide to decrease the allocation to the FX and commodities asymmetric trend-following system at the expense of the equity one and perhaps the fixed income one.

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Synthetic Defensive Baskets

Rationale and implementation

One of the main drawbacks of the traditional iron-clad hedging strategies (like buying puts for example) has been the high cost/ negative carry associated with them. This deficiency is not only relevant for option based strategies but it is easily discernible within delta-one markets as well. For example, buying credit protection is a typical short carry strategy. Obtaining exposure to safe heaven currencies like the Yen, the Swiss Franc and usually the Dollar has been a short carry strategy. Buying credit protection is a short carry strategies.

But there are some assets classes where carry might be supportive for taking defensive positions. Selling a commodity future is a positive carry strategy when the futures curve is in contango (which is the typical case). Similarly, shorting an equity future is a positive carry strategy when there are no dividend payments till the maturity of the future[7].

As a rule we aim to create portfolios (baskets) of assets which use well-established risk premia strategies like carry and momentum to support and fund a hedging position. We can view the baskets of assets as a short synthetic position in the benchmark we are interested to protect. In a risk-off environment (one in which the benchmark falls) the synthetic defensive basket should deliver due to its short exposure to the benchmark. In normal times any adverse (upward in the case of equities) move in the benchmark shall be at least partially offset by positive returns due to exposure the carry and momentum styles.

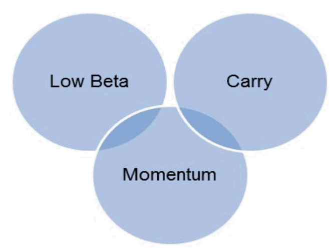
We can view the approach as a simultaneous application of three risk premia styles - low beta, carry and momentum. We prefer (go long) assets with lower beta to the benchmark, positive carry and good momentum. Conversely we would hold short assets with high exposure to the benchmark and with unattractive carry and momentum properties.

Figure 15: Expected performance of the synthetic defensive baskets

Normal times	- Positive carry and momentum - The loss due to negative Beta to be offset by carry and momentum
Bearish Environment	- Benefit from the negative Beta - Top up performance with carry and momentum

Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 16: Synthetic defensive baskets as an intersection of 3 risk premia styles



Source: J.P. Morgan Quantitative and Derivatives Strategy

The backbone of our approach to construct SAFE baskets is the methodology presented in our Market-Neutral Carry Strategies paper. The total return of an asset is separated into a spot return and a carry component. The sport return in turn contains an idiosyncratic trend component, return components due to factor exposure and a residual return.

7 The result holds under the typical assumption of unchanged spot level.

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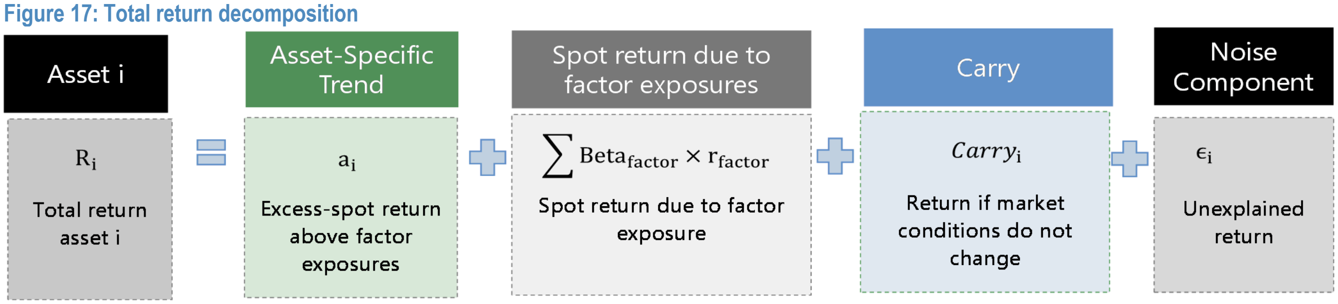
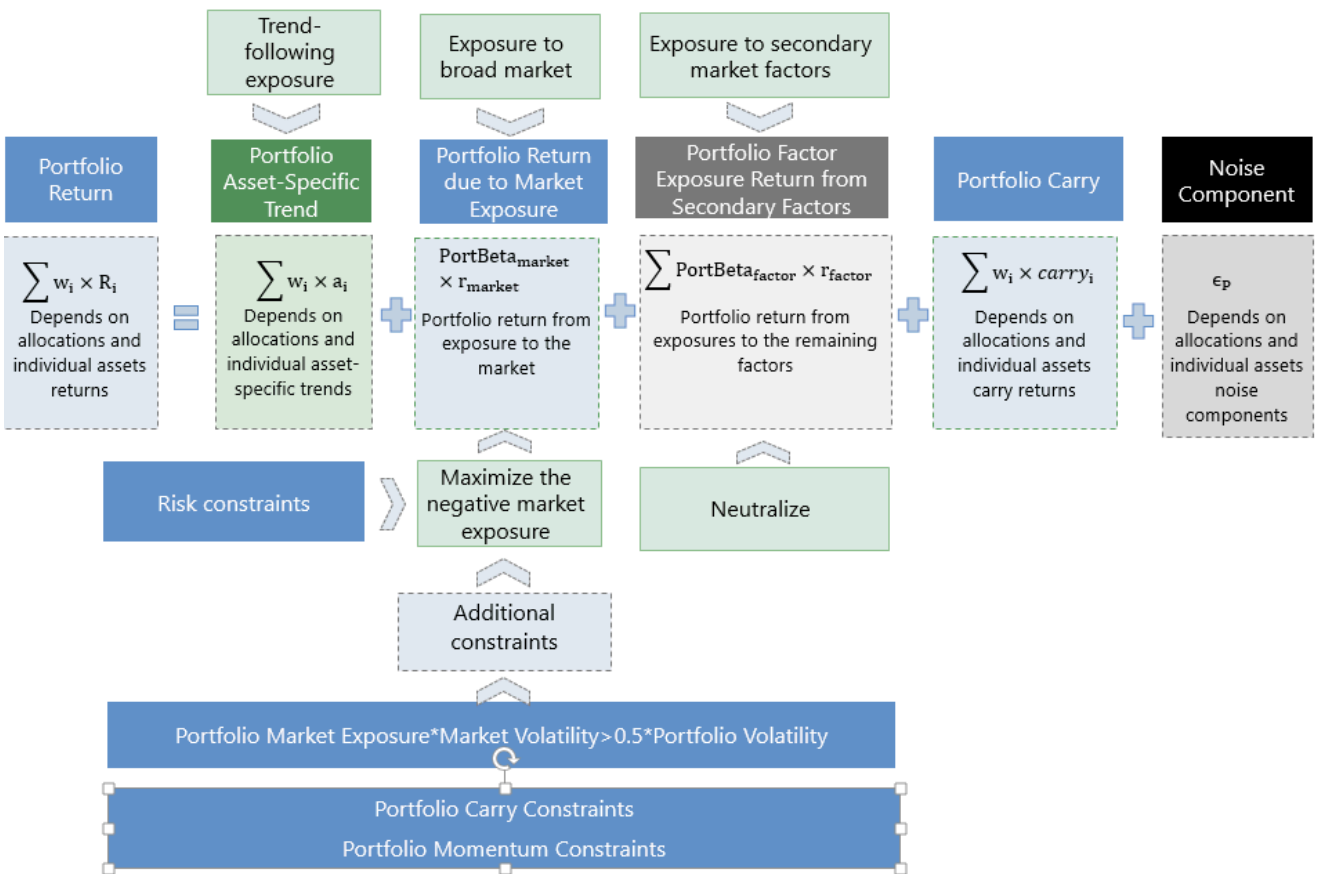
Figure 17: Total return decomposition



Source: J.P. Morgan Quantitative and Derivatives Strategy

Subsequently we maximize the negative exposure to the broad market as represented by the first principal component. We neutralize the exposure to the remaining factors and we try to find the positions in the underlyings that provide sufficient buffer in terms of carry income and momentum returns against a bullish move in the market.

Figure 18: Synthetic defensive basket construction mechanism



Source: J.P. Morgan Quantitative and Derivatives Strategy

Note that we target a minimum negative exposure to the broad market. We aim that at least 25% of the portfolio variance is explained by the exposure to the benchmark. [8]

Furthermore the momentum portfolio return itself consists of two parts. The first momentum component is due to the time-series momentum in the benchmark itself and the portfolio exposure (beta) to the benchmark. The second component is due to the asset specific trends in each of the underlying markets and the allocations to those markets and this component resembles a cross-sectional momentum strategy.

Subsequently we perform an extensive search to find the long/short basket of assets that satisfies the exposure constraint subject to additional constraints on the portfolio carry and momentum returns. It is an iterative search during which if no solution is found the constraints on carry and momentum are gradually relaxed and the optimization is repeated until a solution is found.

More concretely we proceed in the following way:

- First, we impose to offset one daily standard deviation move in the broad market. Half of the buffer against the adverse move should be sourced from carry income while the remaining part (if any) can be offset by momentum returns.
- Second, in case of no solution is found at the first attempt, we relax the carry and momentum constraints and then we aim to offset a half of the daily standard move in the broad market – again at least 50% of the offset shall be sourced from carry income.
- The solution at the second stage is not guaranteed to exist either and in case the second optimization fails to find a solution we proceed with a third one that aims to find a basket with the biggest negative exposure to the broad market subject to a positive carry constraint and the requirement that the combination carry and momentum is positive as well.
- All of the above optimization have the strict requirement that market exposure is negative and explains at least 25% of the portfolio variance. If all of the attempts above fail we perform a final optimization that maximizes the sum of the portfolio carry and momentum subject to the above minimum portfolio beta constraint.

As discussed in the beginning it is easier to find defensive baskets with attractive carry and momentum characteristics in some asset classes but it is much more challenging in others.

Note that if the market benchmark is moving in favor of the defensive position (a bearish market) there will be positive contribution (due to the negative exposure) from the time-series momentum of the benchmark. Therefore the time-series momentum of the benchmark and the carry income are expected to be the main profit drivers while the cross-sectional momentum effect will be of secondary importance. The more sizable (in absolute terms) the negative exposure to the benchmark is, the bigger will be expected contribution of the trend component in the benchmark, when the market sells off.

Conversely, if the market is bullish and trending upwards, there will be a negative contribution for the time-series momentum of the benchmark. In such a case we would expect that the synthetic defensive basket to benefit mainly from the carry and cross-sectional momentum profit drivers which will be offsetting the adverse trend in the market.

Empirical Results for Equity Futures

We apply the above-described methodology to the same universe of 17 equity futures as in our Market-Neutral Carry Strategies paper and we make use of the factor model for spot returns (p.34-35 in Market-Neutral Carry Strategies).

During the optimization the volatility of the synthetic defensive basket is set to the forecasted volatility of the underlying market at the relevant point in time.

[8] As explained later as our portfolio volatility target at every point in time is equal to the volatility of the broad market at this point in time, the constraint also implies a beta of less than -0.5.

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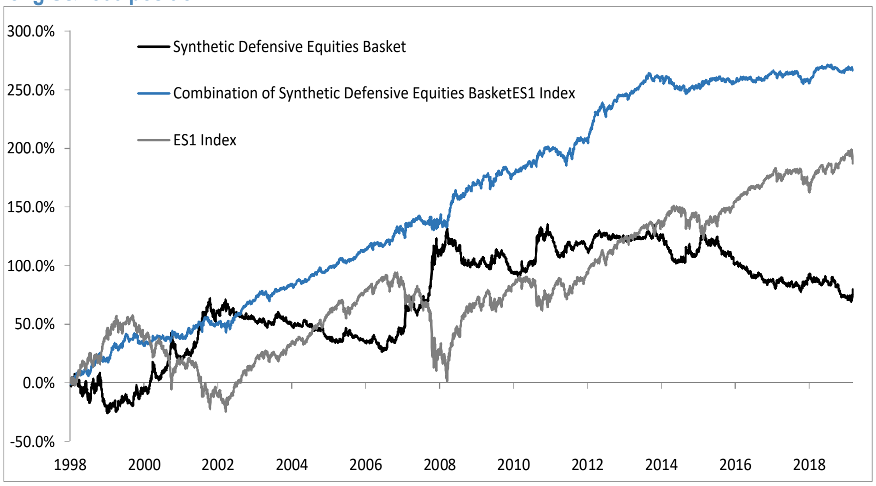
Figure 19: Backtest of the synthetic defensive equity basket– diversification results with a long S&P500 position



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 10:Correlation statistics with ES1 Index

Overall correlation	-73.55%
Correlation when ES1 returns are negative	-64.47%

Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 11: Performance statistics

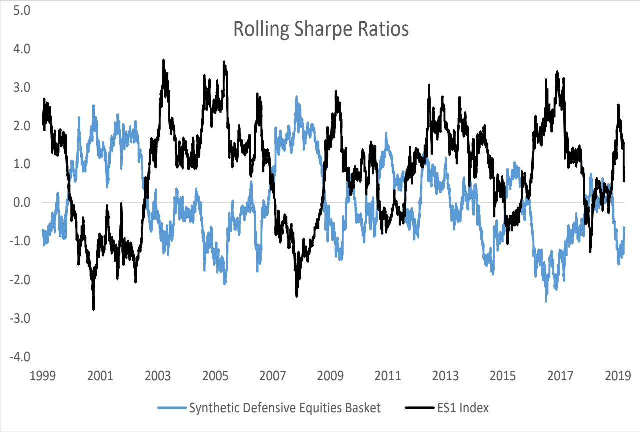
	Synthetic Defensive Equities Basket	ES1 Index	Combination of Synthetic Defensive Equities Basket and ES1 Index
Ann Return	3.7%	8.5%	12.2%
Ann Volatility	17.4%	18.5%	13.1%
Sharpe	0.21	0.46	0.93
Max DD	53.4%	64.2%	16.5%
Skewness	0.27	-0.29	0.59
Kurtosis	4.95	7.49	8.78

Source: J.P. Morgan Quantitative and Derivatives Strategy

The synthetic defensive equity baskets displays strong diversification benefits with strongly negative correlation to underlying market of -0.74. The Sharpe ratio of the combination between the synthetic defensive basket and the underlying market is slightly below one with an attractive drawdown of just 1.25 times the volatility.

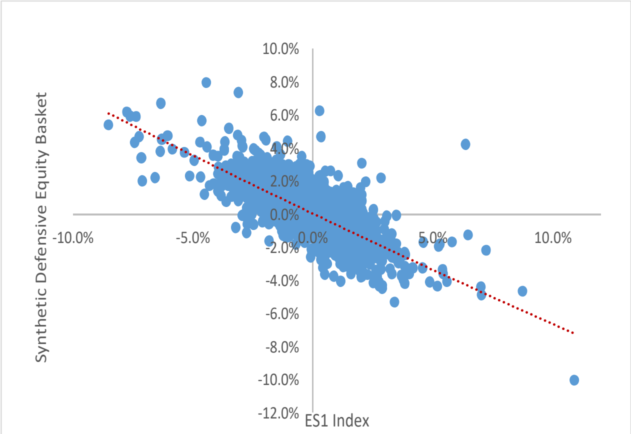
A regression analysis incorporating dummy variables illustrates that the average realized beta has been below -0.7. On an annual basis the strategy locks-in around 10% of carry that is used to offset (and implicitly fund) the short equity exposure.

Figure 20: Rolling yearly Sharpe ratios of the synthetic equities defensive basket and ES1 Index



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 21: Scatter plot of the daily returns of the synthetic defensive equities basket versus ES1 Index



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 12: Regression results of the returns of the synthetic defensive equity basket versus ES1 Index

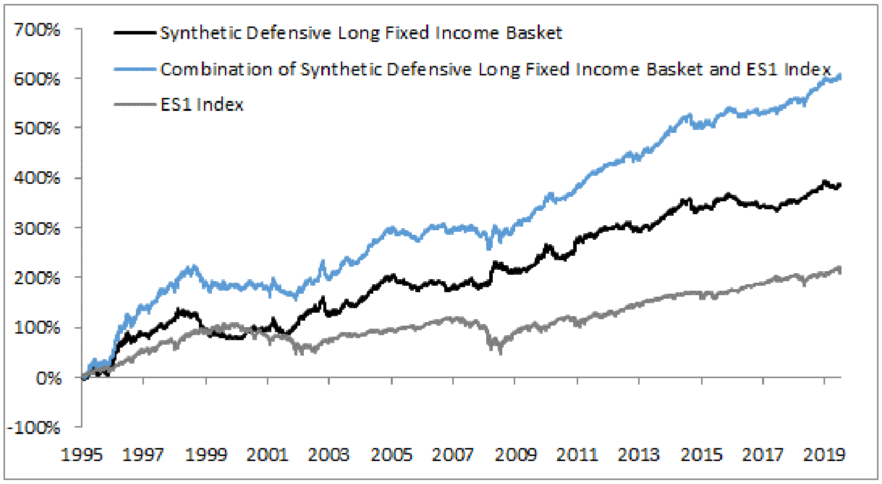
Annualized Carry/Constant	Beta Positive SPX Moves	Beta Negative SPX Moves
8.94%	-0.7287	-0.7338

Source: J.P. Morgan Quantitative and Derivatives Strategy

Empirical Results for Fixed Income Futures

First, we analyze the case where we a long duration exposure is taken to provide diversification and protection for a long S&P500 position.

Figure 22: Backtest of the synthetic defensive long fixed income basket– diversification results with ES1 Index



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 13:Correlation statistics with ES1 Index

Overall correlation	-17.34%
Correlation when ES1 returns are negative	-19.81%

Source: J.P. Morgan Quantitative and Derivatives Strategy

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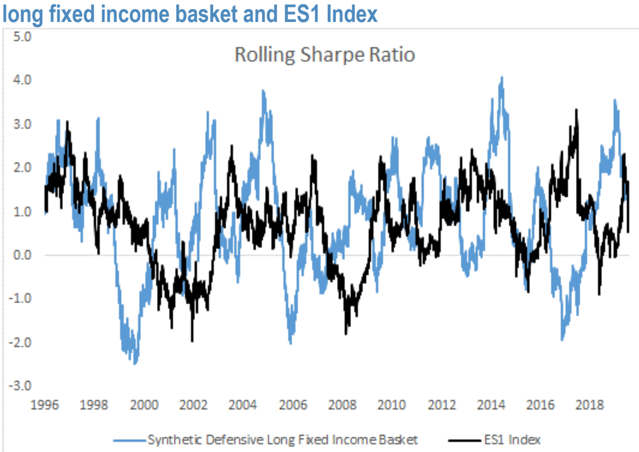
Table 14: Performance statistics

	Synthetic Defensive Long Fixed Income Basket	ES1 Index	Combination of Synthetic Defensive Long Fixed Income Basket and ES1 Index
Ann Return	15.3%	8.2%	23.6%
Ann Volatility	18.2%	18.2%	23.6%
Sharpe	0.84	0.45	1.00
Max DD	48.1%	56.8%	55.2%
Skewness	-0.31	-0.10	-0.09
Kurtosis	3.19	8.76	3.43

Source: J.P. Morgan Quantitative and Derivatives Strategy

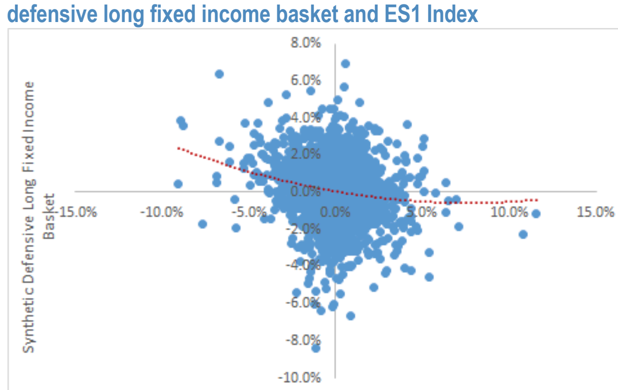
Similarly to the results for the asymmetric trend-following strategy the synthetic defensive basket with a long fixed income bias benefits from the monetary easing policies over the last decade. Despite this bias in performance we find attractive diversification with negative correlation and improved risk-return profile.

