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Global Quantitative & Derivatives Strategy
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Timing FX short-vol strategies

A systematic approach

Global Quantitative and Derivatives Strategy

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- **Short-volatility strategies can be relied upon as systematic sources of income over time and across asset classes, and are well poised to be included within multi-asset, multi-strategy portfolios. Large drawdowns and heavy left-tail distribution risk are, however, unavoidable features that the strategies are exposed to.**
- **In this paper, we introduce a fully systematic methodology for optimizing the timing of short-volatility trades. The goal is to reduce the drawdown of the strategies while preserving their long-term appeal, thus making short-volatility a more palatable choice for a wide range of investors, beyond the dedicated ones.**
- **We rely on a set of global and smile-related indicators for each currency, scaling down short-vol positions when the warning indicators flash higher-risk conditions. As of 5 March, the tactical signals support a maximum allocation to new short-volatility trades on all currencies except USD/HUF (93% allocation).**
- **The methodology is applied to a set of liquid G10/EM FX volatilities, and could be easily extended to other asset classes as well. Results of the filtering methodology are convincing, with a sensible reduction of the volatility and drawdown for the strategies, without impacting much the long-term average returns.**
- **While the focus of the piece is on short-vol, as a corollary analysis, we describe the application of these methodologies for triggering long-vol signals as well.**
- **In the final section of the piece, we apply Machine Learning for aggregating trading signals over time and for selecting dynamically the best predictors on each different underlying. Since April 2009, the Random Forest algorithm has outperformed the benchmark and the un-optimized linear aggregation of the trading signals.**

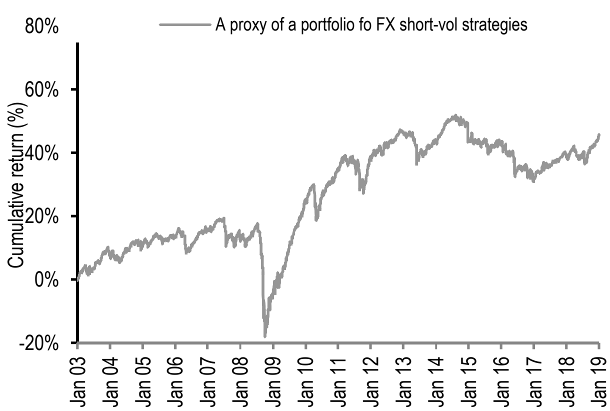
See page 13 for analyst certification and important disclosures, including non-US analyst disclosures.

Short-volatility strategies as sources of returns within diversified portfolios

The possibility of harvesting a risk premium and delivering attractive long-term returns has rendered short-volatility strategies as popular investment vehicles over time, both for hedge funds and, more recently, institutional investors. With some differences, the volatility premium is a feature present across asset classes (see for instance *Optimal option delta-hedging*, Ravagli), which permits a substantial reduction of risk via diversification into a cross-asset portfolio.

For the FX asset class, a proxy portfolio of short-volatility strategies confirms the presence of a vol risk premium, although possibly tighter than for Equities and other markets (Exhibit 1). Given the resilience exhibited by FX vols, especially in the G7 sector, to drift materially higher during the late-2018 risk-off market, their inclusion into a diversified portfolio of cross-asset, short-vol strategies has been highly beneficial.

Exhibit 1. A proxy of a diversified short-vol portfolio in FX



Source: J.P.Morgan

A common problem to short-vol strategies is that there is a systemic component of risk which, by definition, cannot be reduced by diversification. This translates into large drawdowns (37.7%), skewness (negative, -4.1) and Kurtosis (41.1) even for the proxy portfolio above (at the single currency level, where diversification benefits do not kick in, performance statistics point to an even higher left-tail risk).

These features complicate the inclusion of short-vol within multi-asset portfolios, despite the hefty returns enjoyed by the strategy in the long run. Furthermore, the large drawdowns are especially acute in the high-beta G10 / EM sectors, where conversely, an improved liquidity would nowadays facilitate systematic investments.

Especially when looking at the EM space, the past few decades have taught us multiple examples where rapid drops in these currencies have occurred due to a worsening of either global or local market indicators. This naturally motivates the idea of monitoring a set of risk-related indicators to be used as filters for short-vol strategies, as pursued in this piece. Before tackling the issue of filtering the vol strategies, we start by offering a short overview of how we setup FX options backtests.