Figure 23: Rolling yearly Sharpe ratios of the synthetic defensive long fixed income basket and ES1 Index



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 24: Scatter plot of the daily returns of the synthetic defensive long fixed income basket and ES1 Index



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 15: Regression results of the returns of the synthetic defensive long fixed income basket versus ES1 Index

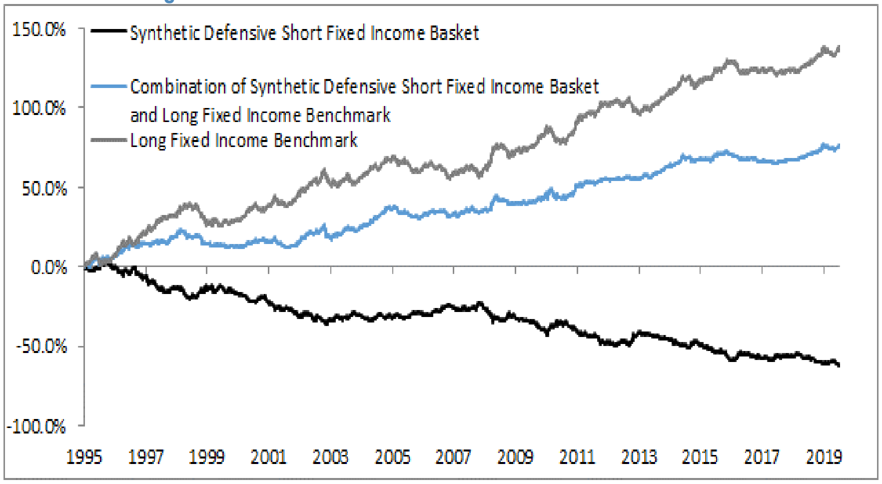
Annualized Carry/Constant	Beta Positive SPX Moves	Beta Negative SPX Moves	Convexity Positive SPX Moves	Convexity Negative SPX Moves
8.16%	-0.0831	-0.1449	-0.8654	2.1780

Source: J.P. Morgan Quantitative and Derivatives Strategy

The strategy provides attractive carry that stands above 8% on an annualized basis. Furthermore, there is the benefit of positive convexity for negative S&P moves.

Secondly, we consider the case of hedging a long fixed income portfolio against a potential rise in rates. The synthetic defensive basket will have a short duration exposure.

Figure 25: Backtest of the synthetic defensive short fixed income basket– diversification results with a long fixed income benchmark



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 16: Correlation statistics with long fixed income benchmark

Overall correlation	-70.40%
Correlation when benchmark returns are negative	-57.94%

Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 17: Performance statistics

	Synthetic Defensive Short Fixed Income Basket	Long Fixed Income Benchmark	Combination of Synthetic Defensive Short Fixed Income Basket and Long Fixed Income Benchmark
Ann Return	-2.4%	5.5%	3.0%
Ann Volatility	4.6%	5.5%	3.8%
Sharpe	-0.53	1.00	0.78
Max DD	49.4%	13.9%	10.8%
Skewness	0.22	-0.27	-0.24
Kurtosis	2.89	1.73	3.83

Source: J.P. Morgan Quantitative and Derivatives Strategy

As expected the short duration exposure is continuous drag on performance as there have been just a few periods of increasing rates in our backtest period. Nevertheless the Sharpe of the combined portfolio is not significantly impacted downwards and the overall volatility is improved.

On average the synthetic short fixed income basket has a positive carry at around 3% per year on an annualized volatility of 4.6%. The sensitivity with respect to the benchmark is in accordance to the constraints of the optimization and the strategy provides positive (though marginal) convexity for moves in both the directions.

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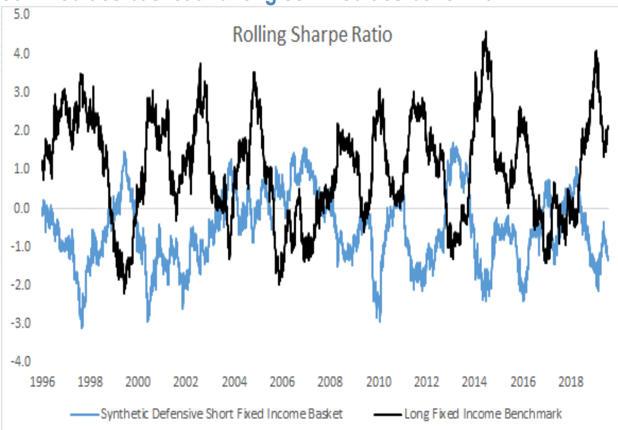
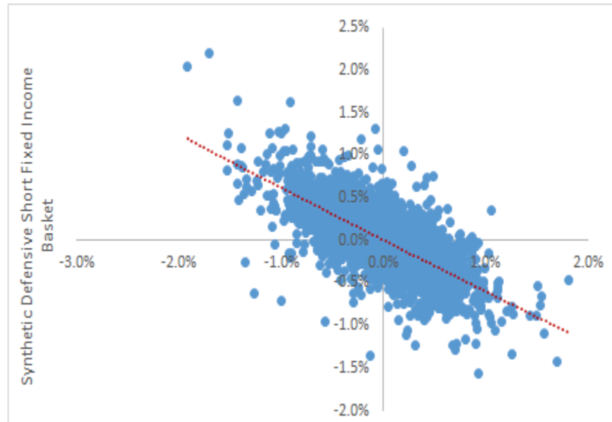
Figure 26: Rolling yearly Sharpe ratios of the synthetic defensive commodities basket and long commodities benchmark



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 27: Scatter plot of the daily returns of the synthetic defensive short fixed income basket versus long fixed income benchmark



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 18: Regression results of the returns of the synthetic defensive short fixed income basket versus long fixed income benchmark

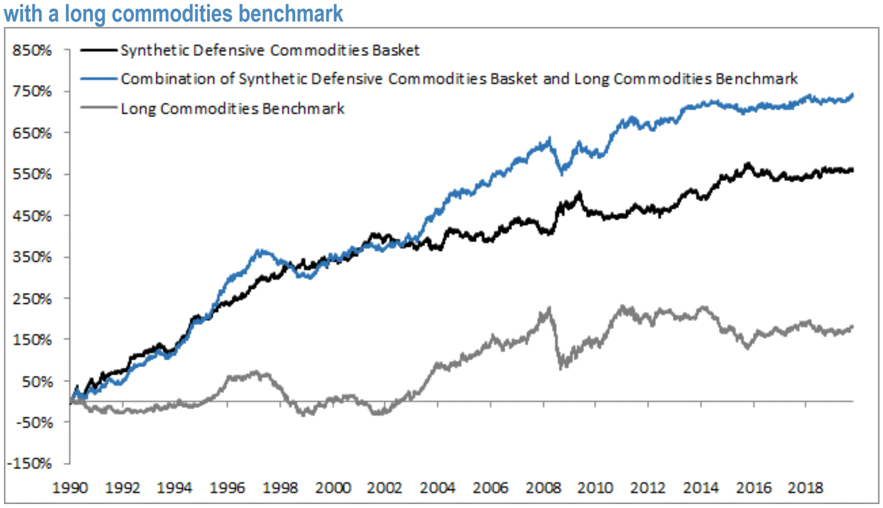
Annualized Carry/Constant	Beta Positive long fixed income benchmark Moves	Beta Negative Long fixed income benchmark Moves	Convexity Positive long fixed income benchmark Moves	Convexity Negative Long fixed income benchmark Moves
2.91%	-.6614	-0.5458	5.20	6.22

Source: J.P. Morgan Quantitative and Derivatives Strategy

Empirical Results for Commodities Futures

Next, we focus on the diversification benefits of a commodities synthetic defensive basket when it is used as an overlay to a long commodities position. As discussed in Market-Neutral Carry Strategies paper commodities as an asset class offers the most attractive ex-ante carry return but it is also one that it is most difficult to capture in real life[9].

Figure 28: Backtest of the synthetic defensive commodities basket– diversification results with a long commodities benchmark



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 19:Correlation statistics with long commodities benchmark

Overall correlation	-61.41%
Correlation when benchmark returns are negative	--47.36%

Source: J.P. Morgan Quantitative and Derivatives Strategy

[9] In Market-Neutral Carry Strategies we found that the carry capture is approximately 1/3 of the ex-ante one.

Table 20: Performance statistics

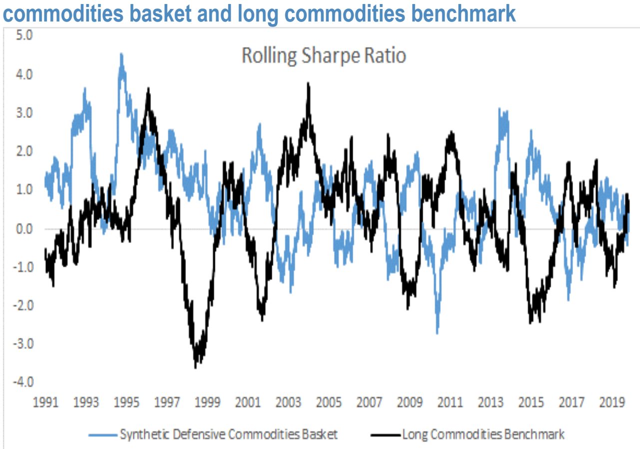
	Synthetic Defensive Commodities Basket	Long Commodities Benchmark	Combination of Synthetic Defensive Commodities Basket and Long Commodities Benchmark
Ann Return	18.5%	5.9%	24.4%
Ann Volatility	24.4%	27.0%	22.4%
Sharpe	0.76	0.22	1.09
Max DD	51.1%	80.5%	61.0%
Skewness	-0.14	-0.24	-0.14
Kurtosis	2.37	4.81	2.24

Source: J.P. Morgan Quantitative and Derivatives Strategy

The defensive synthetic commodities basket posts strong performance on a stand-alone basis. The diversification benefits are quite appealing as well with the overall correlation being below -0.5 and a combined portfolio with an attractive Sharpe ratio. It has to be recognized though that in the initial stage of the GFC the synthetic defensive commodities strategy has not succeeded to provide a complete protection.

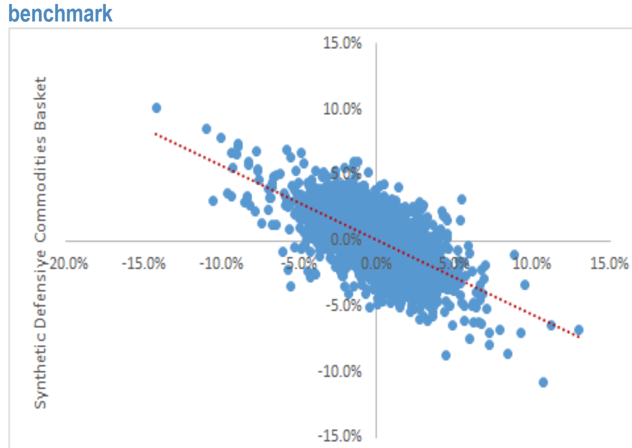
As it has already mentioned the commodities carry is quite attractive. The realized carry stands at 36% versus an annualized volatility of 24%. The synthetic defensive basket achieves a negative beta of -0.5 as per the optimization criteria.

Figure 29: Rolling yearly Sharpe ratios of the synthetic defensive commodities basket and long commodities benchmark



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 30: Scatter plot of the daily returns of the synthetic defensive commodities basket versus long commodities benchmark



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 21: Regression results of the returns of the synthetic defensive commodities basket versus long commodities benchmark

Annualized Carry/Constant	Beta Positive Long Commodities Benchmark Moves	Beta Negative Long Commodities Benchmark Moves
36.26%	-0.6013	-0.5055

Source: J.P. Morgan Quantitative and Derivatives Strategy

Empirical Results for FX

Below we present the empirical results for the application of the synthetic defensive basket methodology to currencies. In this case we aim to obtain a risk-off exposure represented as long dollar exposure and the portfolio that we aim hedge consists of the short dollar G10 FX forwards.

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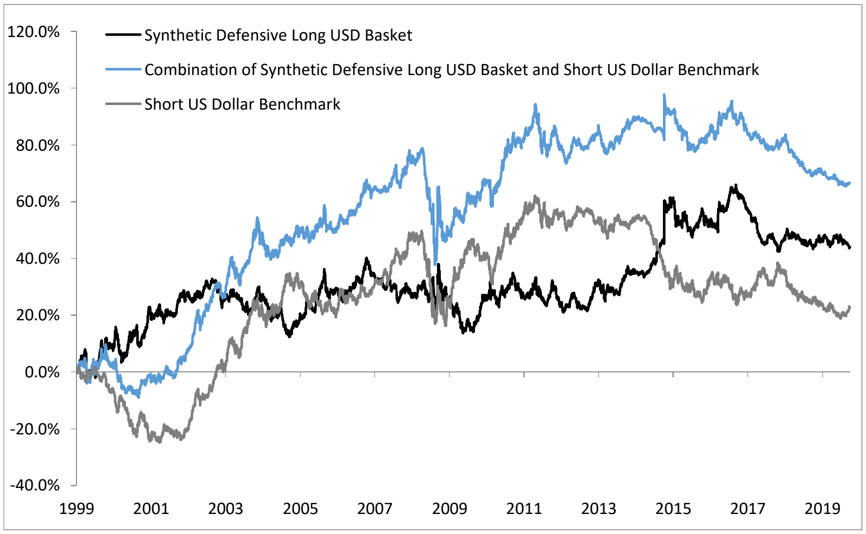
Figure 31: Backtest of the synthetic defensive long USD basket– diversification results with a short US Dollar benchmark



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 22:Correlation statistics with short US Dollar benchmark

Overall correlation	-42.12%
Correlation when benchmark returns are negative	-20.48%

Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 23: Performance statistics

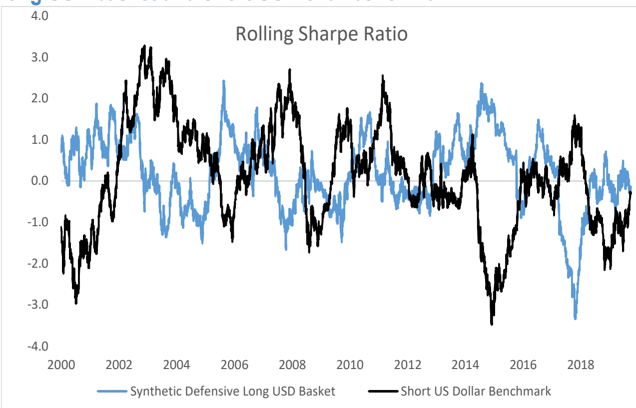
	Synthetic Defensive Long USD Basket	Short US Dollar Benchmark	Combination of Synthetic Defensive Long USD Basket and Short US Dollar Benchmark
Ann Return	2.2%	1.1%	3.3%
Ann Volatility	10.2%	10.2%	11.0%
Sharpe	0.21	0.11	0.30
Max DD	25.1%	37.2%	34.6%
Skewness	0.78	0.23	0.58
Kurtosis	17.49	5.09	24.13

Source: J.P. Morgan Quantitative and Derivatives Strategy

The empirical backtest suggests that the FX synthetic defensive basket provides diversification (the overall correlation is below -0.4). It also manages to benefit from the dollar rally in 2014 but the performance in 2008 is not enough to offset the drawdown in the benchmark.

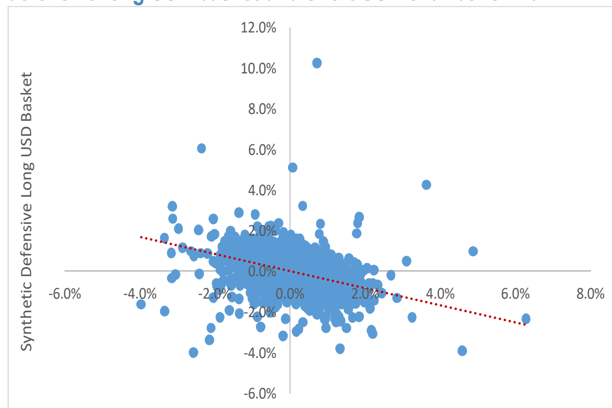
The synthetic defensive FX basket achieves an attractive carry income as well -the realized carry is close to 10% annually for an annualized volatility of 24%. Furthermore, the synthetic defensive basket achieves a negative beta below -0.5 as per the optimization criteria.

Figure 32: Rolling yearly Sharpe ratios of the synthetic defensive long USD basket and short US Dollar benchmark



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 33: Scatter plot of the daily returns of the synthetic defensive long USD basket and short US Dollar benchmark



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 24: Regression results of the returns of the synthetic defensive long USD basket versus short US Dollar benchmark

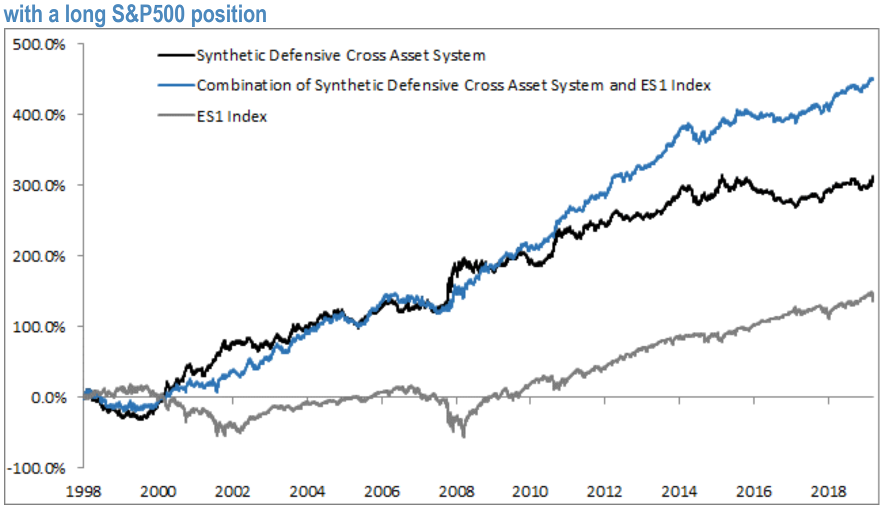
Annualized Carry/Constant	Beta Positive short US Dollar benchmark moves	Beta Negative short US Dollar benchmark Moves
9.99%	-0.6024	-0.5318

Source: J.P. Morgan Quantitative and Derivatives Strategy

Empirical Results for Cross Asset Synthetic Defensive Basket

Below we present the results for the aggregated synthetic defensive basket strategy. The aggregated strategy is an equal combination of the synthetic defensive basket strategies in the different asset classes. Investors can also opt for another asset class split that fits better their preferences with tilts to the asset classes that are more relevant for them.

Figure 34: Backtest of the synthetic defensive cross asset system– diversification results with a long S&P500 position



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 25:Correlation statistics with ES1 Index

Overall correlation	-45.38%
Correlation when ES1 returns are negative	-40.45%

Source: J.P. Morgan Quantitative and Derivatives Strategy

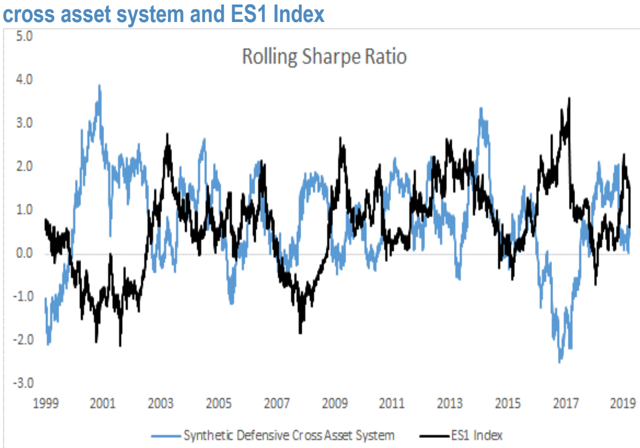
Table 26: Performance statistics

	Synthetic Defensive Cross Asset System	ES1 Index	Combination of Cross Asset System and ES1 Index
Ann Return	14.4%	6.3%	20.7%
Ann Volatility	18.7%	18.7%	19.5%
Sharpe	0.77	0.33	1.06
Max DD	38.5%	61.7%	29.3%
Skewness	0.05	0.14	0.15
Kurtosis	4.02	11.75	3.62

Source: J.P. Morgan Quantitative and Derivatives Strategy

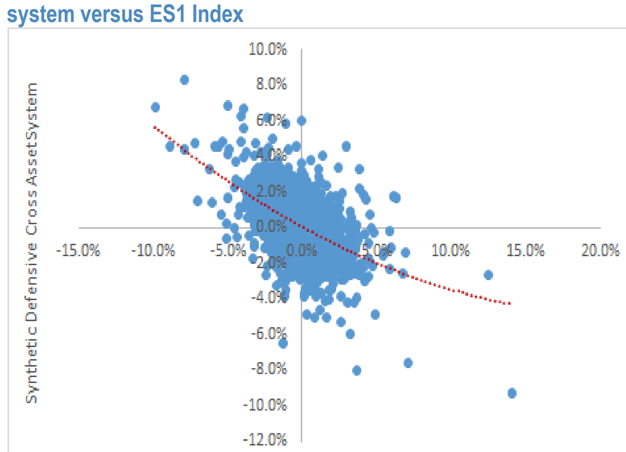
The aggregated synthetic defensive basket performs strongly on a stand-alone basis and has an attractive negative correlation to S&P500 (below -0.4). The aggregated portfolio has a well-controlled drawdown of around 1.5 times the annualized volatility.