The platform for the options backtests

We rely on 1M 25delta strangles as the benchmark for FX short-volatility strategy. On a daily basis, we cumulate positions by entering a new trade, kept in the book until expiry: notionals are chosen as to ensure that options have the same Vega at inception. Given the wider liquidity found on the OTC space for the FX market, all FX options backtests herein presented refer to J.P. Morgan internal pricing system. We monitor a set of the 18 most liquid US dollar pairs, 9 G10 and 9 EM. All starting dates for the backtests herein presented refer to January 2003, with the exceptions of TRY (Jan 05) and CNH (Jan 11). Final date for all backtests is 23 January 2019.

When defining filters are applied to portfolios of vol trades, one could consider different possibilities, including the one of unwinding positions. As the latter implementation would turn out to be quite sensitive to trading costs, we consider the more conservative solution whereby trading signals only determine the new options which enter the book: after inception, all options are kept until expiry.

With these constraints in mind, 1M options stand out, offering a wide vol premium, good liquidity and the possibility of granting a reactive rebalancing. In future research pieces we will shed more light on the choice of strangles vs straddles as pursued here.

Relying on a class of market indicators for filtering short-vol strategies

We want to define a general rule-based methodology for filtering short-vol strategies by relying on market indicators. Compared to previous research published on the topic (see the section *Systematic long vega using straddles,* Jankovic, as contained in *Goldilocks is in the price*, 2018 Outlook), here we focus more specifically on FX short-vol as an asset class: the goal of the tactical approach pursued in this piece will be that of smoothing the PnL profile of short-volatility strategies on each individual currency, rather than aiming at building an optimal long-vol portfolio across different currencies. Also, as it will be clearer in the following, we will target a rather opportunistic filtering procedure, for matching as closely as possible the positive returns enjoyed by short-vol strategies during benign market conditions and losing as little as possible when vol spikes higher.

While the topic presents a multiplicity of possible solutions, it also suffers from the possible drawback of incurring into overfitting problems, an issue we try to avoid by defining a conservative procedure. First, we pre-select a set of market variables which are normally associated with a deterioration of financial conditions. For each of these variables, we associate a trade/no-trade binary signal based on a general, although parametric, assessment related to z-scores. We later aggregate the different signals, here allowing a margin of flexibility by relying on both traditional and ML-algos for defining optimal aggregations.

If ever, as mentioned above, we stress the value of mixing global and local indicators when filtering short-vol strategies. We define a common set of "global" variables that we apply consistently to all vol strategies. We then consider a set of "local", pricing-related variables that are obtained consistently from each vol smile. This conservative approach whereby all variables and currencies are treated exactly the same way should massively reduce the risk of overfitting. The set of global and local variables monitored for each currency are reported in Exhibit 2. The global variables we consider are amongst those commonly used as inputs for market-based sentiment indicators, as tested in the financial literature. Gold-to-silver ratio isolates the risk-off element present in gold while eliminating the inflationary bias as generally present in commodity prices. US swaptions are measured in normal (basis point) terms.

Exhibit 2. Global and local risk-indicators (with % activations)

Global variables	Signals	Local variables	Signals (EUR/USD)
JPM VXY G7 Index	13%	1M imp vol	11%
VIX Index	10%	1M real vol	11%
3M1Y USD swaptions	12%	1M - 3M vol TS	10%
Ted spread	15%	|RR|/vol	12%
Gold/silver ratio	16%	BF/Vol	10%
		1M real vol of imp vol	13%
		PnL loss of short-vol strategy	5%

Source: J.P.Morgan

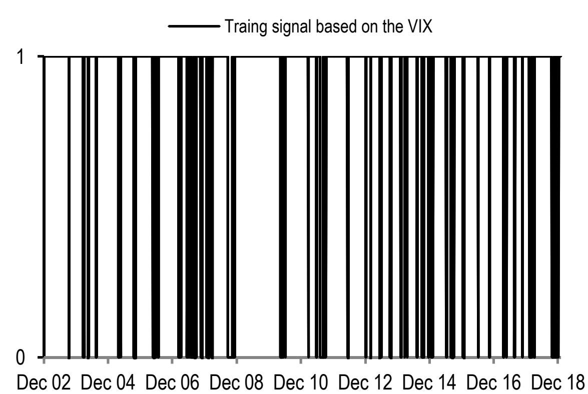
The local variables we monitor for each currency are displayed in the right-hand chart above. The five variables listed at the top are commonly used as a measure of risk, whereas the bottom two less so: the first measures the realized vol of implied vol, the second measures directly the realized PnL (in fact, the loss or – PnL) generated by the strategy, mimicking stop-loss features as commonly introduced in trading systems.