Figure 35: Rolling yearly Sharpe ratios of the synthetic defensive cross asset system and ES1 Index



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 36: Scatter plot of the daily returns of the cross asset system versus ES1 Index



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 27: Regression results of the returns of the synthetic defensive cross asset system versus ES1 Index

Annualized Carry/Constant	Beta Positive SPX Moves	Beta Negative SPX Moves	Convexity Positive SPX Moves	Convexity Negative SPX Moves
11.30%	-0.4159	-0.4303	0.1448	2.3438

Source: J.P. Morgan Quantitative and Derivatives Strategy

The aggregated synthetic defensive basket brings an annualized carry of around 11% for a volatility of an annualized volatility 19% and has positive convexity with respect to the S&P moves, especially on the negative side.

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Single Asset Mean-Reversion

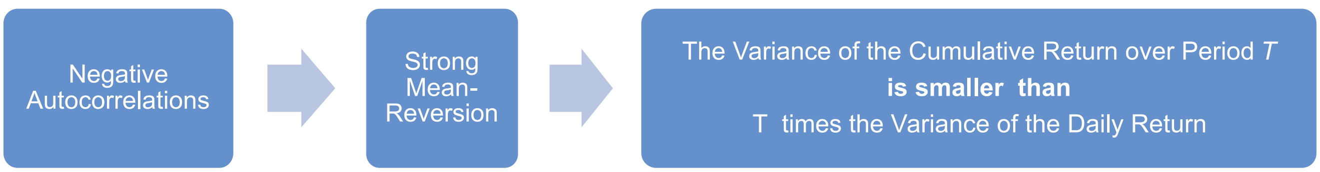
Mean-reversion signal based on the replication of the difference between variances calculated over different timescales

Recently investment practitioners have started to use mean-reversion signals based on the difference between the daily variance multiplied by *T* (where *T* is measured in days) and the variance of the cumulative return calculated over a certain period *T* (for example weekly variance).

Let R_t denote the asset return at time t. Let $Var_T = Var(\sum_{i=0}^{T-1} R_{t-i})$. If $Var(R_t) = Var_1 = \sigma^2$ it follows $Var_T = \sigma^2 * (T + 2 * \sum_{i=1}^{T-1}(T-i) * \rho_i)$ where ρ_i is the autocorrelation coefficient at lag *i*.

Hence, the difference in variances is $TVar_1 - Var_T = -2 * \sigma^2(\sum_{i=1}^{T-1}(T-i) * \rho_i)$. This difference is guaranteed to be positive if $\rho_i < 0$ for *i=1,…T-1*.

Figure 37: Single-asset mean-reversion signal



Source: J.P. Morgan Quantitative and Derivatives Strategy

Such an approach has also long been known in the academic world and used as a test for market efficiency:

- Lo, A. W. and MacKinlay, A. C. (1988): **Stock Market Prices Do Not Follow Random Walks: Evidence from a Simple Specification Test**, Review of Financial Studies, 1, 41 - 66.
- Lo, A. W. and MacKinlay, A. C. (1989): **The Size and Power of the Variance Ratio Test in Finite Samples: A Monte Carlo Investigation**, Journal of Econometrics, 40, 203 - 238.

Lo and MacKinlay (1988, 1989) proposed the **Variance Ratio** test:

- If $VR_T = Var_T/(T * Var_1)$ and there are a total of nT daily return observations under the assumption of random walk $\sqrt{nT}(VR_T - 1) \sim N(0, 2(T-1))$.
- If $\rho_i < 0$ for *i=1,…T-1* it follows that $VR_T < 1$.

We can replicate the difference the difference between variances calculated over different timescales of via holding *Delta-1* position:

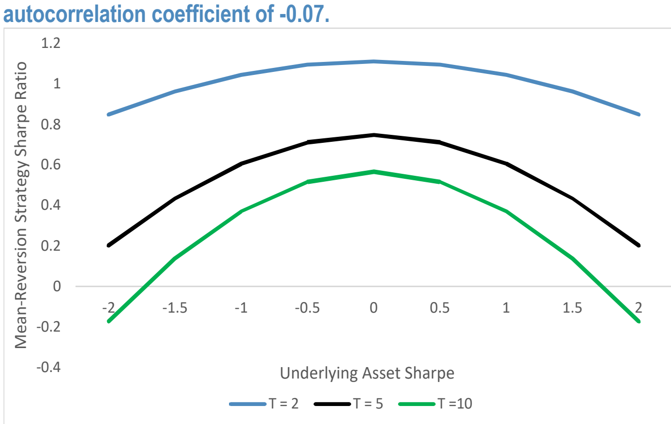
$$Position_{t,T} = -\sum_{i=0}^{T-2}(T-i-1) * R_{t-i}$$

$$PnL_{t+1,T} = -R_{t+1}\sum_{i=0}^{T-2}(T-i-1) * R_{t-i}$$

$$E(PnL_{t+1,T}) = -\sigma^2\sum_{i=1}^{T-1}(T-i) * \rho_i - \mu^2 * T * \frac{T-1}{2} = \frac{TVar_1 - Var_T}{2} - \mu^2 * T * \frac{T-1}{2}$$

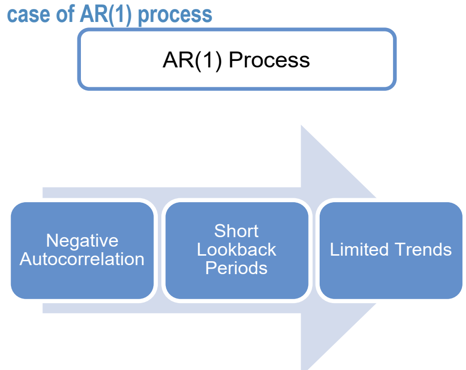
If we assume a strict AR(1) process we can derive analytical expression for the expected P&L and its variance as a function of the autocorrelation coefficient and the lookback period T (please refer to the Appendix for more information). The graph on the left below demonstrates the profitability (Sharpe ratio) of the mean-reversion strategy versus the Sharpe ratio of the underlying asset for various timeframes over which the variance is aggregated and for a daily autocorrelation value of -0.07 (empirical value of daily autocorrelation for S&P500).

Figure 38: Mean-reversion strategy Sharpe ration versus the Sharpe ratio of the underlying for different timeframes (in days) and autocorrelation coefficient of -0.07.



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 39: Profitability of the mean-reversion strategy in case of AR(1) process



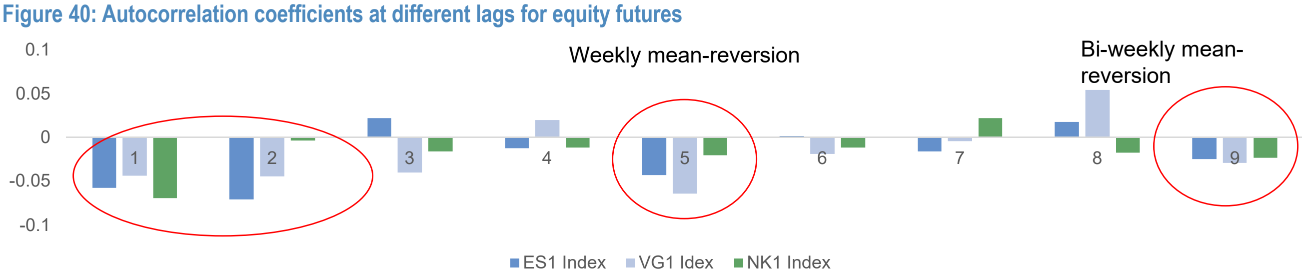
Source: J.P. Morgan Quantitative and Derivatives Strategy

First, the mean-reversion strategy has a concave P&L profile and the stronger the mean (trend) of the underlying market, the lower the profitability of the strategy. Nevertheless, the mean-reversion strategy can tolerate relatively sizable drifts/trends in the underlying market in any of the directions.

Second, note that if the process is strictly an AR(1) one the optimal variance aggregation timeframe is 2 days, i.e. the optimal position of the strategy is the negative of the previous day return.

The AR(1) process is an idealistic representation of the reality and empirical facts demonstrate that the time series dependence spans far beyond 1-st lag. Below we show the auto-correlation structures at different time lags for the markets in our universe and we find strong mean-reversion effects in over different time-frames. We can see that in addition to daily mean-reversion patterns, often weekly and bi-weekly ones appear.

Figure 40: Autocorrelation coefficients at different lags for equity futures



Source: J.P. Morgan Quantitative and Derivatives Strategy

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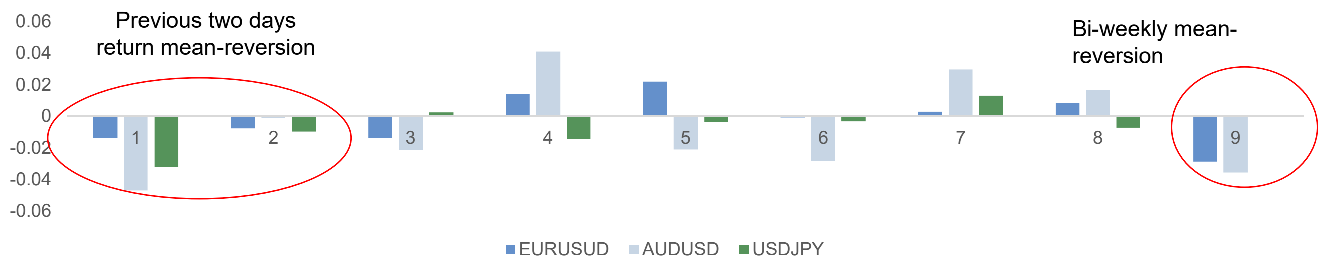
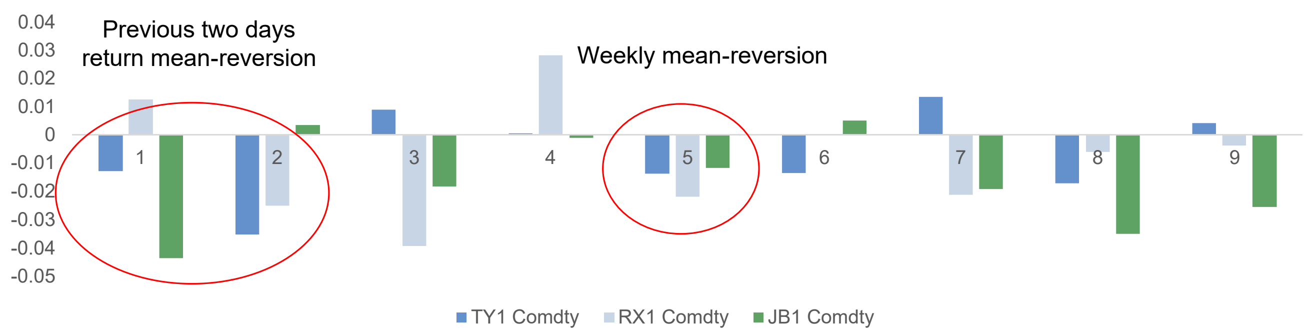
Figure 41: Autocorrelation coefficients at different lags for FX forwards



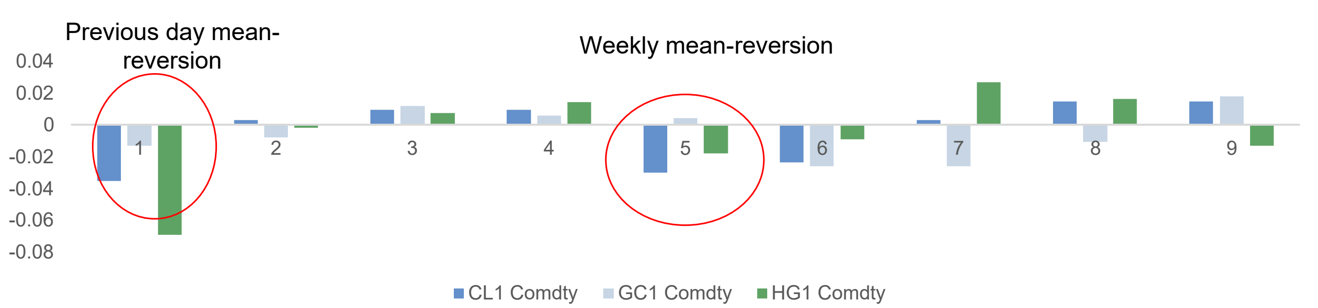
Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 42: Autocorrelation coefficients at different lags for fixed income futures



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 43: Autocorrelation coefficients at different lags for fixed income futures



Source: J.P. Morgan Quantitative and Derivatives Strategy

For the subsequent implementation we have chosen 10 working days (2 calendar weeks) as our variance aggregation timeframe so that we can incorporate even bi-weekly mean-reversion patterns.

We plan to investigate adaptive selection of the aggregation timeframe, expected costs calculation and ways to decrease the dependence on the trend in a future publication.

Why Does Mean-Reversion Work in Risk-Off Times?

Let's refresh the P&L function of the mean-reversion strategy:

$$\boxed{E\left(PnL_{t+1,T}\right) = -\sigma^2 \sum_{i=1}^{T-1} (T-i) * \rho_i - \mu^2 * T * \frac{T-1}{2}}$$

It is well-known that volatility clusters and spikes significantly during crisis times.

Higher volatility increases the P&L and the impact is even quadratic as the P&L is actually proportional to variance. If the volatility doubles, the P&L will increase four times.

More negative autocorrelations also impact positively the P&L. There has been plenty of quantitative research at JP Morgan and also external academic research that demonstrates that higher volatility leads to more negative autocorrelation (more on this relationship can be found below).

A potential headwind for the mean-reversion strategy during sell-offs is the appearance of strong trends that will impact the strategy negatively.

When the markets calm down the volatility drops and even if autocorrelations turn positive (which is unlikely), the negative P&L impact will be limited in comparison to the profits during the crisis times.

Kolanovic et al. in Market Impact of Derivatives Hedging-Weekly Patterns analyzed both the structural and behavioral reasons for mean-reversion.

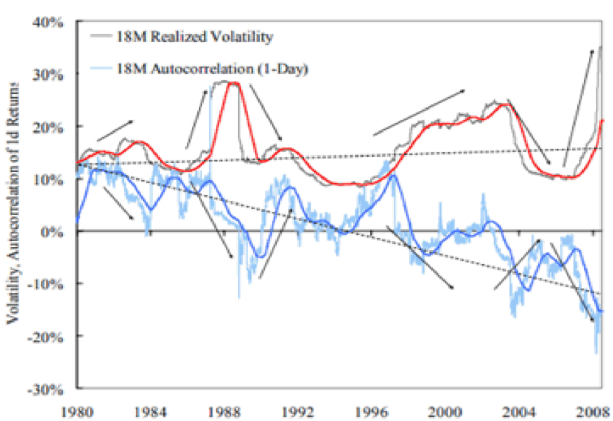
As structural reasons Kolanovic points out:

- The typical net short Gamma position of dealers leads to intraday momentum towards the close that is likely to be reverse at the open next day.
- Fixed ratio asset allocators have to buy the equity market after a drop.

The behavioral reasons also play a role as a high volatility environment leads to an overreaction in a low liquidity environment.

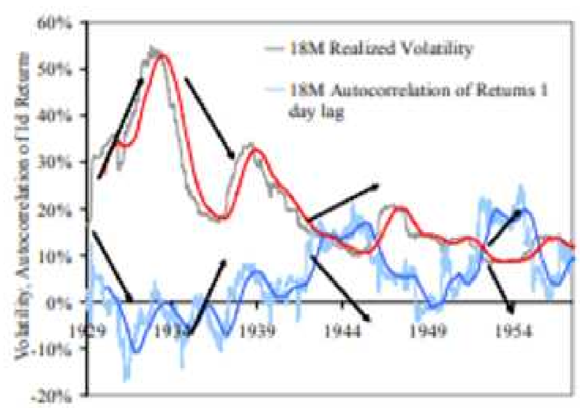
Furthermore, the first order negative autocorrelation of index returns was empirically analyzed and evidence for the inverse relationship between volatility and autocorrelation over more than a century was found.

Figure 44: Market volatility and lag-1 autocorrelation between 1980-2008



Source: J.P. Morgan Quantitative and Derivatives Strategy

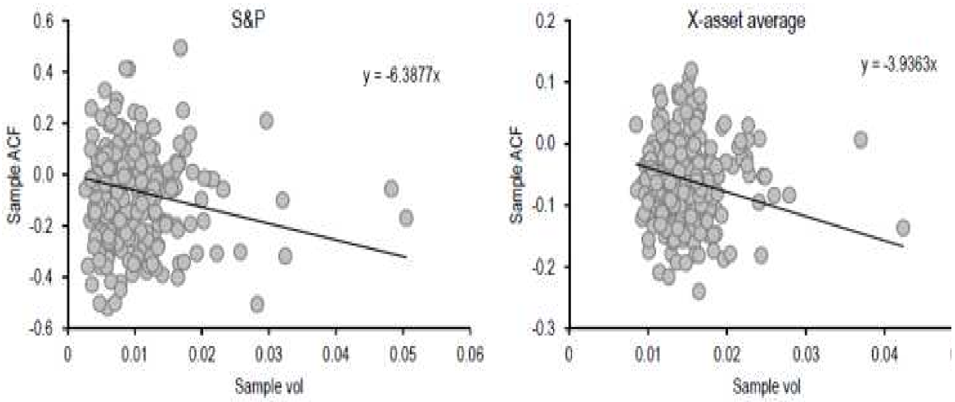
Figure 45: Market volatility and lag-1 autocorrelation between 1928-1958



Source: J.P. Morgan Quantitative and Derivatives Strategy

The relationship between autocorrelation and volatility in light of the optimal frequency of delta-hedging has also been discussed in Optimal Option Delta-Hedging by Ravagli et al. and supportive evidence was found across asset classes.

Figure 46: Higher volatility tends to stimulate more negative autocorrelation



Source: J.P. Morgan Quantitative and Derivatives Strategy

There has also been a lot of academic evidence for the link between negative autocorrelation and volatility:

- Sentana, Enrique & Wadhwani, Sushil B. (1992), "**Feedback Traders and Stock Return Autocorrelations: Evidence from a Century of Daily Data**," *Economic Journal*, Royal Economic Society, vol. 102(411), pages 415-425, March. Two groups of traders: positive feedback (trend-followers and negative feedback (smart money). When trend-followers dominate, there is negative autocorrelation. Furthermore, when volatility is low, daily stock returns exhibit positive autocorrelation, but when it is high, returns exhibit negative serial correlation.

- Booth, G. & Koutmos, Gregory. (1998), "**Volatility and autocorrelation in major European stock markets**". *European Journal of Finance*. 4. 61-74. There is an inverse relationship between first order autocorrelations and volatility. While this relationship is statistically significant in daily returns, it is absent from weekly returns.

- Campbell, John & Grossman, Sanford & Wang, Jiang (1993), **Trading Volume and Serial Correlation in Stock Returns**. *The Quarterly Journal of Economics*. For both stock indexes and individual large stocks, the first-order daily return autocorrelation tends to decline with volume.

- Nagel, S. (2012), "**Evaporating Liquidity**", *The Review of Financial Studies*, Volume 25, Issue 7, p. 2005–2039. The returns of short-reversal strategies are a proxy for liquidity provision and predictable with the VIX index. Expected returns increase enormously along with the VIX during times of financial market turmoil, such as the financial crisis 2007-09.

- Anna Cieslak & Adair Morse & Annette Vissing-Jorgensen (2019), "**Stock Returns over the FOMC Cycle**," *Journal of Finance,* American Finance Association, vol. 74(5), pages 2201-2248, October. The Fed put leads to mean-reversion in stock returns post declines.

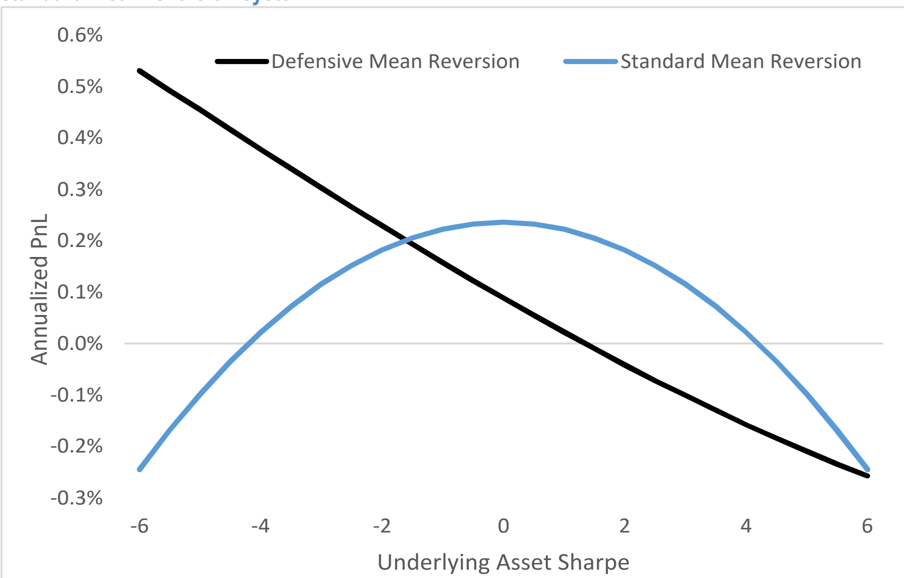
Defensive mean-reversion

In order to reinforce the defensive properties of the mean-reversion we impose similar constraints to the case of asymmetric trend-following:

- Only short-positions in equities and in commodities (except for gold) are taken
- Only long USD and fixed income positions are allowed

In the Appendix we have derived the P&L profile of the defensive mean-reversion strategy under the assumption of an AR(1) process. Below we compare the P&L profile to the one of the standard (two-sided) mean-reversion system:

Figure 47: Annualized P&L with daily auto-correlation of -0.07 for a defensive mean-reversion system (taking negative positions only) and a standard mean-reversion system



Source: J.P. Morgan Quantitative and Derivatives Strategy

When the Sharpe ratio of the underlying asset is negative and sizable, the defensive mean-reversion strategy manages to benefit not only from the negative autocorrelation but also from the trend/drift in the underlying asset. During rapid sell-offs risky assets develop strong negative drifts that can be profitable for the defensive mean-reversion system but are a drag on the performance of the standard mean-reversion strategy.

When the underlying asset has a zero Sharpe ratio (no trend), the standard mean-reversion strategy is more profitable than the defensive one. The main reason for that is that the defensive mean-reversion can only take positions in one direction and cannot fully benefit from the negative autocorrelation.

When the underlying trend is positive (for example bullish markets) the defensive mean-reversion strategy will underperform the standard one as short positions position of the defensive mean-reversion strategy will often incur losses due to the trend in the opposite direction.

Empirical Results

Below we present the results of the backtests of the defensive mean-reversion strategy applied to various asset classes as well an aggregated backtest across asset-classes. Similarly to the case of asymmetric trend-following we target the volatility of the asset to which we apply the overlay (in this case S&P500) at the time the strategy has open positions.

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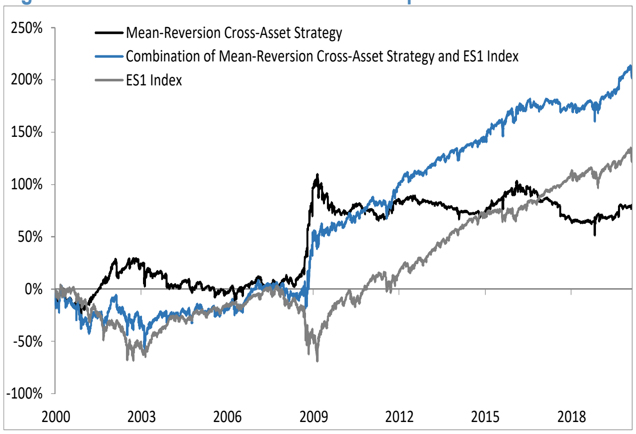
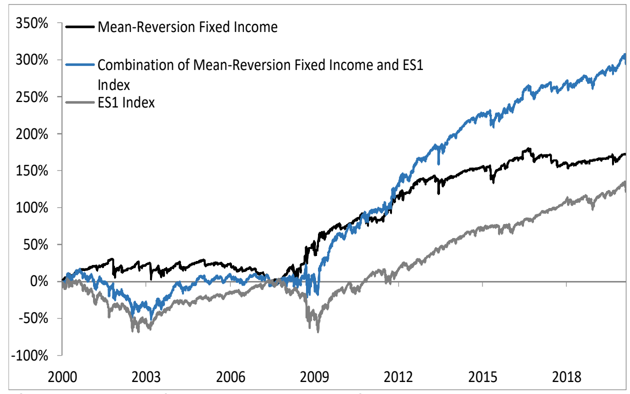
Figure 48: Backtest results for defensive equities mean-reversion



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 49: Backtest results for defensive fixed-income mean-reversion



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 28: Performance statistics for the defensive mean-reversion strategy in equities and fixed income

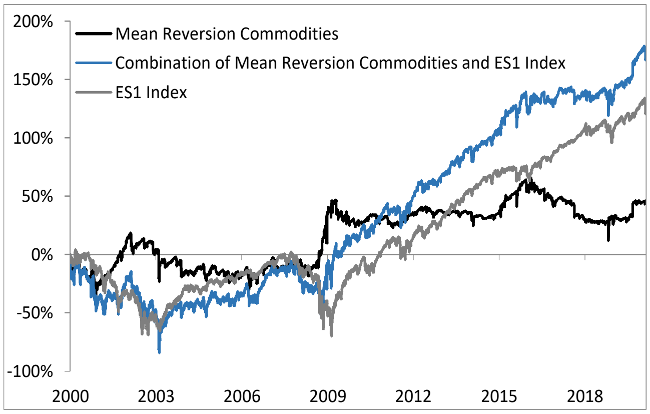
	Equities			Fixed Income		
	Defensive Equities Mean-Reversion	ES1 Index	Combination of Defensive Equities Mean-Reversion and ES1 Index	Defensive Fixed Income Mean-Reversion	ES1 Index	Combination of Defensive Fixed Income Mean-Reversion and ES1 Index
Ann Return	2.39%	6.02%	8.40%	8.30%	6.02%	14.32%
Ann Volatility	17.65%	18.69%	20.75%	17.65%	18.69%	24.08%
Sharpe	0.14	0.32	0.41	0.47	0.32	0.59
Max DD	66.10%	61.38%	39.78%	35.79%	61.38%	54.85%
Skewness	13.32	0.15	5.67	0.08	0.15	-0.06
Kurtosis	561.35	12.40	173.17	25.10	12.39	9.05

Source: J.P. Morgan Quantitative and Derivatives Strategy

The equity defensive mean-reversion strategy brings much needed respite and diversification, especially during the GFC period. Note that the combined portfolio of the defensive equity mean-reversion strategy and S&P500 has positive skewness.

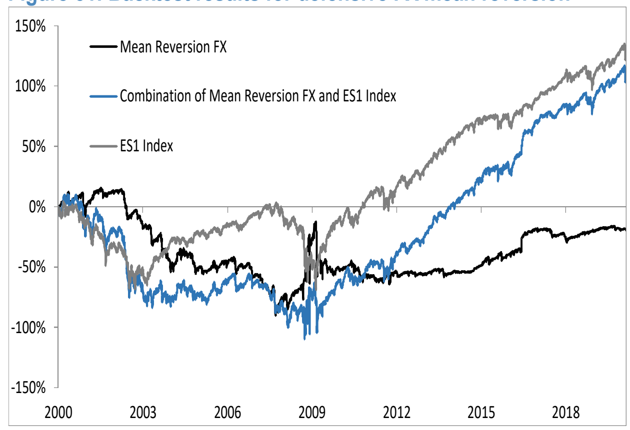
The fixed income defensive mean-reversion strategy displays a strong performance due to the monetary easing policies embarked after 2008 but the diversification benefit is much more limited, especially prior GFC.

Figure 50: Backtest results for defensive commodities mean-reversion



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 51: Backtest results for defensive FX mean-reversion



Source: J.P. Morgan Quantitative and Derivatives Strategy

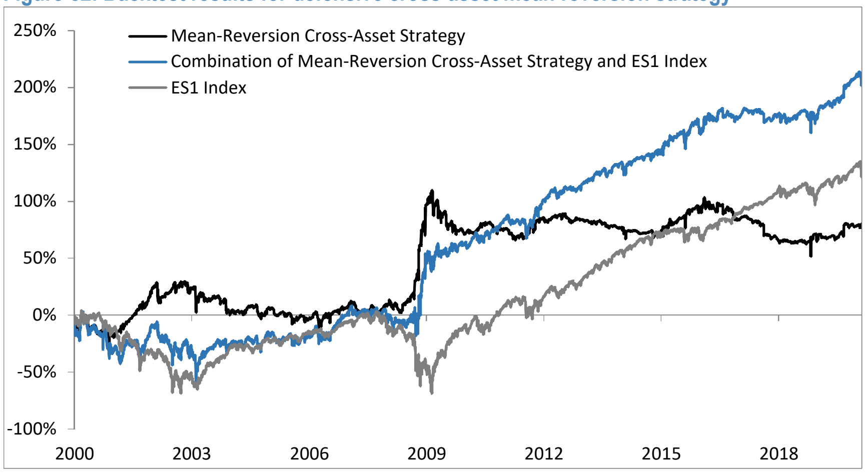
Table 29: Performance statistics for the defensive mean-reversion strategy in commodities and FX

	Commodities			FX		
	Defensive Commodities Mean-Reversion	ES1 Index	Combination of Defensive Commodities Mean-Reversion and ES1 Index	Defensive FX Income Mean-Reversion	ES1 Index	Combination of Defensive FX Mean-Reversion and ES1 Index
Ann Return	2.26%	6.01%	8.28%	-0.93%	6.00%	5.08%
Ann Volatility	18.58%	18.78%	25.12%	17.88%	18.67%	23.79%
Sharpe	0.12	0.32	0.33	-0.05	0.32	0.21
Max DD	43.50%	61.85%	63.86%	67.61%	61.38%	79.46%
Skewness	2.76	0.15	0.88	1.50	0.15	0.39
Kurtosis	75.19	12.26	23.49	122.82	12.44	35.56

Source: J.P. Morgan Quantitative and Derivatives Strategy

The commodities defensive mean-reversion strategy has a positive performance on a stand-alone basis. While it does not help to substantially improve the risk profile of S&P500 when it is used an overlay it does bring diversification benefit during the GFC. FX is the only asset class where we find that the defensive mean-reversion strategy does not deliver on a stand-alone basis and brings limited diversification benefits.

Figure 52: Backtest results for defensive cross-asset mean-reversion strategy



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 30:Correlation statistics with ES1 Index

Overall correlation	-22.70%
Correlation when ES1 returns are negative	-23.91%

Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 31: Performance statistics

	Mean-Reversion Cross-Asset Strategy	ES1 Index	Combination of Mean-Reversion Cross-Asset Strategy and ES1 Index
Ann Return	3.86%	6.00%	9.86%
Ann Volatility	18.67%	18.67%	23.21%
Sharpe	0.21	0.32	0.42
Max DD	50.02%	61.38%	52.23%
Skewness	3.10	0.15	1.09
Kurtosis	66.59	12.44	22.84

Source: J.P. Morgan Quantitative and Derivatives Strategy

The defensive cross-asset mean-reversion strategy provides strong diversification benefit and its gain more than offsets the loss in S&P500 during the GFC. There are diversification benefits after the dot-com bubble as well. The overall correlation to S&P is below -0.2.

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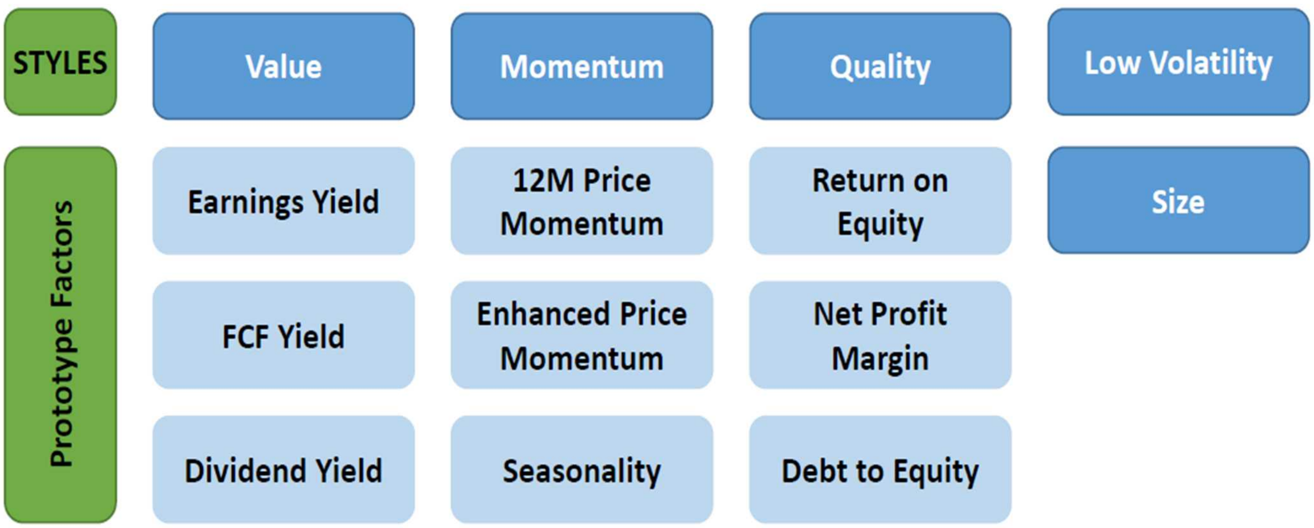
Defensive Long/Short Equity Factors

Post the global financial crisis, the quant community has focused more on multi-factor stock allocation models rather than single factors. In the Equity Risk Premia Strategies primer by Kolanovic (2014) a framework for Equity Risk factor investing including Value, Momentum Quality and Volatility was introduced.

Figure 53: Equity risk factor framework



Source: J.P. Morgan Quantitative and Derivatives Strategy

The defensive characteristics of **quality** and **low volatility low/short equity factors** have already been discussed in Equity Risk Premia Strategies primer by Kolanovic (2014). For the current application, we use the pure quality and low volatility factors described in The Quest for Pure Equity Factor Exposure

The universe of stocks is the applicable MSCI regional index (MSCI World), excluding stocks that are undergoing corporate actions. Each month-end we calculate the measure (or measures) used to construct the Risk Factor.

Pure Defensive Long/Short Equity Factors

The common definition of a pure equity factor is an equity factor portfolios that solely contains an exposure to one particular style with no any overlap with other styles and no impact of country or sector exposures on the portfolio return.

In the Equity Risk Premia Strategies primer by Kolanovic (2014) various ways to construct beta-neutral styles as well sector/country normalization methods have been analyzed. Removing any potential overlap among styles calls for additional techniques and processes. Nowadays achieving pure factor exposure almost certainly entails a statistical/numerical procedure.

Let's assume that the cross-section of *n* stock returns is driven by a *m* factor model:

$$R_i = \alpha + \beta_i R_m + RF_1 Score_{i,1} + RF_2 Score_{i,2} + \cdots + RF_m Score_{i,m} + \varepsilon_i,$$

where R_i is the return of stock i, R_m is the market return, β_i is the market beta of stock i, RF_j is the excess return of factor j and $Score_{i,j}$ is the score/exposure of stock i with respect to factor j.

The factors are the various equity styles – quality, value, momentum, size and low volatility and also the respective region and sector affiliations. Similarly the scores of the individual stocks are either Z-scores for the equity factors or 0/1 dummy variables for the region/sector affiliation.

For our standard pure factors implementation we maximize the exposure to desired factor subject to the following constraints:

- Neutrality to the other factors
- No market, country or regional exposure
- Volatility target
- Realistic trading constraints (max position size, turnover etc).
- Note that without those constraints there is analytical solution (the so-called factor mimicking portfolios).

For achieving a more defensive stance for the current implementation we have relaxed the constraint on the market exposure and we impose a negative exposure to the market in our optimization approach. In particular:

- We maximize the combined expected portfolio return represented as:

$$Max\ \boldsymbol{w}'\mathbf{Scores}_{EqFactor} * Vol(EqFactor) + \boldsymbol{w}'\boldsymbol{Betas}_{EqBenchmark} * Vol(EqBenchmark),$$

  where $\boldsymbol{w}$ are the positions to be found, $EqFactor$ denotes the factor of interest – in this case either quality or low volatility, $\mathbf{Scores}_{EqFactor}$ are the scores of the stock with respect to the factor of interest and $\boldsymbol{Betas}_{EqBenchmark}$ are the betas of the stocks in our universe with respect to the benchmark.

- We impose the following constraint guaranteeing a certain level of negative market exposure:

$$\boldsymbol{w}'\boldsymbol{Betas}_{EqBenchmark} * Vol(EqBenchmark) < -0.5 * \boldsymbol{w}'\mathbf{Scores}_{EqFactor} * Vol(EqFactor)$$

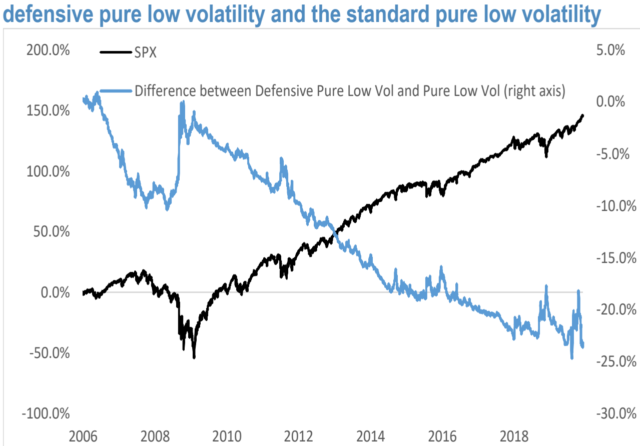
$$\boldsymbol{w}'\mathbf{Scores}_{EqFactor} > 0$$

- We keep the remaining constraints from the standard implementation mentioned above - no country or regional exposure, volatility target, trading constraints

Therefore in this approach we have preference for stocks that have high score with respect to the factor of interest and low beta to the equity benchmark.

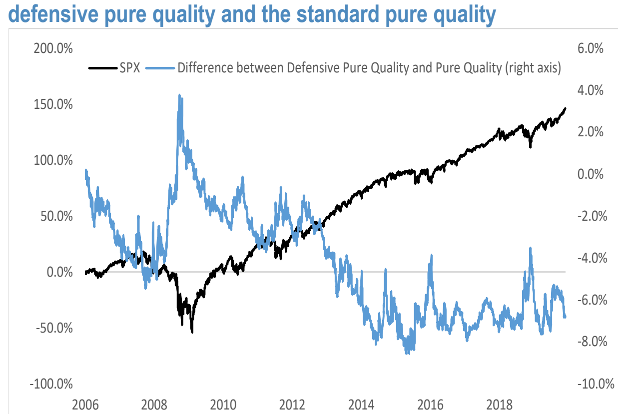
Below we show the difference in the performance between the defensive pure quality and low vol factors and there standard pure implementation. We can clearly notice the impact the negative market exposure through time.

Figure 54: Cumulative difference in the performance between the defensive pure low volatility and the standard pure low volatility



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 55: Cumulative difference in the performance between the defensive pure quality and the standard pure quality



Source: J.P. Morgan Quantitative and Derivatives Strategy

Low-vol Defensive Pure Equity Factor

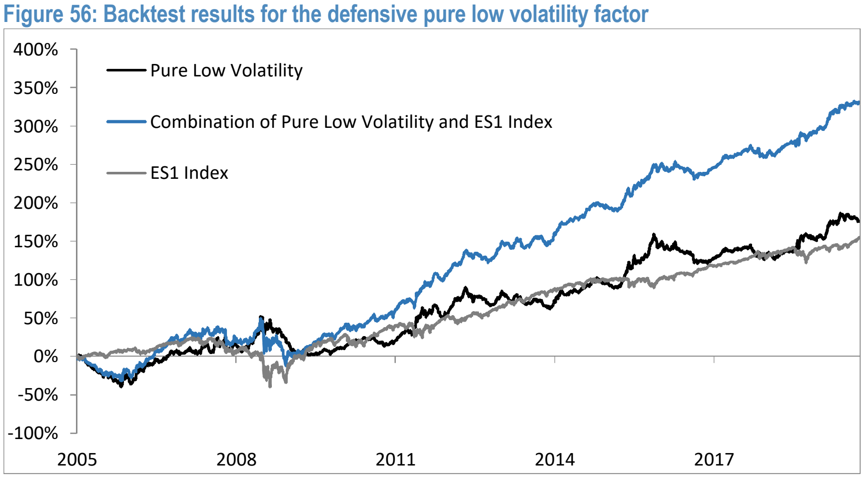
Various explanations have been put forward for existence of the low-vol risk premia. While detailed discussion is beyond the scope of the current paper below we have listed the ones we find the most important:

- The structurally low beta of low vol stocks restrains long only institutional investors tracking equity benchmarks from overweighting them.
- A behavioral explanation of Low Volatility phenomenon is the "Lottery Effect". In any given period, like a lottery, a high volatility stock can have a small probability to deliver very high return. This may result in overpaying for high volatility stocks and thus lead to an associated lower future performance.