While we don't pursue the approach here, one could introduce additional flexibility and select for each currency indicators which are well known to bring extra value. Also, one could consider including indicators related to Economic activity (see [Economic Activity Surprise Index Report](), Chandan) or a newer set of information based on big data (see for instance, [Big Data and AI Strategies](), Kolanovic).

In all cases, the variables herein considered are all risk-off, i.e. a rise of the variable is associated with an increase of risk. Then, in order to obtain trading signals, we simply compute z-scores on each of the variables (over 6M rolling periods). Quite arbitrarily, we rely on the 1.5 threshold – this corresponds to the 93% quantile of the Gaussian distribution; the comparison with average activations as reported in Exhibit 2 shows that variables tend to possess fatter tails than for a Gaussian distribution, so that 1.5 z-score values are reached more often. Depending on the goal pursued, one could obtain more aggressive scaling down of the short-vol trades by choosing lower threshold values for the z-scores.

For each variable, the trading signal is therefore a binary choice, zero or one: zero means that we don't trade, one that we trade at max notional. Exhibit 3 displays the time series of the signals corresponding to the VIX Index.

Exhibit 3. Trade on/off signals from the VIX Index



Source: J.P.Morgan

We flag that we apply this calculation also to two variables, gold-to-silver ratio and PnL loss, which in principle are not stationary and which could exhibit long-term trends. Still, by measuring the z-score over

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relatively short time horizons, we can assume that the impact of the long-term trends in the variables to be modest, if not negligible at all.

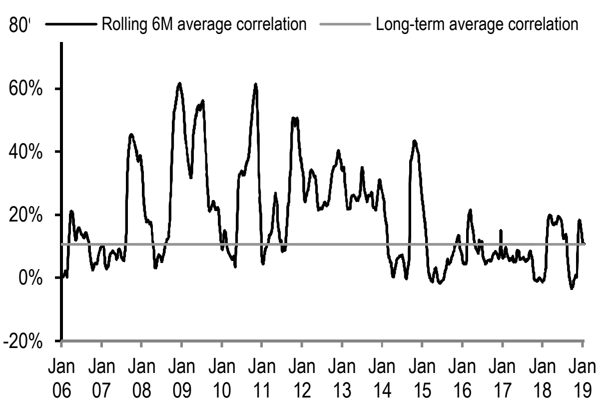
We acknowledge that, by relying on just the binary signals described above, some valuable information contained in the *value* of the z-scores might get lost. In this first part of the piece, we decide to proceed like this, for favoring intuitive understanding of the methodology over high degree of flexibility. In the final section of the article, when introducing a ML-based procedure for aggregating the signals, we show how the oversimplification above could be easily relaxed.

Given that options PnLs are calculated at London close, and some of the global variables refer to US trading hours, we consistently apply a 1-d lag to all "global" variables. All local variables are computed at London time, and we don't apply the 1-d lag on these.

The value of combining local and currency-specific information

Before assessing directly the efficacy of the signals for trading purposes, which will be done in the next subsection, we start by investigating the added value of aggregating global and local risk indicators together. We'll focus on GBP/USD as a case study, as will appear clearer later when reviewing actual PnLs.

Exhibit 4. Average correlation (6M rolling) of risk variables

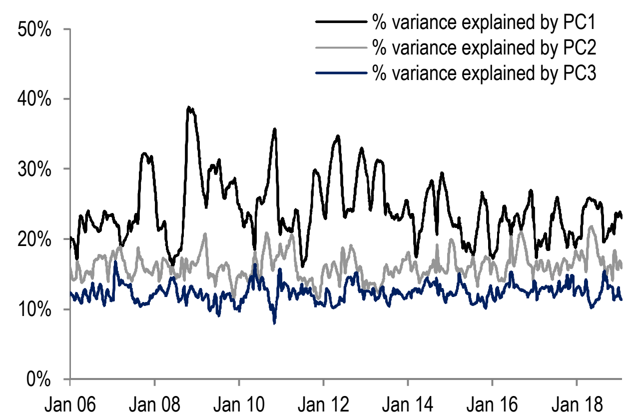


Source: J.P.Morgan

The time series of (6M rolling) average correlation between all variables is displayed in Exhibit 4: the grey line refers to the average correlation by using 15 yrs of data. What we see is that the average correlation tends to spike during risk-off episodes (reaching a high of around 60% in early 2009) and to drop when markets are quieter. This means that, if the benefit of diversification at the peak of global or regional market crash is limited, collecting risk-related information before the onset of such episodes could prove extremely valuable.

A few other interesting conclusions regarding the interdependence of the variables can be drawn by running a PCA on the basket of variables. Exhibit 5 displays the percentage of risk (i.e., variance, for normalized variables) explained by the three factors explaining the highest proportion of variance.

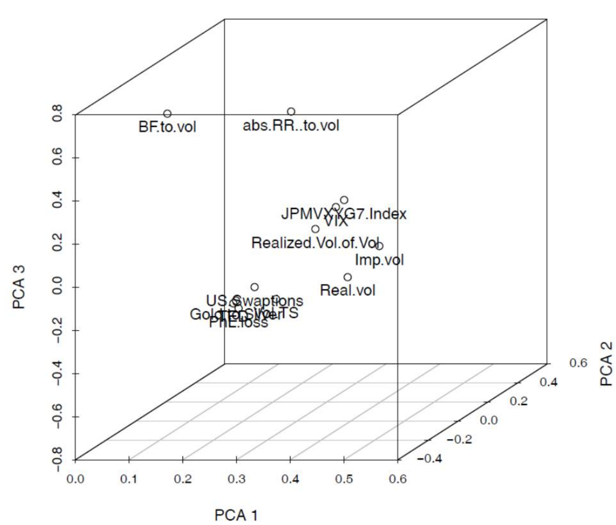
Exhibit 5. Variance explained by the first three principal components (PCA run on the basket of risk variables)



Source: J.P.Morgan

The higher the fraction of variance explained by factors beyond the first one (average risk-off factor), the more there is value in collecting information from different sources. From the chart, we see that the added value of this cross-sectional screening is highest during periods ahead of spikes in volatility.

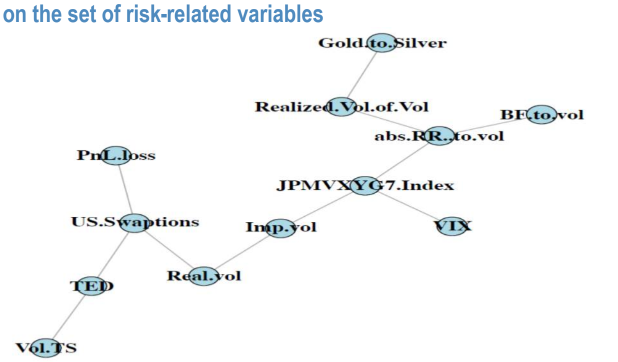
Exhibit 6. Grouping the variables by their sensitivity to the first three principal components



Source: J.P.Morgan

Still based on PCA, we can group the variables based on their sensitivities to the three main common drivers of variance (Exhibit 6). Representing an average risk-off factor, all sensitivities to the first PCA are positive. We can roughly group our basket of risk factors into one well-identified cluster with high sensitivity to the first factor, comprising vol measures (VIX, VXY, Implied vol, Realised vol, Realised vol of vol). A second group with weak betas to PC1 and negative to PC3 includes (Ted spread, Gold-to-Silver ratio, US swaptions, Vol term structure and PnL-loss). Two smile-related variables (RR and BF to vol ratios) appear as outliers, separated from other variables. Basically, the analysis above confirms the previous observation that the set of global and local variables considered allows capturing additional exposures to risk, as expressed to the betas to PC2 and PC3, beyond a general risk-off sensitivity (as expressed by PC1). The added value of including these extra sensitivities to risk is higher at times when the corresponding explained variances are higher (see again Exhibit 5), namely at the onset, rather than at the peak, of market crashes.

Exhibit 7. VXY is the variable at the center of a spanning tree run on the set of risk-related variables



Source: J.P.Morgan

A minimum spanning tree (Exhibit 7) displays nicely the variables exhibiting the strongest link with each other, by using the past 15 yrs of data as a reference. We can see that JP Morgan VXY Index lies at the center of the chart; variables like Gold-to-Silver ratio and the PnL-loss of the strategy, conversely, stand at the extreme, exhibiting less communality with the rest of the variables.

Assessing the efficacy of the trading signals

Having introduced some theoretical framework for justifying our proposed approach, we move on to investigate the actual results of the filtering methodology. We start by assessing the added value of each of the different variables taken independently, before considering their aggregation into a combined filter.