During crisis times high volatility/beta stocks are the first to be sold to meet risk budgets and stop-loss constraints which benefits the low volatility strategy.

Below in turn we show the backtest of the defensive pure low volatility strategy and the relevant performance characteristics.

Figure 56: Backtest results for the defensive pure low volatility factor



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 32:Correlation statistics with ES1 Index

Overall correlation	-26.36%
Correlation when ES1 returns are negative	-19.76%

Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 33: Performance statistics

	Defensive Pure Quality	ES1 Index	Combination of Defensive Pure Quality and ES1 Index
Ann Return	11.7%	10.3%	21.9%
Ann Volatility	18.2%	18.2%	22.1%
Sharpe	0.64	0.56	0.99
Max DD	42.5%	52.0%	51.5%
Skewness	-0.43	0.31	0.44
Kurtosis	12.73	16.97	14.33

Source: J.P. Morgan Quantitative and Derivatives Strategy

As it has been well-documented the pure low volatility strategy displays strong performance. Furthermore, due to the additional short market constraint the returns of the pure defensive low volatility strategy are negatively correlated to S&P500.

As our pure equity factors are constantly targeted to a certain level of volatility their diversifying properties are not that evident in combination with S&P500. Note that instead we can have a varying volatility target through time in order to match the recent volatility of S&P500.

Quality Pure Long/Short Equity Factor

The Quality factor relies on the balance sheet and income statement that indicate the company's ability to sustain earning over time.

The market appears to reward relative earnings certainty and penalize the stocks that carry a large degree of earning volatility.

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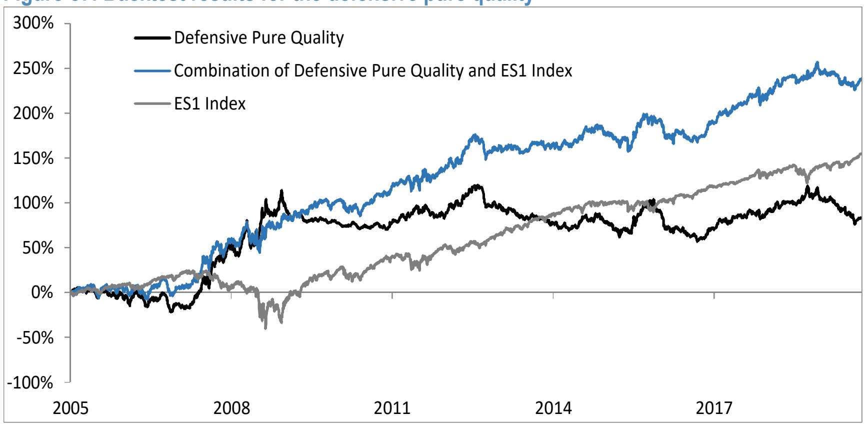
Figure 57: Backtest results for the defensive pure quality



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 34:Correlation statistics with ES1 Index

Overall correlation	-14.15%
Correlation when ES1 returns are negative	-20.19%

Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 35: Performance statistics

	Defensive Pure Quality	ES1 Index	Combination of Defensive Pure Quality and ES1 Index
Ann Return	5.6%	10.3%	15.8%
Ann Volatility	18.2%	18.2%	23.9%
Sharpe	0.31	0.56	0.66
Max DD	49.8%	52.0%	31.0%
Skewness	-0.01	0.31	0.27
Kurtosis	2.04	16.97	4.89

Source: J.P. Morgan Quantitative and Derivatives Strategy

The defensive pure quality factor displays strong diversification properties especially during the sell-off during 2008. Similarly to the defensive low volatility strategy its overall correlation to S&P500 is negative and the combination of S&P500 and the pure defensive quality strategy has attractive risk-return characteristics.

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Tactical hedging

Tactical hedging approach aspires at determining the right time to place hedges and their optimal size. This goal is achieved by a systematic signal that should provide us with an early warning. We position for a risk-off environment depending on the strength of the signal by taking short positions in equities, oil and credit (buying credit protection) and long positions in bonds, USD, gold and volatility. For the current application the tactical hedging approach itself consists of two approaches: a **comprehensive flow-based sentiment indicator** and the **cross-asset volatility-based sentiment indicator**.

Comprehensive Flow-based Sentiment Indicator

Comprehensive sentiment indicator has been designed to measure the sentiment in the equity markets and has been proposed by Das et al. in Asia Portfolio Strategy: Utilising Sentiment for Better Positioning. The aggregated indicator includes technical inputs, flow, volatility, positioning and sentiment surveys.

The table below details the inputs for the calculation of the comprehensive flow-based indicator[10]:

Figure 58: Inputs for the calculation of the comprehensive flow-based indicator

	Methodology?	Why used?
Equity flows	3m rolling sum of subscriptions to both mutual funds and ETFs.	Faster inflows indicate higher optimism among retail investors.
Equity futures positioning	Aggregated (dollar terms) net long Non-commercial positioning / total open positions on SPX (large and mini), INDU, RTY and NDX.	Larger net long positioning indicates higher optimism among macro investors and asset managers.
Equity to bond volatility (inverted)	Ratio of VIX / MOVE.	Relative risk pricing in equities vs bonds. Lower level indicates higher equity optimism towards equities among cross-asset investors.
Survey-based sentiment	AAII's survey of individual investors, sentiment towards the stock market over the next 6 months. BULL - BEAR Spread is used.	More expressions of bullish sentiment also indicate higher optimism among retail investors.
HF positioning	5m beta of HFR equity hedge fund index beta to MSCI ACWI	Higher beta of hedge funds' performance to equity index reflects higher net exposure (more optimism) among HFs.
Put / Call volumes (inverted)	CBOE total equity put option volume divided by total equity call option volume.	More investors buying calls (vs puts) indicates greater upside expectation among derivatives investors.
Technicals	9D Exponential moving average of 12D-26D moving average of MSCI ACWI.	One popular measure of technicals. Positive technicals likely to result in increased equity buying from systematic investors (like CTAs). Note that the combination of passive/index, systematic and quant investors makes up a vast majority of trading volumes in the US.

Source: J.P. Morgan Quantitative and Derivatives Strategy

[10] The indicator can be found on Bloomberg under the following ticker: JPMEQGSI Index.

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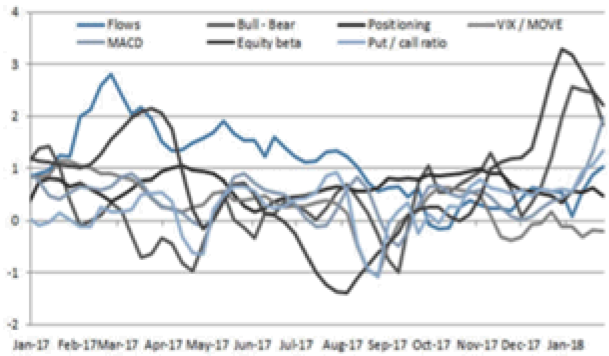
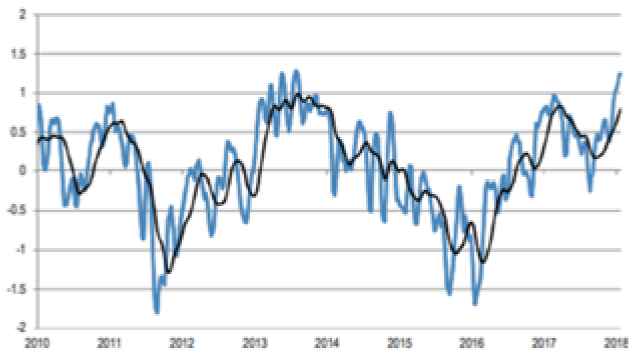
Figure 59: Various measures of sentiment



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 60: Composite Sentiment Indicator



Source: J.P. Morgan Quantitative and Derivatives Strategy

J.P. Morgan Research launched the indicator in Feb 2018 and it has been running live since then.

There are four distinct states of the indicator and each one of them has different hedging implications:

- **Benign**: When the 3MMA is above the long-term trend (based on 2Y) and the weekly index is not far from the 3MMA, market sentiment is broadly positive. Investors should have relatively high equity positioning in this environment. There is no hedge exposure in this scenario.
- **Contrarian bullish:** When the 3MMA is below the long-term trend and weekly indicator is materially lower than the 3MMA, investors should be opportunistic and position for a contrarian rally until the indicator normalizes relative to the moving average. Hence, there is no hedge exposure in this scenarios as well.
- **Cautious**: When the 3MMA is above the long term trend and weekly indicator is materially higher than the 3MMA, investors should be cautious about a potential mean reversion in sentiment and reduce risk exposure until the indicator normalizes relative to the moving average. The suggested hedge exposure is 25%.
- **Unfavorable:** When the 3MMA is below the long term trend and the weekly index is not far from the 3MMA, market sentiment is unfavorable, investors should avoid equity exposure. The suggested hedge exposure is 100%.

The backtest results of the application of the indicator are shown below. Note that in this case we apply the hedging strategy solely to S&P500 and we do not use assets from other asset classes to perform hedging.

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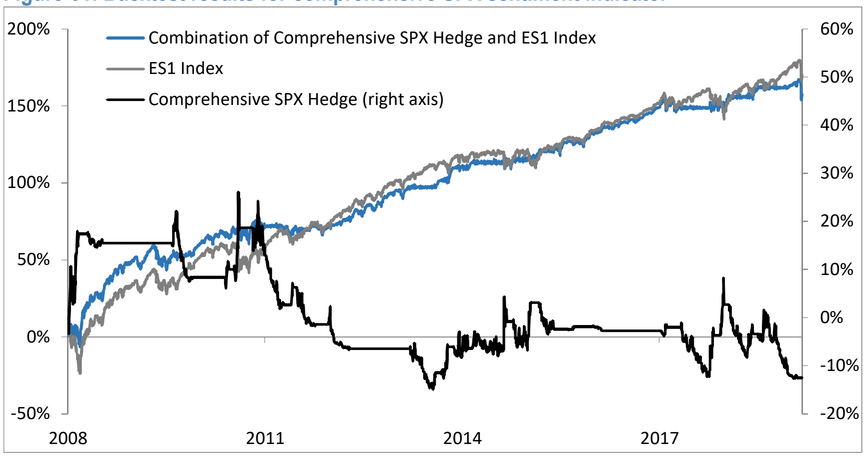
Figure 61: Backtest results for comprehensive SPX sentiment indicator



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 36: Performance statistics

	Comprehensive SPX Hedge	ES1 Index	Combination of Comprehensive SPX Hedge and ES1 Index
Ann Return	-1.1%	15.2%	14.1%
Ann Volatility	10.5%	16.4%	20.0%
Sharpe	-0.11	0.93	0.70
Max DD	35.1%	27.4%	16.4%
Skewness	0.72	-0.29	-0.52
Kurtosis	19.57	5.31	9.80

Source: J.P. Morgan Quantitative and Derivatives Strategy

While the use of comprehensive flow based sentiment as an overlay does not improve upon the Sharpe ratio of the standalone long position in S&P500, the combined portfolio displays attractive risk-return characteristics with the drawdown of the combined portfolio dropping below the annualized volatility[11].

Cross-asset Volatility-based Sentiment Indicator

The volatility-based indicator has originally been constructed to time the investments in short FX volatility strategies (Ravagli, L. and Duran-Vara, J.; Timing FX Short-Vol Strategies: A systematic Approach). The majority of the inputs are volatility related and for the current application we have used the global components of the indicator plus the 1M realized volatility of the underlying as an asset specific variable.

For the current application we have used the global components of the indicator plus the 1M realized volatility of the underlying. The majority of indicators are vol related.

Figure 62: Inputs for the calculation of the Cross-asset Volatility-based Sentiment Indicator

Global variables		
JPM VXY G7 Index		
VIX Index	+	1M Realized Vol
3M1Y USD swaptions		
Ted spread		
Gold/silver ratio		

Source: J.P. Morgan Quantitative and Derivatives Strategy

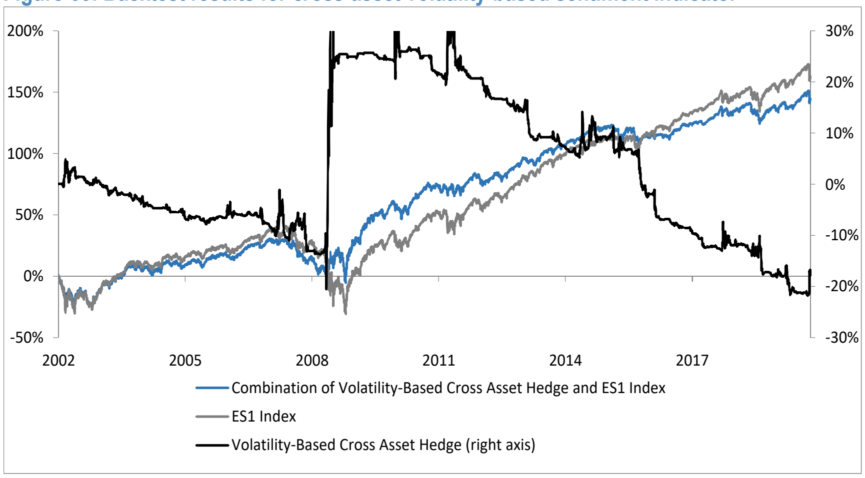
[11] The netting effect between the long position of S&P500 and the hedging position have been taken into account when the transaction costs have been calculated.

Every input is converted to a binary signal depending on its own Z-score based on 6M history. Then the global inputs are averaged and subsequently this average of the global variables is in turn averaged with the binary signal for the 1M realized volatility. The final signal varies from 0 to 1 with 1 implying 100% hedging position.

Note that the resulting volatility-based indicator is calculated for assets from different asset classes. The hedging approach is analogical to the one for the asymmetric trend-following and the defensive mean-reversion strategy.

First, the signals are calculated for various equity, fixed income and credit, currencies and volatilities. Second, according to the size of the signals we take short positions in equities, commodities (except for gold), credit (we buy credit protection) and long positions in fixed income, the dollar and volatility. In the end we obtain the aggregated records for hedging performance per asset class and then we arrive at aggregated cross-asset volatility-based hedging solution.

Figure 63: Backtest results for cross-asset volatility-based sentiment indicator



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 37: Performance statistics

	Volatility-Based Cross Asset Hedge	ES1 Index	Combination of Volatility-Based Cross Asset Hedge and ES1 Index
Ann Return	-1.0%	8.8%	7.8%
Ann Volatility	9.6%	18.3%	14.9%
Sharpe	-0.10	0.48	0.52
Max DD	43.9%	56.3%	34.2%
Skewness	0.11	0.18	-0.04
Kurtosis	99.79	14.81	6.30

Source: J.P. Morgan Quantitative and Derivatives Strategy

While on a standalone basis the performance of the cross-asset volatility based sentiment indicator is close to flat it brings substantial diversification benefits (especially during the GFC). The overall Sharpe ratio has been marginally improved and the drawdown has also been much better controlled.

Satellite Strategies

The satellite defensive strategies are more recent innovative systematic strategies that display risk-off characteristics and typically may face capacity constraints. We have put forward two satellite defensive strategies: intraday momentum and correlation break-out capture**.**

Intraday Momentum

Rationale for the Existence of Intraday Momentum

The reasons for the existence of the intraday momentum pattern have been extensively analyzed by Kolanovic et al. in Market Impact of Derivatives Hedging-Daily Patterns and Ravagli et al. in Optimal Option Delta-Hedging.

Intraday momentum and mean-reversion are closely related strategies.

Kolanovic (2009) shows that intra-day momentum can lead to mean-reversion:

- The over-reaction into the close is corrected in the next days
- The asset allocation rebalances can result in mean-reversion

In turn mean-reversion can lead to intra-day momentum (Ravagli et al. (2018)):

- Mean-reversion leads to an expected move during the day (conditional on the previous day return).
- This move is most likely to be realized in a momentum fashion

While the intra-day momentum pattern has been actively discussed by practitioners for some time it has only recently been analysed on the academic side:

- Gao, L.; Han, Y.; Li, S. and Zhou, G. (2018), "**Market Intraday Momentum**", *Journal of Financial Economics*, Volume 129, Issue 2, August 2018, Pages 394-414.A strong intraday momentum pattern is found in the S&P500 ETF: the first half-hour return on the market as measured from the previous day's market close predicts the last half-hour return. The predictability has been found to be stronger on: more volatile days, higher volume days, recession days and on days with major macro-economic announcements. One potential explanation is the fact that most news are released before the start of trading and on positive news the market goes up. Speculators provide liquidity by going short and if the market keeps on trending during the day they will rush to close the shorts towards the end of the trading day (disposition effect). Another explanation is that the trading volume has a U-shaped pattern and informed traders trade tend to trade during high volume- if they bid at the open, they will most probably buy into the close as well.

- Heston, S.; Korajczyk, R. and Sadka, R. (2010), "**Intraday Patterns in the Cross-Section of Stock Returns**". *Journal of Finance*, 65, 1369–1407. A statistically significant positive relation between a stock's return over a given half-an-hour interval and its subsequent returns during the same time interval at daily frequencies.

- Bogousslavsky, V. (2013), "**Infrequent Rebalancing, Return Autocorrelation, and Seasonality**", *Journal of Finance*, Volume 71, Issue 6, December 2016, p. 2967-3006. A model with infrequent rebalancing is proposed that can explain the two effects above.

Intraday Momentum Signal based on the Replication of the Difference between Variances Calculated over Different Timescales

As we have discussed in Designing Robust Trend-Following System when the momentum signals are based on just a few observations the profitability is more dependent on the magnitude of the positive autocorrelations than on the magnitude of the trend. Therefore, to benefit from the positive autocorrelation at the nearby lags we can employ the same logic as in the case of mean-reversion and invert the mean-reversion signal.

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$$Position_{t,T} = \sum_{i=0}^{T-2} (T - i - 1) * R_{t-i}$$

$$PnL_{t+1,T} = R_{t+1} \sum_{i=0}^{T-2} (T - i - 1) * R_{t-i}$$

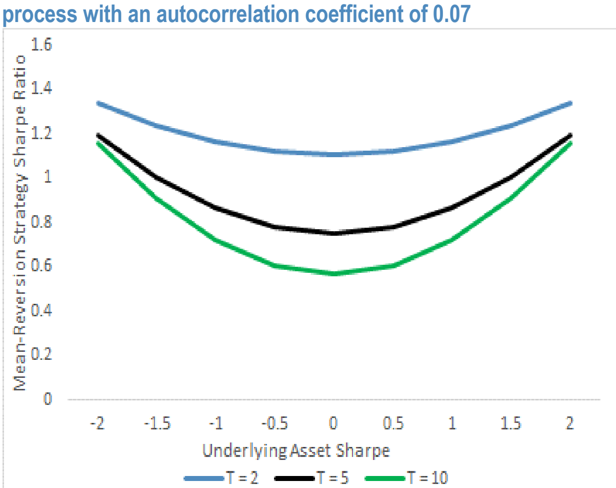
$$E(PnL_{t+1,T}) = \sigma^2 \sum_{i=1}^{T-1} (T - i) * \rho_i + \mu^2 * T * \frac{T-1}{2} = \frac{Var_T - TVar_1}{2} + \mu^2 * T * \frac{T-1}{2}$$

The intraday momentum strategy profits when the volatility increases and the autocorrelations at lag i are positive. In contrast to mean-reversion, the intraday momentum strategy benefits from convexity with respect to the trend of the underlying asset (μ^2).

Furthermore, intraday momentum strategy can profitable even if there is no trend but the autocorrelations are positive or if there is a trend but the autocorrelations are zero.

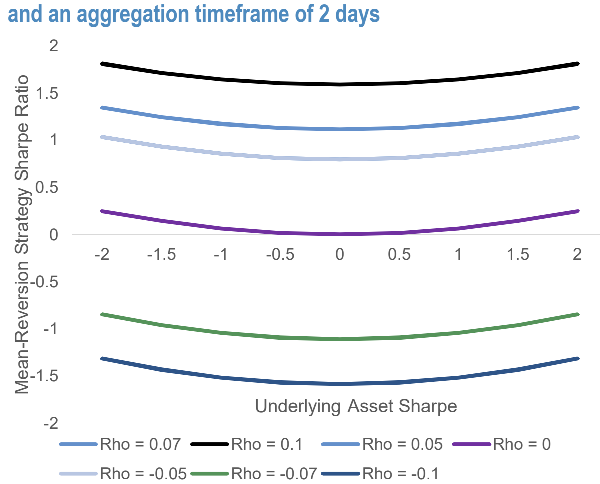
If we assume an AR(1) process we can use the analytical derivations for the risk-return profile for the mean-reversion strategy.