Exhibit 8 collects the main performance measures, as averaged across the 18 currencies, of the benchmark short-vol strategy and of the filtered solutions using just one variable as a filter at a time. Properties at the portfolio level will be discussed later in the piece.

Exhibit 8. Average results (across all currencies) for short-vol strategies in FX by using just one variable as a filter at a time

Filter	Ret	Vol	Sharpe	MDD	MDD/Vol	% Success
Benchmark	2.9%	13.0%	0.23	65%	4.9	60.8%
JPM VXY G7 Index	3.5%	9.7%	0.35	44%	4.5	61.2%
VIX Index	3.4%	10.4%	0.34	46%	4.3	60.8%
USD swaptions	3.5%	10.3%	0.34	46%	4.4	60.7%
Ted spread	2.9%	11.2%	0.27	51%	4.6	60.7%
Gold/silver ratio	4.0%	10.3%	0.40	39%	3.7	61.3%
1M imp vol	4.0%	9.9%	0.43	41%	4.1	61.6%
1M real vol	3.8%	10.2%	0.39	45%	4.3	61.7%
1M - 3M vol TS	4.2%	10.3%	0.43	41%	3.9	61.5%
|RR|/vol	2.8%	11.1%	0.29	54%	4.8	60.8%
BF/Vol	2.6%	12.1%	0.24	60%	4.9	60.7%
1M real vol of vol	3.1%	10.4%	0.33	46%	4.3	61.4%
PnL loss	3.9%	10.6%	0.38	44%	4.1	61.5%

Source: J.P.Morgan

We see that, on average, all variables help improve all performance measures, although the added value varies. Vols are reduced sharply compared to the benchmark, and (average yearly) returns often outperform the passive, short-vol strategy: as a consequence, Sharpe ratios are up to 75% vs the benchmark. The maximum drawdown is drastically reduced, both in absolute terms and if measured as a ratio to the vol of the strategies; the skewness, a measure of the left-tail risk embedded in the strategy, is also generally reduced. The success rate of the different signals (measured as percentage of time the signal gets the sign of the PnL at expiry right) usually lies above that of the benchmark. On average, global variables tend to slightly outperform in terms of yearly return, and local variables in terms of Sharpe ratios.

1M implied vol, term structure of vol and gold-to-silver ratio appear as the best-performing variables; at the other end of the spectrum, riskies and butterflies over vol and Ted spread stand out as the worst predictors, underperforming the benchmark strategy in terms of hit ratio. In the following, we will stick to this pre-specified set of variables and will not give in to the temptation of removing those whose metrics are least attractive. Hopefully, this will reduce the in-sample biases embedded in the methodology.

Considering the low activation fraction for each variable, generally averaging up to 13% of the time (with a few exceptions), one would hope to generally track (or slightly underperform) the benchmark during bullish periods for the short-vol strategy, and to sensibly reduce the losses during market crashes. In the long run, the goal

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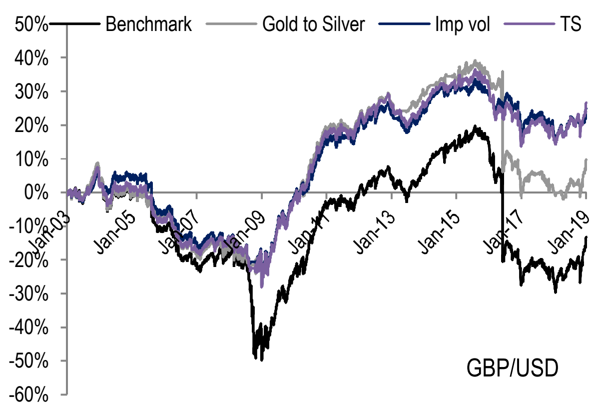
would be to match the return of the benchmark, but with much lower volatility.

We then move on to considering application of the methodology to actual case studies. Given that most short-vol strategies suffered sharp losses in late 2008, we prefer focusing on those examples where additional large drawdowns were experienced post 2008, just to assess the performance of the filtering methods. This will also help highlight the added value of the local variables vs more general proxies of risk, which generally correctly tracked the big September 2008 sell-off.