Figure 64: P&L profile for different timeframes in case of an AR(1) process with an autocorrelation coefficient of 0.07



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 65: P&L profile for different autocorrelation coefficients and an aggregation timeframe of 2 days



Source: J.P. Morgan Quantitative and Derivatives Strategy

Naturally the strategy benefits from positive convexity (the reverse of mean-reversion) and a strong trend in either direction increases the profitability. Similarly to mean-reversion the optimal timeframe for the returns aggregation and calculating the variance is 2 days, i.e. the position is just the previous day return. Even small levels of negative autocorrelation are sufficient to offset the profitability of the strategy.

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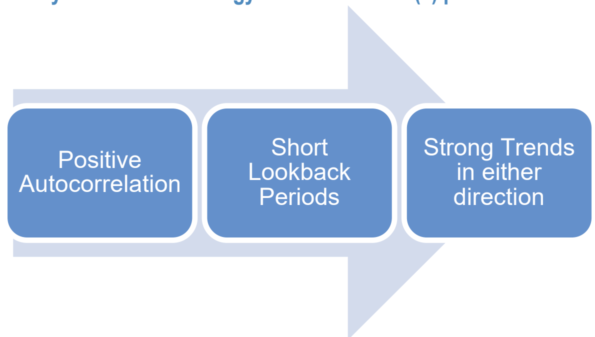
Figure 66: Profitability drivers for the intraday momentum strategy in case of an AR(1) process



Source: J.P. Morgan Quantitative and Derivatives Strategy

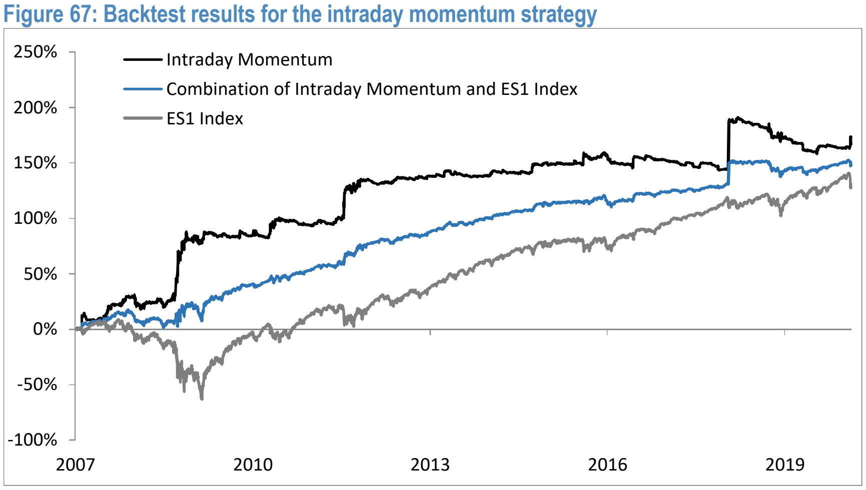
Furthermore, an additional benefit of the intraday momentum strategy is that it does not warehouse risk overnight as any positions are closed at the end of the day.

As in the case of mean-reversion, the defensive profile of the strategy can be increased even further if positions are taken only in desired direction – for example short equities and long volatility.

Empirical Results

Below we present an aggregated backtest of the intraday momentum strategy applied to S&P500 future and the VIX future. The intraday momentum signal is based on the daily versus hourly variance.

Figure 67: Backtest results for the intraday momentum strategy



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 38: Performance statistics

	Intraday Momentum	ES1 Index	Combination of Intraday Momentum and ES1 Index
Ann Return	12.7%	10.0%	11.4%
Ann Volatility	19.6%	19.6%	11.9%
Sharpe	0.65	0.51	0.95
Max DD	29.3%	56.3%	15.8%
Skewness	12.89	0.15	6.75
Kurtosis	363.72	15.14	128.44

Source: J.P. Morgan Quantitative and Derivatives Strategy

The intraday momentum strategy demonstrates string diversification properties. The combined portfolio displays attractive risk-return characteristics with an improved Sharpe ratio and drawdown smaller than two times the volatility.

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Correlation Breakout Capture

Rationale

Correlation break-out capture is an innovative strategy that aims to capture the transition to a new volatility/correlation regime of higher volatility/higher correlation among risky assets during sell-offs. A systematic strategy is constructed that profits in risk-off times and has contained losses when markets normalize.

It is an empirical fact that volatilities and correlations among risky-assets can increase sharply during risk-off times. Also, riskier assets and assets with safe heaven features will de-correlate.

A strategy can be designed in the delta-one space that aims captures the transition to the new correlation/vol regime.

Let's first look at the case for assets that get more correlated during risk off. We are aiming to design a strategy with a P&L function like the one below:

$$E(PnL) \sim (\rho_{1D} - \rho_{2D})\,\sigma_{Asset1}\sigma_{Asset2}$$

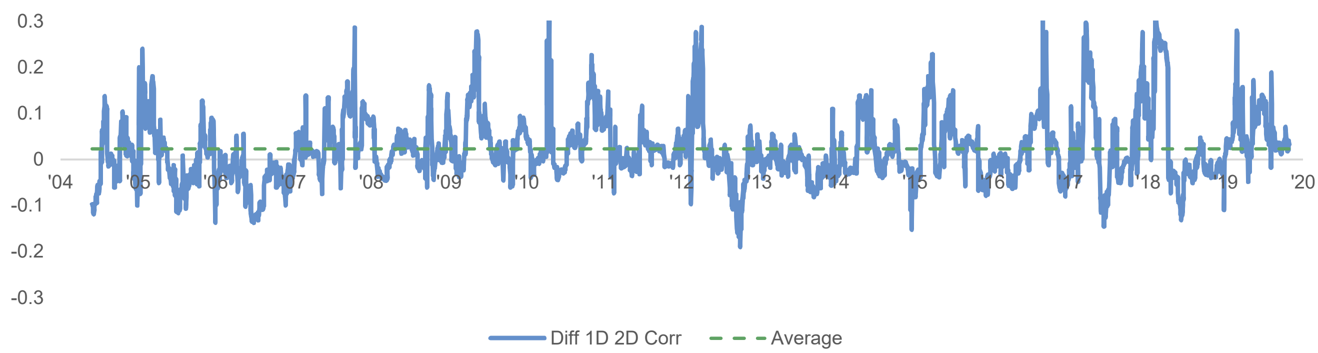
where ρ_{1D} is the correlation between the daily returns of the two assets and ρ_{2D} is the correlation between the cumulative two-day returns of the two assets, σ_{Asset1} and σ_{Asset2} are the volatilities of the two assets.

Then during risk-off times we can benefit from the simultaneous jump in correlations (with $\rho_{1D} - \rho_{2D}$ increasing and being positive) and increase in volatilities.

Similarly to a mean-reversion strategy during normalization (post the sell-off) we would expect the strategy to incur a loss ($\rho_{1D} - \rho_{2D}$ can turn negative). As the losses will be happening in an environment of lower volatility, the negative P&L impact will be contained.

As an example, below we consider the correlations between the daily returns (ρ_{1D}) and the two-day cumulative returns (ρ_{2D}) of a long S&P500 position and a short VIX position.

Figure 68: Difference between the correlation of the daily returns (ρ_{1D}) and the correlation of two-day cumulative returns (ρ_{2D}) of a long S&P500 position and a short VIX position



Source: J.P. Morgan Quantitative and Derivatives Strategy

We can clearly see the pattern of increasing correction during crisis periods with subsequent normalization after that.

For assets that de-correlated during risk-off times the reverse holds: we aim to get exposure to $\rho_{2D} - \rho_{1D}$. As an example we can consider a combination of long Gold futures position and a long Gold Miners position. During risk-off times Gold and Gold miners will de-correlate due to the safe-haven nature of gold.

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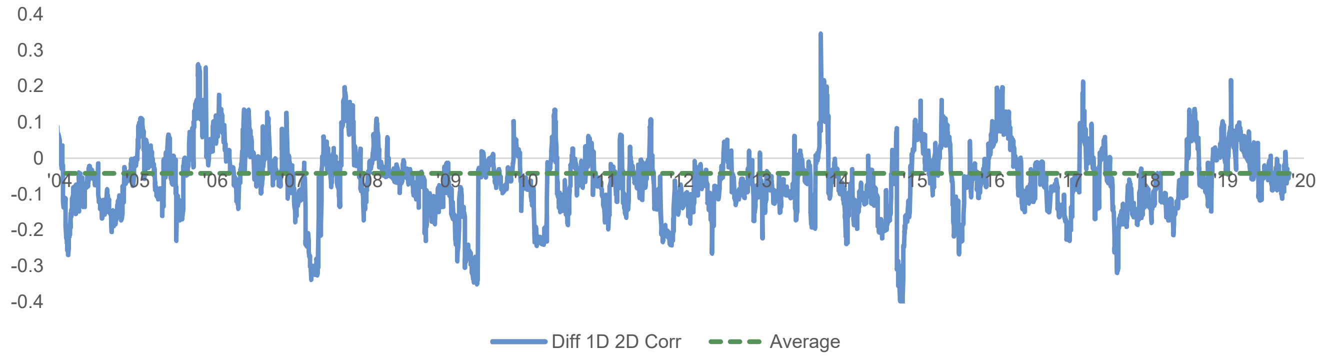
Figure 69: Difference between the correlation of the daily returns (ρ_{1D}) and the correlation of two-day cumulative returns (ρ_{2D}) of long positions in Gold and Gold miners

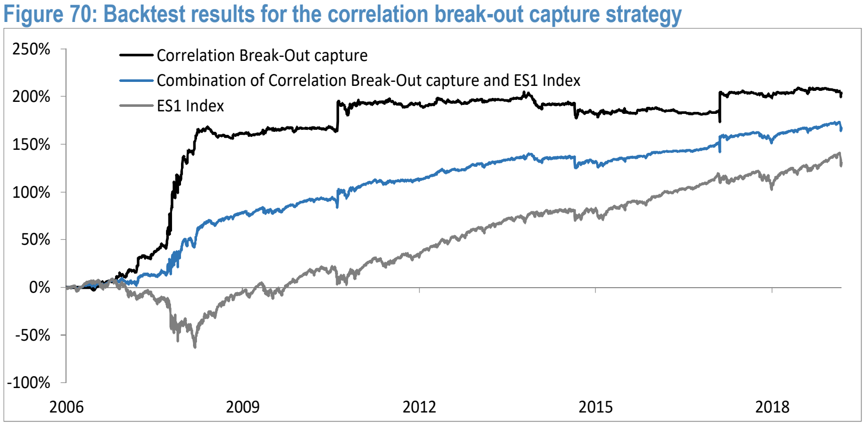


Source: J.P. Morgan Quantitative and Derivatives Strategy

Empirical results

Below we present an aggregated backtest of the intraday breakout capture strategy applied to 5 asset pairs: VIX and S&P 500, S&P500 and Emerging equity markets (EEM), S&P 500 and Chinese equity markets (FXI), Gold and Gold Miners (GDX), S&P 500 & US Treasuries.

Figure 70: Backtest results for the correlation break-out capture strategy



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 39: Performance statistics

	Correlation Break-Out capture	ES1 Index	Combination of Correlation Break-Out capture and ES1 Index
Ann Return	15.0%	9.6%	12.3%
Ann Volatility	19.2%	19.2%	14.8%
Sharpe	0.78	0.50	0.83
Max DD	29.4%	56.3%	15.9%
Skewness	6.38	0.15	2.96
Kurtosis	131.85	15.84	66.95

Source: J.P. Morgan Quantitative and Derivatives Strategy

Similarly to intraday momentum the strategy demonstrates strong diversification properties. The combined portfolio has an attractive risk-return characteristics with an improved Sharpe ratio and with a drawdown commensurate to the historical volatility.

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Portfolio Construction for Risk-off Times

In our opinion the portfolio construction approach for a defensive risk premia portfolio should incorporate at least three specific elements:

- Taking into account the higher moments (like skewness and kurtosis) in the optimisation process.
- Account for the specific features of the asset (or the portfolio) for which we are seeing protection.
- The results of the optimization process shall be easily implementable in real-life.

First, it is well-known that many of the less appealing statistical properties of traditional markets (like negative skewness and outsized kurtosis) are linked to the sizable negative returns during periods of sell-offs and rising risk aversion.

We make use of a portfolio optimization approach that takes into account the higher moments of the portfolio return (like skewness and kurtosis) in addition to the mean and the variance. The methodology relies on the optimization of **CRRA** (constant relative risk aversion) utility function and has been introduced in Optimal Portfolio Construction – Beyond Risk Parity by Cheng et al. Another recent application can be found in From Relative Value Signals to Optimal Portfolio Weights. The methodology allows for the incorporation of higher moments like skewness and kurtosis in addition to the mean and the variance.

In more detail we try to find a set of strategies weights w that will be the result of the optimization of the following **CRRA** function below. r_{def} is the vector of the returns of the defensive risk premia and w is the set of weights we aim to determine:

$$\max_w E[U(w)] = \frac{1}{1-\gamma} E[\left(1 + w^T r_{def}\right)^{1-\gamma}]$$

The overall portfolio expected return is $r_p = w^T r_{def}$. Applying Taylor expansion to the CRRA utility function above we can see how the higher moments impact the optimisation:

$$E[U(r_p)] = U(0) + U'(0).E[r_p] + \frac{1}{2!}U''(0).E[{r_p}^2] + \frac{1}{3!}U^{(3)}(0).E[{r_p}^3] + \frac{1}{4!}U^{(4)}(0).E[{r_p}^4] + \cdots,$$

with $U(0) = \frac{1}{1-\gamma}$, $U'(0) = 1$, $U''(0) = -\gamma$, $U^{(3)}(0) = \gamma^2 - \gamma$, $U^{(4)}(0) = -\gamma^3 - \gamma^2 + 2\gamma$ etc.

Second, the optimization of the defensive portfolio should not be a stand-alone process and performed in isolation. It is important to take the inherent characteristics of the market that the defensive risk premia portfolio will provide protection for are taken into account during the portfolio construction process. In our optimization approach we take into account the moments of the combined portfolio (consisting of asset to be hedged plus overlay defensive risk portfolio) to arrive at our recommendation. Optimizing the defensive risk premia portfolio on a stand-alone basis can be shown to lead to suboptimal results.

Therefore in the optimisation function we add the return of SPX to the combined return of the portfolio of defensive risk premia strategies:

$$\max_w E[U(w)] = \frac{1}{1-\gamma} E[\left(1 + ret_{spx} + w^T r_{def}\right)^{1-\gamma}]$$

In this way we expect to achieve a combined portfolio of defensive risk premia strategies as an overlay and S&P500 with superior risk-return characteristics.

Last but not the least the portfolio recommendations shall be implementable in the real-life environment. We have already discussed that some of the strategies have lower capacity constraints than some of the rest. During the optimization process we impose particular constraints so that the core, tactical hedging and satellite strategies receive allocations that can be implemented in a real-life setting.

We start by defining a static portfolio of defensive risk premia strategies that has constant allocations to the various strategies through time. This is static allocation is based predominantly on reasoning around capacity constraints and the investors experience with some of the strategies. The breakdown of this static allocation is shown below:

Table 40: Allocation breakdown for the static portfolio of defensive risk premia strategies

	Core Strategies	Tactical Hedging	Satellite Strategies
Group Allocation	70%	15%	15%
Per Single Strategy within the Group	14%	7.5%	7.5%

Source: J.P. Morgan Quantitative and Derivatives Strategy

Subsequently we compare the performance of the optimized portfolio to the static one. To perform the optimization we allow for some flexibility around the static weights by imposing the following constraints:

Table 41: Allocation bounds for the optimized defensive portfolios

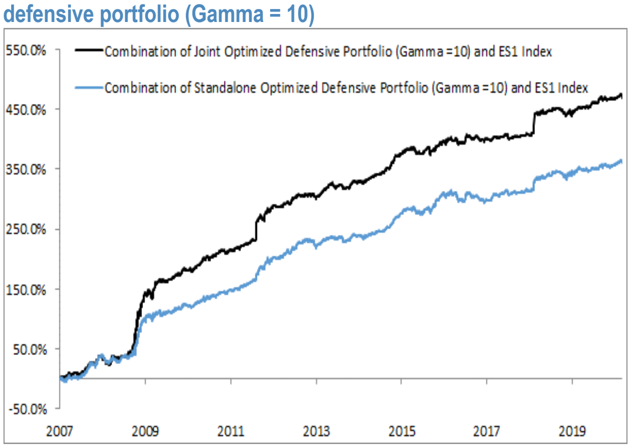
	Core Strategies		Tactical Hedging		Satellite Strategies	
	Lower Bound	Upper Bound	Lower Bound	Upper Bound	Lower Bound	Upper Bound
Group Allocation	50%	90%	0%	30%	0%	30%
Per Single Strategy within the Group	5%	36%	0%	30%	0%	30%

Source: J.P. Morgan Quantitative and Derivatives Strategy

Performance of the Optimized Defensive Portfolios

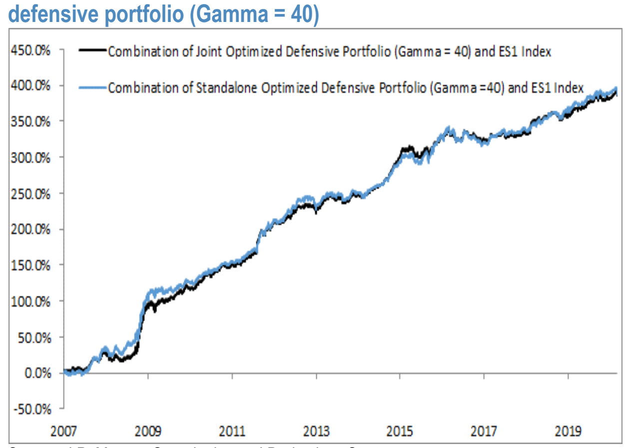
We start our analysis by performing optimizations with different Gamma parameters (10 and 40) and investigate the performance of the combined portfolios with S&P500 when the S&P 500 return has been taken into account (joint optimization) and when it has not (stand-alone optimization). This initial part of the analysis is done in-sample and subsequently we focus on the out-of-sample performance.

Figure 71: Performance of the joint and standalone optimized defensive portfolio (Gamma = 10)



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 72: Performance of the joint and standalone optimized defensive portfolio (Gamma = 40)



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 42: Performance statistics for the Joint and Standalone Optimized defensive portfolio (Gamma = 10 and 40)

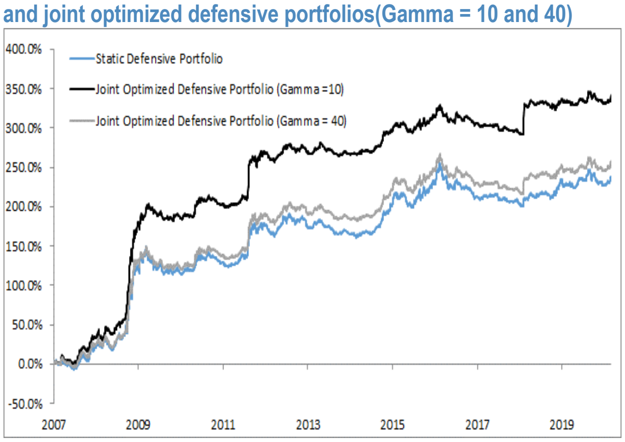
	Gamma = 10		Gamma = 40	
	Combination of Joint Optimized Defensive Portfolio and ES1 Index	Combination of Standalone Defensive Portfolio and ES1 Index	Combination of Joint Optimized Defensive Portfolio and ES1 Index	Combination of Standalone Defensive Portfolio and ES1 Index
Ann Return	34.2%	26.1%	28.3%	28.5%
Ann Volatility	20.9%	19.4%	17.1%	19.8%
Sharpe	1.63	1.35	1.66	1.44
Max DD	15.8%	20.8%	18.5%	28.1%
Skewness	4.93	2.66	1.63	1.69
Kurtosis	64.94	30.12	16.45	17.76

Source: J.P. Morgan Quantitative and Derivatives Strategy

We can witness that taking into account the properties of S&P500 results in a better overall performance of the combined portfolio (defensive strategies+S&P500) -the Sharpe ratios are better and the drawdowns are quite well-controlled. All of the combined portfolios achieve positive skewness and the difference in the performance between a standalone and joint optimization seems more important when Gamma parameter is lower. Note that the higher Gamma decreases the kurtosis but also pushes the positive skewness down (skewness and kurtosis are interlinked via the relationship $kurtosis > 1 + skewness^2$).