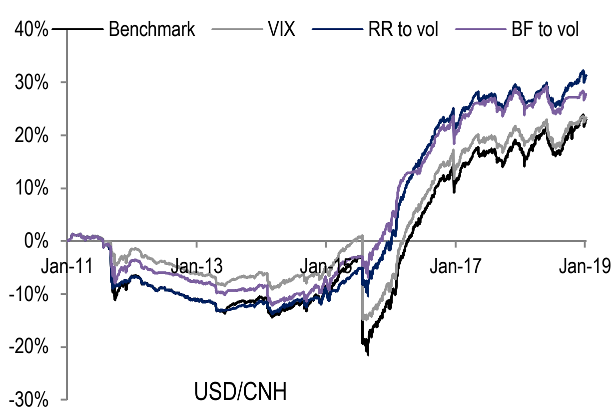
Exhibit 9. Local variables helped cutting losses on GBP in 2016



Source: J.P.Morgan

For GBP/USD (Exhibit 9), the three variables considered here helped reduce drastically the late-2008 drawdown suffered by the strategy. The two local variables (Implied vol and Term structure of vol) also helped substantially over the 2016 Brexit referendum.

Exhibit 10. Smile parameters reduced the 2011 CNH drawdown

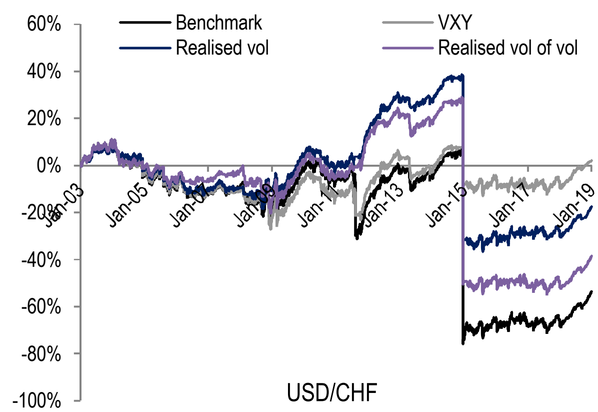


Source: J.P.Morgan

For CNH (Exhibit 10), the large August 2015 drawdown could be largely avoided by relying on riskies and butterflies as filters. The September 2011 repricing higher of USD/CNH, on the other hand, was dealt with better by using VIX as a filter.

A third interesting case to review is the one of the SNB removing the peg of CHF on the EUR on 15 January 2015, with the CHF appreciating by almost 20% in one single day (Exhibit 11). On this occasion, when the short-vol strategy suffered miserable losses, the JP Morgan VXY Index is the variable which helped the most, cutting drawdown vs the benchmark. Realised vol and vol of vol, on the other hand, nicely allowed to scale down positions ahead of the 6 September 2011 episode, when the peg was introduced (for curbing CHF strength) and EUR/CHF rallied by almost 10% on the day.

Exhibit 11. VXY beat local indicators for the CHF 2015 de-peg



Source: J.P.Morgan

The case studies overviewed above generally suggest that the combination of global and asset-specific proxies of risk can realistically allow reducing the risk embedded in short-vol strategies. It is worth pointing out that such filtering methodologies based on market parameters are, by definition, not expected to reduce the exposure to natural disasters, like the one of March 2011 in Japan, or fat-finger / intra-day crashes, as occurred on a couple of occasions in 2018.

Aggregating the trading indicators

Having assessed the value for short-vol strategies of collecting risk-off indicators from different sources, a question which naturally rises is how the signals should be combined into an aggregated indicator. The most intuitive (and least prone to overfitting risk) solution is simply to consider their linear combination. We will show in the final section of the piece how a ML-algo could come in handy for this purpose. Machine Learning (ML) can also be relied upon for selecting dynamically the set of predictors, which allows introducing some

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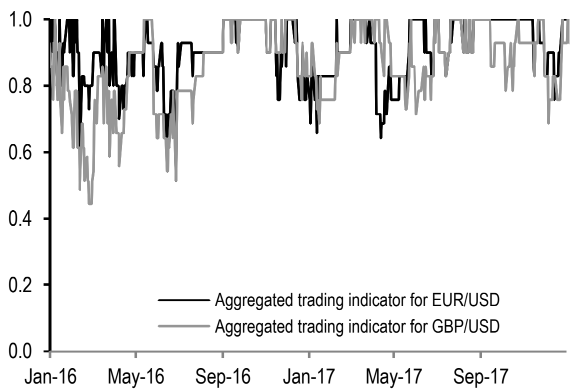
flexibility in the choice of the variables without adding severe in-sample biases (i.e., discarding worst performers).

For defining the aggregated indicator for each currency, we first take the averages of the global and local signals, and then again the average of the latter two. While still range-bound between zero and one, the aggregated indicator will be smoother in the 0-1 range (it moves by much increments) and less volatile over time. Average activation per currency ranges from 11.9% on EUR/USD to 13.6% on USD/CNH (GBP/USD follows at 13.5%).

Exhibit 12.Aggregated trading indicators for EUR/USD and GBP/USD in 2016-17



Source: J.P.Morgan

We compare (Exhibit 12) the final aggregated indicators for EUR/USD and GBP/USD, by focusing on the 2016-17 period. The aggregated indicator for GBP/USD consistently undershot the one for EUR/USD in H1 2016 (average of 75% vs 86%) due to the higher premia priced on cable's smile ahead of the Brexit referendum.

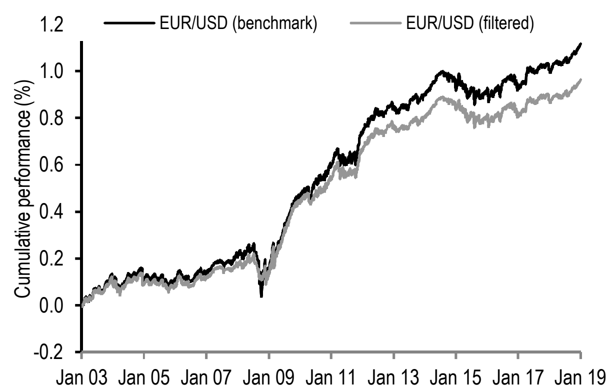
Exhibit 13. Application of the filter to G10 short-vol strategies

Asset	Strategy	Ret	Vol	Sharpe	MDD	MDD/Vol
EUR-USD	Passive	6.8%	8.9%	0.76	23%	2.5
EUR-USD	Filtered	5.8%	7.5%	0.77	13%	1.8
GBP-USD	Passive	-0.8%	11.1%	-0.07	59%	5.3
GBP-USD	Filtered	0.1%	8.4%	0.01	43%	5.2
USD-JPY	Passive	4.6%	12.3%	0.37	52%	4.2
USD-JPY	Filtered	4.3%	9.7%	0.44	33%	3.4
USD-CHF	Passive	-3.2%	22.0%	-0.15	87%	4.0
USD-CHF	Filtered	-2.1%	16.6%	-0.12	62%	3.7
USD-CAD	Passive	-0.3%	8.5%	-0.04	52%	6.2
USD-CAD	Filtered	0.7%	6.7%	0.10	32%	4.8
USD-NOK	Passive	-2.3%	12.5%	-0.18	68%	5.4
USD-NOK	Filtered	-1.2%	10.2%	-0.12	54%	5.2
USD-SEK	Passive	-0.3%	10.7%	-0.02	48%	4.5
USD-SEK	Filtered	0.4%	8.8%	0.05	34%	3.9
AUD-USD	Passive	-3.2%	14.7%	-0.22	112%	7.6
AUD-USD	Filtered	0.0%	9.7%	0.00	61%	6.3
NZD-USD	Passive	-3.4%	14.3%	-0.24	88%	6.2
NZD-USD	Filtered	-0.9%	10.7%	-0.09	51%	4.8

Source: J.P.Morgan

Results for G10 currencies are collected in Exhibit 13. The filtered solutions markedly outperform the benchmark in terms of drawdowns and Sharpe ratios. In several cases, the methodology helps lifting yearly returns from negative to positive values. For USD/JPY and EUR/USD (Exhibit 14), the filtered strategy slightly underperforms the benchmark return-wise, having reduced the drawdown at the peak of the late-2008 market crash. We notice that for several G10 high-betas (and especially AUD, NZD and NOK), passive short-vol strategies are associated with negative returns: in other words, volatility levels are not commensurate with the fluctuations these currencies have exhibited historically. This motivates why FX vols are often used as long vol legs within hybrid Equity/FX L/S payoffs, for instance implemented via variance swaps. Putting aside the idiosyncratic event of June 2016 for cable, it appears that the widest vol premia are found for G4 currencies.

Exhibit 14. Filtering at work on EUR/USD short-vol strategy



Source: J.P.Morgan

We display the results for the filtering of EM short-vol strategies in Exhibit 15. One first thing we notice is that, despite the higher trading costs, Sharpe ratios are higher for the EM strategies compared to G10, indicating wider vol premia in this space. Improved liquidity now allows investigating such opportunistic ventures on EMFX. Compared to the high-beta currencies we commented on earlier, it appears that EM front-end vol levels are more than adequate (if ever, slightly too high) compared to the amount of short-Gamma risk they are associated with.