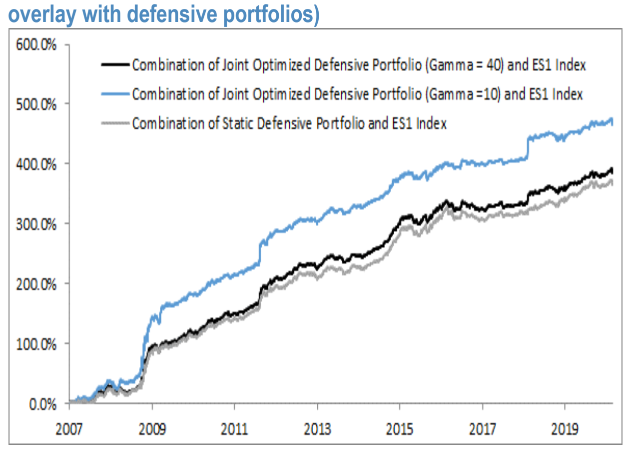
We proceed by comparing the performance of the static allocation to optimized versions.

Figure 73: Performance statistics for the static defensive portfolio and joint optimized defensive portfolios(Gamma = 10 and 40)



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 74: Performance of the combined portfolios (S&P500 overlay with defensive portfolios)



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 43: Performance statistics for the static defensive portfolio and joint optimized defensive portfolios (Gamma = 10 and 40)

	Static Defensive Portfolio	Joint Optimized Defensive Portfolio (Gamma = 10)	Joint Optimized Defensive Portfolio (Gamma = 40)	Combination of Static Defensive Portfolio and ES1 Index	Combination of Joint Optimized Defensive Portfolio (Gamma = 10) and ES1 Index	Combination of Joint Optimized Defensive Portfolio (Gamma = 40) and ES1 Index
Ann Return	17.5%	24.8%	18.9%	26.9%	34.2%	28.3%
Ann Volatility	19.2%	19.2%	19.2%	17.8%	20.9%	17.1%
Sharpe	0.91	1.29	0.98	1.51	1.63	1.66
Max DD	55.9%	38.0%	51.2%	24.5%	15.8%	18.5%
Skewness	0.79	3.58	2.15	0.98	4.93	1.63
Kurtosis	12.24	36.55	22.77	10.36	64.94	16.45

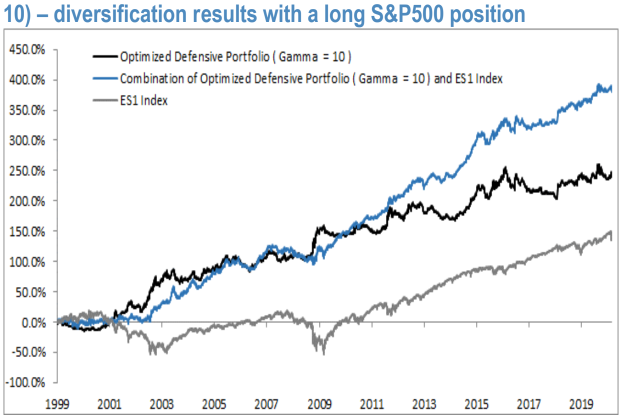
Source: J.P. Morgan Quantitative and Derivatives Strategy

The optimized portfolios outperform the statistic version in term of Sharpe ratios and higher moments. Nevertheless it is fair to say that even static allocation results in a portfolio that displays attractive diversification and defensive characteristics. This result to some extent reflects the fact that the majority of the defensive risk premia strategies display strong defensive properties and as a consequence the allocation/selection process might be not be that important.

As it has already been mentioned the above results were done in-sample. Below we perform the optimization out-of-sample using the strategies returns present with a minimum of five years of history.

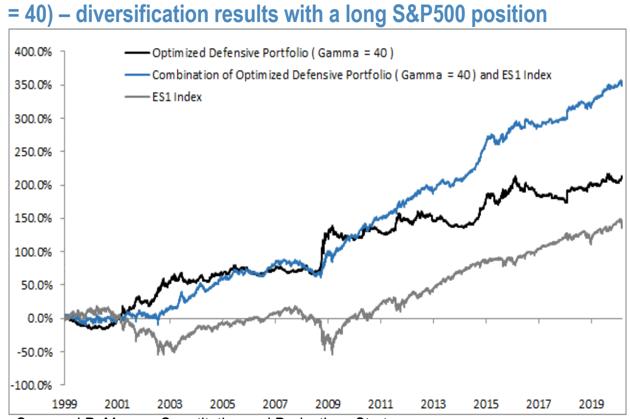
Even the out-of-sample performance of the optimized portfolio is convincing and brings the necessary diversification. Note that the portfolio based on Gamma =40 – the more risk-averse/frugal parameter choice – leads to a slightly better performance and better protection during 2008. A more detailed examination of the actual results of the optimization show the optimization with Gamma=40 allocates more weight to the core strategies at the expense of the satellite ones while the reverse holds true when Gamma=10 is being used.

Figure 75: Performance of optimized defensive portfolio (Gamma = 10) – diversification results with a long S&P500 position



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 76: Performance of an optimized defensive portfolio (Gamma = 40) – diversification results with a long S&P500 position



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 44: Performance statistics for the optimized defensive portfolio (Gamma = 10 and 40) – diversification results with a long S&P500 position

	Gamma = 10			Gamma = 40		
	Optimized Defensive Portfolio	ES1 Index	Combination of Optimized Defensive Portfolio and ES1 Index	Optimized Defensive Portfolio	ES1 Index	Combination of Optimized Defensive Portfolio and ES1 Index
Ann Return	11.2%	6.2%	17.4%	9.7%	6.2%	15.9%
Ann Volatility	17.8%	18.6%	18.6%	14.5%	18.6%	15.7%
Sharpe	0.63	0.33	0.94	0.67	0.33	1.01
Max DD	43.1%	61.4%	30.1%	34.4%	61.4%	24.6%
Skewness	1.86	0.16	0.92	1.03	0.16	0.26
Kurtosis	36.05	12.00	12.58	30.23	12.00	4.71

Source: J.P. Morgan Quantitative and Derivatives Strategy

Optimized Portfolios of Safe-Haven Assets

Defensive risk premia strategies are perhaps not the first choice for investors when it comes to hedging despite the benefits that we have extensively discussed.

Below we focus on some more traditional choices of strategies and safe-haven assets for hedging and we compare the performance of the optimized portfolio of defensive risk premia strategies to the performance of the optimized portfolio of safe-haven assets.

In particular we consider:

- A traditional hedging strategy of buying puts on S&P500 - 90% delta, 1 year maturity

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- Gold future
- Dollar – DXY index
- Government bonds – 10Y Treasuries and Bund futures
- Buying credit protection on iTraxx Europe 5Y, iTraxx Europe Crossover 5Y, CDX IG 5Y, CDX HY 5Y

The relevant optimization bounds that we have set up are shown below.

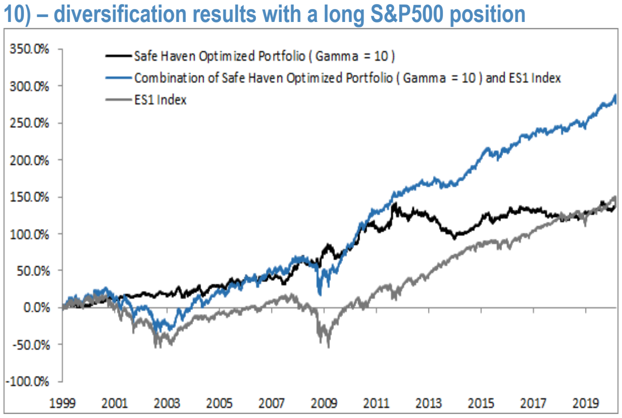
Table 45: Allocation bounds for safe-haven assets

		Group Allocation	Per Single Strategy within the Group
Fixed Income	Lower Bound	10%	2.5%
	Upper Bound	30%	27.5%
Commodities	Lower Bound	10%	10%
	Upper Bound	30%	30%
Currencies	Lower Bound	10%	10%
	Upper Bound	30%	30%
Put Buying	Lower Bound	10%	10%
	Upper Bound	30%	30%
Credit Protection	Lower Bound	10%	2.5%
	Upper Bound	30%	27.5%

Source: J.P. Morgan Quantitative and Derivatives Strategy

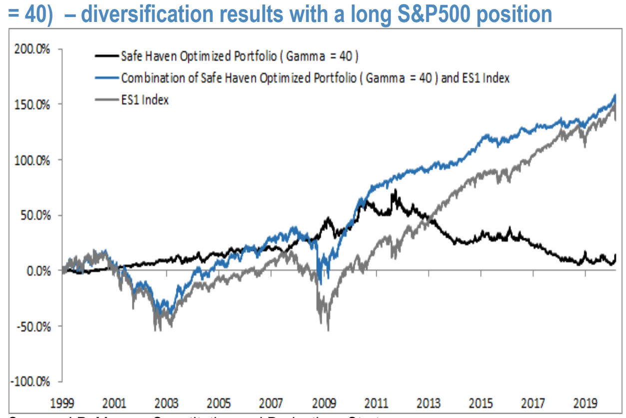
Similarly to the case for optimized defensive risk premia portfolios we proceed by optimizing using a joint approach and two Gamma parameters values (10 and 40):

Figure 77: Performance of safe haven optimized portfolio (Gamma = 10) – diversification results with a long S&P500 position



Source: J.P. Morgan Quantitative and Derivatives Strategy

Figure 78: Performance of safe haven optimized portfolio (Gamma = 40) – diversification results with a long S&P500 position



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 46: Performance statistics for the safe haven optimized portfolio (Gamma = 10,40) – diversification results with a long S&P500 position

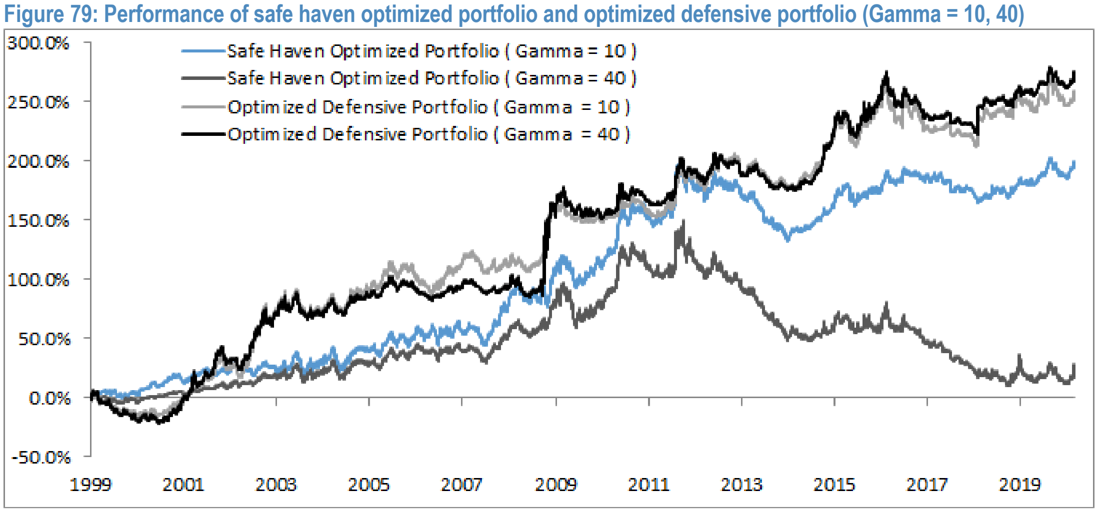
	Gamma = 10			Gamma = 40		
	Safe Haven Optimized Portfolio	ES1 Index	Combination of Safe Haven Optimized Portfolio and ES1 Index	Safe Haven Optimized Portfolio	ES1 Index	Combination of Safe Haven Optimized Portfolio and ES1 Index
Ann Return	6.4%	6.2%	12.6%	0.6%	6.2%	6.8%
Ann Volatility	13.2%	18.6%	18.9%	9.1%	18.6%	16.4%
Sharpe	0.49	0.33	0.67	0.07	0.33	0.42
Max DD	39.8%	61.4%	50.0%	51.2%	61.4%	50.6%
Skewness	0.48	0.16	-0.01	0.91	0.16	0.30
Kurtosis	7.90	12.00	9.05	16.09	12.00	14.93

Source: J.P. Morgan Quantitative and Derivatives Strategy

The portfolio optimization with Gamma=40 produces inferior results to the one when Gamma=10 has been used. When allocations through time have been analyzed we have found out that the optimisation with Gamma=40 is more conservative as expected and allocates more heavily to the put-buying protection strategy. In contrast the portfolio based on the optimization with Gamma=10 invests more heavily in Bunds.

Below we compare the performance of the optimized portfolios of defensive risk premia to the performance of the optimized portfolios of safe-haven assets.

Figure 79: Performance of safe haven optimized portfolio and optimized defensive portfolio (Gamma = 10, 40)



Source: J.P. Morgan Quantitative and Derivatives Strategy

Table 47: Performance statistics for the safe haven optimized portfolio and optimized defensive portfolio (Gamma = 10, 40)

	Safe Haven Optimized Portfolio (Gamma = 10)	Safe Haven Optimized Portfolio (Gamma = 40)	Optimized Defensive Portfolio (Gamma = 10)	Optimized Defensive Portfolio (Gamma = 40)
Ann Return	9.1%	1.3%	11.7%	12.5%
Ann Volatility	18.6%	18.6%	18.6%	18.6%
Sharpe	0.49	0.07	0.63	0.67
Max DD	52.0%	78.6%	44.7%	42.2%
Skewness	0.48	0.91	1.86	1.03
Kurtosis	7.90	16.09	36.05	30.23

Source: J.P. Morgan Quantitative and Derivatives Strategy

We can notice that the portfolios of defensive risk premia are able to provide a much better protection during 2008 and deliver better performance afterwards GFC. Furthermore, in case of defensive risk premia strategies we can rationalize and often quantify the expected performance during a sell-off. But safe-haven status of some of the traditional assets might be questioned going forward: bonds might no longer be supported by further QE policies, dollar appeal as a reserve currency might lessen etc.

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Appendix

P&L Profile Asymmetric Trend-Following System

We make use of some of the derivations in Designing Robust Trend-Following System by Tzotchev et al. For simplicity let's assume that the return process is a random walk with a drift, $R_t = \mu + \varepsilon_t$ where $\varepsilon_t \sim N(0, \sigma^2)$. It follows that $R_t \sim N(\mu, \sigma^2)$.

Let's assume that the signal is based on a lookback period of T and only the positive signals are used to take positions $\mathrm{AsymmS}_{t,T} = \mathrm{Max}(\mathrm{S}_{t,T}, 0)$ where $\mathrm{S}_{t,T} = 2\Phi(d1_{t,T}) - 1$ and $d1_{t,T} = \frac{\sqrt{T}\,\overline{R_{t,T}}}{\sigma}$. Note that $\mu_{d1,T} = \frac{\sqrt{T}\mu}{\sigma}$ and $\sigma^2_{d1,T} = 1$.

We know that $PL_{t+1,T} = \frac{R_{t+1}S_{t,T}}{\sigma}$. Hence $E(PL_{t+1,T}) = \left(\frac{\mu}{\sigma}\right) * E(\mathrm{AsymmS}_{t,T}) = \left(\frac{\mu}{\sigma}\right) * P(\mathrm{S}_{t,T} > 0) * E(\mathrm{S}_{t,T} \mid \mathrm{S}_{t,T} > 0)$.

The expression $P(\mathrm{S}_{t,T} > 0) * E(\mathrm{S}_{t,T} \mid \mathrm{S}_{t,T} > 0)$ has already been derived in the Section '**Expected Running Costs**' in Designing Robust Trend-Following System.

It can be shown that $P(\mathrm{S}_{t,T} > 0) * E(\mathrm{S}_{t,T} \mid \mathrm{S}_{t,T} > 0) = 2\Phi\left(\frac{\mu_{d1,T}}{\sqrt{\sigma^2_{d1,T}+1}}\right) - 2BvN\left(\frac{\mu_{d1,T}}{\sqrt{\sigma^2_{d1,T}+1}}, -\frac{\mu_{d1,T}}{\sigma_{d1,T}}; corr = -\sigma_{d1,T}/\sqrt{\sigma^2_{d1,T}+1}\right) - \left(1 - \Phi(-\mu_{d1,T}/\sigma_{d1,T})\right)$, where $BvN(U, W; \rho)$ stands for the c.d.f of the standard bivariate normal distribution with correlation ρ evaluated at U and W.

For simplicity, let's derive the volatility of the P&L under the assumption of an asset process of a random walk without a drift. Let's denote $X = \frac{R_{t+1}}{\sigma} \sim N(0, 1)$ and $Y = d1_{t,T} \sim N(0,1)$. It follows that:

$$Var(PL_{t+1,T}) = E(PL^2_{t+1,T}) = E(x^2 S^2_{t,T} \mid \mathrm{S}_{t,T} > 0) * P(\mathrm{S}_{t,T} > 0) = 2 * E\left((\Phi(y))^2 | y > 0\right) - 2E(\Phi(y)|y > 0) + 0.5$$

Let $g(y|y > 0)$ denote the density of y conditional on y being positive. We can make use of the properties of the truncated normal distribution and it follows $g(y|y > 0) = 2f(y)$ where $f(y)$ is the standard normal cdf.

$E\left((\Phi(y))^2 | y > 0\right) = \int_0^\infty (\Phi(y))^2 g(y|y > 0)dy = 2\int_0^\infty (\Phi(y))^2 f(y)dy = \frac{2}{3} * (\Phi(y))^3 |_0^\infty = 7/12$. Making use of the properties of the uniform distribution $E(\Phi(y)|y > 0) = 0.75$. It follows that $Var(PL_{t+1,T}) = E(PL^2_{t+1,T}) = 1/6$.

Furthermore, from $E(\Phi(y)|y > 0) = 0.75$ it follows that the average signal is 0.5:

$$E(\mathrm{S}_{t,T} \mid \mathrm{S}_{t,T} > 0) = 2E(\Phi(y)|y > 0) + 1 = 0.5$$

P&L Profile Two-Sided Mean-Reversion

Let's assume that returns follow an AR(1) process, i.e. $R_t = a + \rho R_{t-1} + \varepsilon_t$ where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. It follows that $R_t \sim N\left(\frac{a}{1-\rho}, \frac{\sigma_\varepsilon^2}{1-\rho^2}\right) \sim N(\mu, \sigma^2)$. The position of the mean-reversion strategy is: $d_{t,T} = -\sum_{i=0}^{T-1} R_{t-i}(T-i)$. It follows that $E(d_{t,T}) = -\sum_{i=0}^{T-1} \mu(T-i) = -\mu * \frac{T(T+1)}{2}$. Proceeding further:

$$Var(d_{t,T}) = Var\left(-\sum_{i=0}^{T-1} R_{t-i}(T-i)\right) = \sigma^2 \sum_{i=0}^{T-1}(T-i)^2 + 2\sigma^2 \sum_{i=0}^{T-1}\sum_{j=i+1}^{T-1}(T-i)(T-j)\rho^{j-i}$$

$$Var(d_{t,T}) = \sigma^2 \frac{(2T+1)T(T+1)}{6} + 2\sigma^2 \sum_{i=0}^{T-1}\sum_{j=i+1}^{T-1}(T-i)(T-j)\rho^{j-i}$$

We continue to calculate the expectation of the P&L.

$$Cov(R_{t+1,} d_{t,T}) = Cov\left(R_{t+1,}, -\sum_{i=0}^{T-1} R_{t-i}(T-i)\right) = -\sum_{i=0}^{T-1}(T-i) * Cov(R_{t+1,}, R_{t-i})$$

$$Cov(R_{t+1,} d_{t,T}) = -\sigma^2 \sum_{i=0}^{T-1}(T-i) * \rho^{i+1} = -\sigma^2 \rho\left(\frac{T(1-\rho) - \rho(1-\rho^T)}{(1-\rho)^2}\right)$$

$$Cor(R_{t+1,} d_{t,T}) = Cov(R_{t+1,} d_{t,T}) / \left(\sqrt{Var(R_{t+1,}) \mathrm{Var}(d_{t,T})}\right)$$

It follows that:

$$E(PL_{t+1,T}) = E(R_{t+1} d_{t,T}) = -\mu^2 * \frac{T(T+1)}{2} + \sigma * \left(\sqrt{Var(d_{t,T})}\right) * Cor(R_{t+1,} d_{t,T})$$

Note that $\sigma * \left(\sqrt{Var(d_{t,T})}\right) * Cor(R_{t+1,} d_{t,T}) \sim -\sigma^2 \rho$. Therefore, the P&L is increasing with variance and more negative autocorrelation and decreasing with the square of the mean return.

To calculate the volatility of the P&L we will make use of the properties of the product distribution:

$Var(PL_{t+1,T}) = \left(-\mu * \frac{T(T+1)}{2}\right)^2 * \sigma^2 + \mu^2 * Var(d_{t,T}) + \sigma^2 * Var(d_{t,T}) + 2 * \mu * \left(-\mu * \frac{T(T+1)}{2}\right) * \sigma * \sqrt{Var(d_{t,T})} * Cor(R_{t+1,} d_{t,T})$. Subsequently, the Sharpe ratio can be derived as $harpe\ Ratio = E(PL_{t+1,T}) / \sqrt{Var(PL_{t+1,T})}$.

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P&L Profile Defensive Mean-Reversion

Let's assume that returns follow an AR(1) process, i.e. $R_t = a + \rho R_{t-1} + \varepsilon_t$ where $\varepsilon_t \sim N(0, \sigma_\varepsilon^2)$. It follows that $R_t \sim N\left(\frac{a}{1-\rho}, \frac{\sigma_\varepsilon^2}{1-\rho^2}\right) \sim N(\mu, \sigma^2)$. Furthermore, let's proceed with an example strategy that consists of taking only negative positions and with a time-frame of two days, i.e. we trade two-day variance versus the daily one.

Hence $\mathrm{AsymmS}_t = \mathrm{Min}(\mathrm{S}_t, 0)$ where $\mathrm{S}_t = -R_t$. It follows that $PL_{t+1,T} = R_{t+1}\,\mathrm{AsymmS}_t$ and $E(PL_{t+1,T}) = E(R_{t+1}\mathrm{AsymmS}_t) = -P(R_t > 0) * E(R_{t+1}R_t | R_t > 0)$.

Note that $P(R_t > 0) = \Phi(-\mu/\sigma)$ where Φ is standard normal cdf. Proceeding further $E(R_{t+1}R_t | R_t > 0) = aE(R_t | R_t > 0) + \rho E(R_t^2 | R_t > 0)$.

Making use of the properties of the truncated normal distribution:

$$E(R_t | R_t > 0) = \mu + \sigma f(-\mu/\sigma) / \left(1 - \Phi\left(-\frac{\mu}{\sigma}\right)\right)$$

$$VaR(R_t | R_t > 0) = \sigma^2 \left(1 - \frac{\mu f\left(-\frac{\mu}{\sigma}\right)}{\sigma\left(1 - \Phi\left(-\frac{\mu}{\sigma}\right)\right)} - \left(\frac{f\left(-\frac{\mu}{\sigma}\right)}{1 - \Phi\left(-\frac{\mu}{\sigma}\right)}\right)^2\right)$$

Hence, $E(R_t^2 | R_t > 0) = VaR(R_t | R_t > 0) + \left(E(R_t | R_t > 0)\right)^2 = \mu^2 + \sigma^2 + \frac{\mu\sigma f\left(-\frac{\mu}{\sigma}\right)}{\left(1-\Phi\left(-\frac{\mu}{\sigma}\right)\right)}$. Proceeding further:

$$E(PL_{t+1,T}) = -\Phi\left(-\frac{\mu}{\sigma}\right)\left(\mu(1-\rho)\left(\mu + \frac{\sigma f\left(-\frac{\mu}{\sigma}\right)}{\left(1 - \Phi\left(-\frac{\mu}{\sigma}\right)\right)}\right) + \rho\left(\mu^2 + \sigma^2 + \frac{\mu\sigma f\left(-\frac{\mu}{\sigma}\right)}{\left(1 - \Phi\left(-\frac{\mu}{\sigma}\right)\right)}\right)\right)$$

$$= -\Phi\left(-\frac{\mu}{\sigma}\right)\left(\mu^2 + \rho\sigma^2 + \frac{\mu\sigma f\left(-\frac{\mu}{\sigma}\right)}{\left(1 - \Phi\left(-\frac{\mu}{\sigma}\right)\right)}\right) = \sigma^2\Phi\left(-\frac{\mu}{\sigma}\right)\left(-\left(\frac{\mu}{\sigma}\right)^2 - \rho - \frac{\mu f\left(-\frac{\mu}{\sigma}\right)}{\sigma\left(1 - \Phi\left(-\frac{\mu}{\sigma}\right)\right)}\right)$$

Therefore the P&L is naturally increasing with more negative autocorrelation and the more negative is the Sharpe ratio of the underlying asset, the bigger is the P&L.

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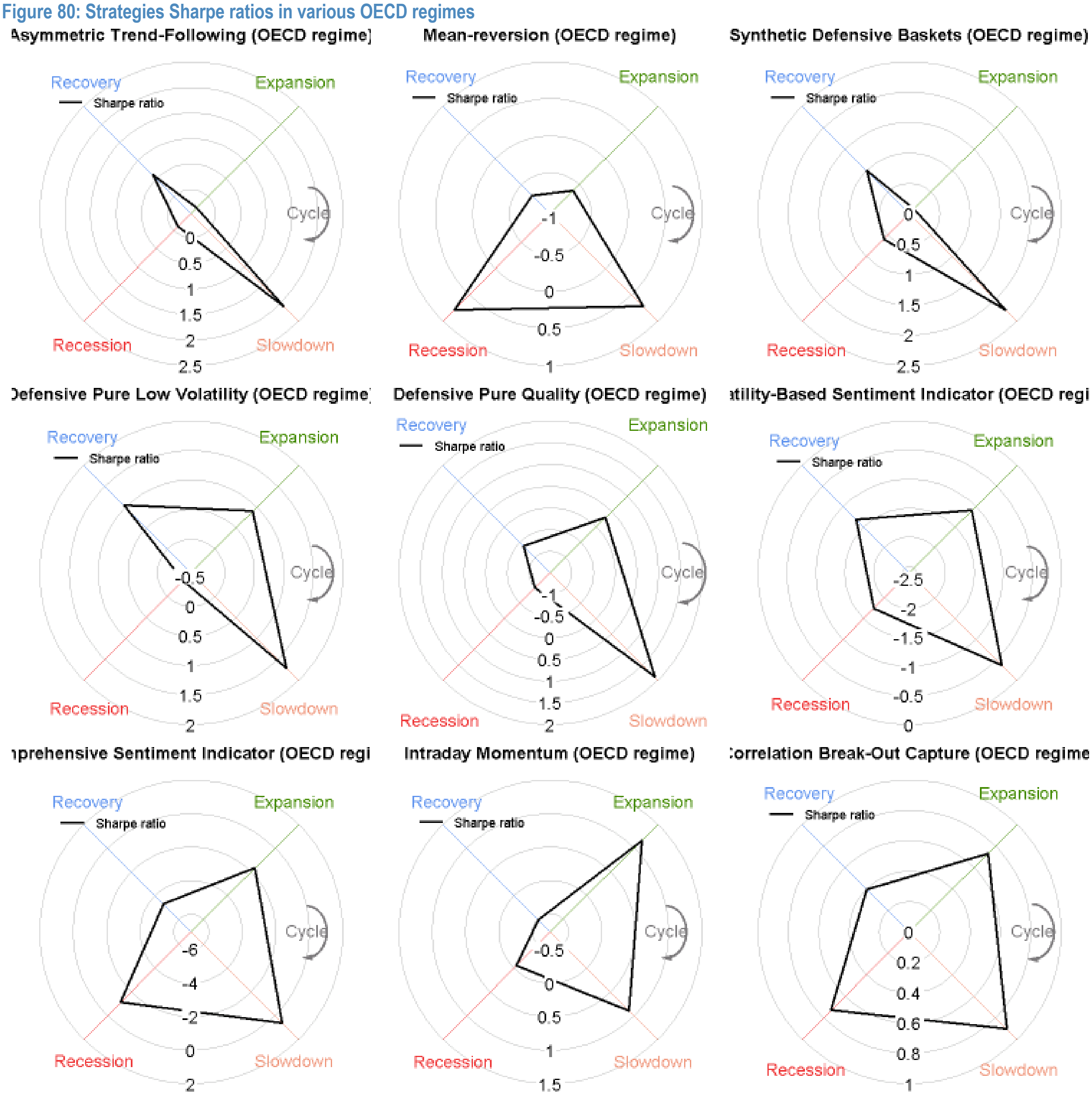
Performance in Various OECD regimes

Figure 80: Strategies Sharpe ratios in various OECD regimes



Source: J.P. Morgan Quantitative and Derivatives Strategy

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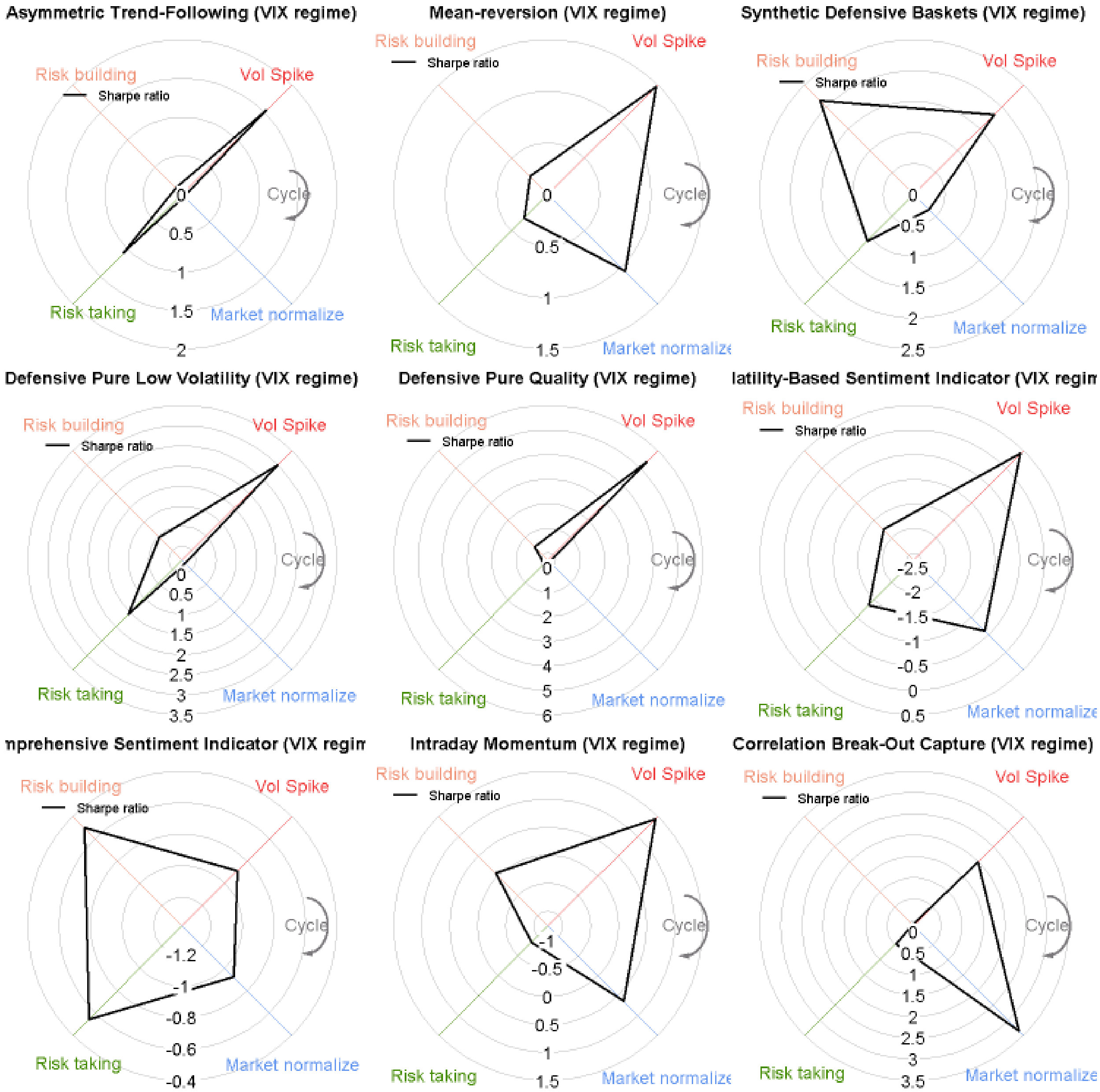
Performance in Various VIX regimes

Figure 81: Sharpe ratios in various VIX regimes



Source: J.P. Morgan Quantitative and Derivatives Strategy

Performance during the 10 Biggest S&P500 Drawdowns

Start Date	19-Jul-99	27-Mar-00	4-Sep-00	28-Nov-02	10-Oct-07	26-Apr-10	2-May-11	22-May-15	29-Jan-18	21-Sep-18	Average	Average	Sharpe
End Date	15-Oct-99	14-Apr-00	9-Oct-02	11-Mar-03	9-Mar-09	2-Jul-10	3-Oct-11	11-Feb-16	8-Feb-18	24-Dec-18	Retrun	Volatility	ratio
Strategy													
SPX	-12.4%	-11.6%	-61.5%	-15.3%	-73.6%	-16.7%	-19.9%	-14.1%	-10.5%	-21.5%	-45.1%	24.7%	-1.8
Synthetic Defensive Baskets	-0.2%	0.5%	56.7%	6.1%	36.5%	5.4%	23.5%	18.3%	1.1%	7.9%	27.3%	10.0%	2.7
Defensive Pure Quality					31.6%	1.4%	3.0%	10.4%	-3.0%	5.6%	16.2%	6.1%	2.6
Asymmetric Trend-Following	-9.7%	1.9%	93.7%	39.2%	53.1%	18.9%	27.5%	34.7%	-0.8%	10.2%	47.1%	19.7%	2.4
Defensive Pure Low Volatility					5.8%	2.8%	13.1%	23.9%	-0.5%	7.8%	17.5%	7.3%	2.4
Optimized Defensive (Gamma = 40)	-1.6%	0.7%	73.7%	19.1%	68.6%	11.4%	27.8%	40.0%	17.7%	11.8%	47.2%	24.2%	2.0
Optimized Defensive (Gamma = 10)	-2.9%	0.9%	87.8%	26.8%	54.9%	10.2%	37.7%	47.6%	22.2%	16.7%	53.0%	28.1%	1.9
Mean-reversion		1.4%	11.2%	-2.9%	25.9%	1.8%	3.6%	3.8%	0.4%	1.7%	8.6%	5.7%	1.5
Comprehensive Sentiment					17.4%	0.0%	10.3%	10.2%	2.1%	15.0%	18.2%	12.5%	1.5
Correlation Break-Out Capture					20.1%	0.6%	2.3%	-1.1%	2.6%	-0.4%	7.9%	6.3%	1.3
Intraday Momentum					11.9%	3.4%	7.8%	0.1%	9.7%	-1.9%	10.3%	12.2%	0.8
Volatility-Based Sentiment			0.9%	-0.4%	9.3%	0.4%	2.3%	-0.5%	1.2%	0.8%	2.6%	3.7%	0.7

Performance during the 10 Biggest Weekly S&P500 Drops

Start Date	17-Sep-01	17-Jul-02	1-Oct-08	2-Oct-08	3-Oct-08	6-Oct-08	21-Oct-08	14-Nov-08	2-Aug-11	19-Aug-15	Average	Average	Sharpe
End Date	21-Sep-01	23-Jul-02	7-Oct-08	8-Oct-08	9-Oct-08	10-Oct-08	27-Oct-08	20-Nov-08	8-Aug-11	25-Aug-15			ratio
Strategy													
SPX	-12.1%	-12.0%	-15.4%	-16.1%	-19.7%	-19.5%	-14.5%	-18.6%	-13.6%	-11.4%	-996.9%	36.8%	-27.1
Defensive Pure Quality			2.3%	2.9%	4.4%	4.9%	5.2%	4.8%	0.5%	-1.4%	186.9%	6.5%	28.6
Volatility-Based Sentiment		0.9%	4.3%	5.0%	4.8%	6.6%	4.9%	2.8%	2.3%	0.2%	222.7%	9.4%	23.8
Optimized Defensive (Gamma = 40)	4.5%	4.2%	15.6%	19.1%	17.6%	24.2%	19.1%	14.3%	8.9%	4.2%	858.8%	36.9%	23.3
Asymmetric Trend-Following	10.0%	11.3%	9.3%	11.1%	10.2%	14.1%	14.7%	12.0%	7.9%	3.1%	676.7%	33.1%	20.4
Optimized Defensive (Gamma = 10)	4.8%	6.5%	7.8%	10.6%	8.9%	12.2%	9.4%	10.5%	11.0%	6.7%	576.3%	29.1%	19.8
Synthetic Defensive Baskets	3.0%	1.6%	6.0%	8.4%	7.0%	9.6%	6.6%	8.3%	3.7%	1.7%	363.3%	18.6%	19.5
Mean-reversion	1.0%	0.3%	0.3%	0.3%	0.2%	0.2%	1.0%	0.3%	0.2%	0.0%	25.2%	2.1%	11.8
Comprehensive Sentiment									5.7%	6.5%	370.7%	64.5%	5.8
Intraday Momentum			0.3%	-0.1%	0.7%	0.6%	-1.0%	1.0%	5.0%	1.8%	67.0%	13.4%	5.0
Defensive Pure Low Volatility			-0.1%	0.3%	-2.3%	-2.6%	0.4%	1.5%	2.8%	1.3%	10.4%	13.6%	0.8
Correlation Break-Out Capture			-2.0%	-1.1%	0.0%	1.0%	-0.9%	-1.4%	0.0%	-1.6%	-46.7%	11.7%	-4.0

Performance during the 10 Biggest Daily S&P500 Drops

Starting Month	14-Apr-00	29-Sep-08	7-Oct-08	9-Oct-08	15-Oct-08	22-Oct-08	19-Nov-08	20-Nov-08	1-Dec-08	8-Aug-11	Start Date	Average	Average	Sharpe
Ending Month	14-Apr-00	29-Sep-08	7-Oct-08	9-Oct-08	15-Oct-08	22-Oct-08	19-Nov-08	20-Nov-08	1-Dec-08	8-Aug-11		Retrun	Volatility	ratio
Strategy														
SPX	-5.8%	-8.8%	-5.7%	-7.6%	-9.0%	-6.1%	-6.1%	-6.7%	-8.9%	-6.7%	1-Jan-99	-1802.6%	21.1%	-85.3
Intraday Momentum		2.9%	1.1%	1.1%	2.5%	0.6%	1.3%	0.4%	1.8%	2.9%	18-Jan-07	410.1%	15.4%	26.7
Optimized Gamma = 40	0.5%	8.7%	1.2%	2.5%	8.1%	5.3%	3.7%	5.7%	4.9%	4.1%	1-Jan-99	1123.2%	42.7%	26.3
Volatility-Based Sentiment		2.3%	0.4%	0.7%	2.2%	1.1%	0.8%	0.8%	0.4%	1.2%	22-May-02	280.7%	11.0%	25.5
Synthetic Defensive Baskets	0.7%	2.3%	0.0%	0.8%	3.5%	2.4%	1.7%	4.3%	2.3%	2.5%	1-Jan-99	515.5%	20.6%	25.0
Defensive Pure Quality		0.1%	1.2%	1.4%	1.4%	1.1%	1.6%	1.3%	0.0%	0.2%	1-Apr-05	235.6%	10.0%	23.6
Optimized Gamma = 10	0.1%	4.1%	0.0%	1.0%	4.4%	3.3%	2.2%	5.4%	4.4%	5.3%	1-Jan-99	767.6%	32.5%	23.6
Asymmetric Trend-Following	-1.1%	4.1%	0.5%	1.5%	3.8%	4.1%	3.3%	5.4%	5.9%	3.3%	1-Jan-99	777.0%	34.4%	22.6
Mean-reversion		2.7%	0.0%	0.0%	0.3%	0.6%	0.0%	0.1%	2.6%	0.0%	17-Jan-00	176.1%	17.9%	9.9
Defensive Pure Low Volatility		3.6%	0.8%	-2.2%	0.9%	0.2%	0.8%	0.4%	0.0%	0.1%	1-Apr-05	125.8%	23.4%	5.4
Correlation Break-Out Capture		-0.9%	-1.5%	0.7%	-0.4%	-0.1%	-0.4%	-1.4%	-0.7%	-0.2%	5-Jun-07	-140.3%	10.7%	-13.2
Comprehensive Sentiment										-5.4%	30-Dec-08	-1372.1%		

Source: J.P. Morgan Quantitative and Derivatives Strategy

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