Filtered results also look more appealing than for G10 FX. Drawdowns are sharply reduced, as it was before, but the added value on Sharpe ratios and yearly returns is more evident. This could reflect the evidence that EM assets tend to lag the most liquid global markets, and that therefore relying on cross-asset information is beneficial in anticipating market sell-offs.

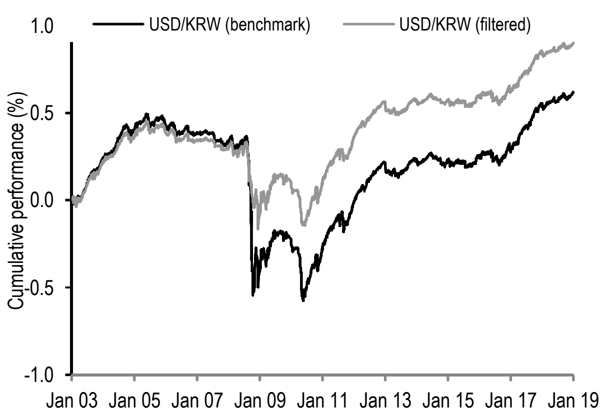
Exhibit 15. Application of the filter to EM short-vol strategies

Asset	Strategy	Ret	Vol	Sharpe	MDD	MDD/Vol
USD-BRL	Passive	15.3%	17.5%	0.87	64%	3.7
USD-BRL	Filtered	14.2%	13.6%	1.04	27%	2.0
USD-MXN	Passive	13.9%	16.7%	0.83	67%	4.0
USD-MXN	Filtered	12.7%	10.1%	1.25	34%	3.4
USD-ZAR	Passive	4.9%	17.7%	0.28	72%	4.1
USD-ZAR	Filtered	4.5%	14.9%	0.30	65%	4.4
USD-PLN	Passive	3.0%	13.0%	0.23	68%	5.2
USD-PLN	Filtered	4.1%	10.7%	0.38	59%	5.5
USD-HUF	Passive	-2.8%	13.0%	-0.21	103%	7.9
USD-HUF	Filtered	-1.5%	11.0%	-0.14	91%	8.3
USD-KRW	Passive	3.7%	13.6%	0.28	107%	7.9
USD-KRW	Filtered	5.4%	9.1%	0.60	62%	6.8
USD-CNH	Passive	2.8%	6.8%	0.41	23%	3.4
USD-CNH	Filtered	2.6%	5.3%	0.48	17%	3.2
USD-SGD	Passive	2.6%	5.6%	0.46	22%	3.9
USD-SGD	Filtered	2.8%	4.6%	0.61	13%	2.9
USD-TRY	Passive	11.7%	16.0%	0.73	49%	3.1
USD-TRY	Filtered	10.7%	12.9%	0.83	38%	2.9

Source: J.P.Morgan

USD/KRW (Exhibit 16), USD/MXN and USD/PLN are three stand-out cases; for the former asset, the large reduction of losses in late-08 and then again in May/June 2010 (and to a lesser extent, September 2011) justifies the long-term added value in terms of yearly returns, too.

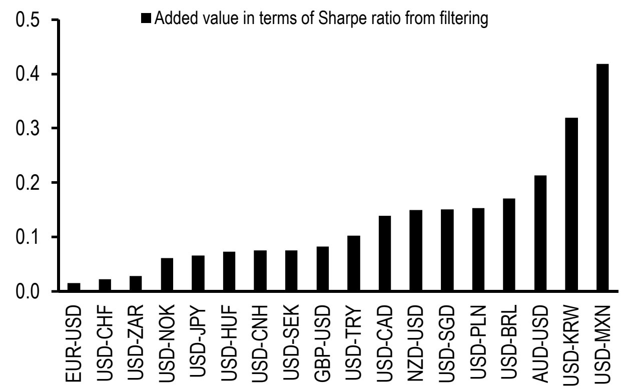
Exhibit 16. Filtering helps if applied to short-vol on USD/KRW



Source: J.P.Morgan

We summarize the added value introduced by filtering short-vol trades with two charts. In the first (Exhibit 17), we highlight the extra Sharpe generated thanks to filtering. It is comforting to see that the added value is positive in all cases considered if measured over long-term periods. The largest added value is found on USD/MXN, USD/KRW and AUD/USD (with Sharpes increased from 0.21 to 0.42). The asset where the added value in terms of Sharpe is the tightest (+0.02) is EUR/USD.

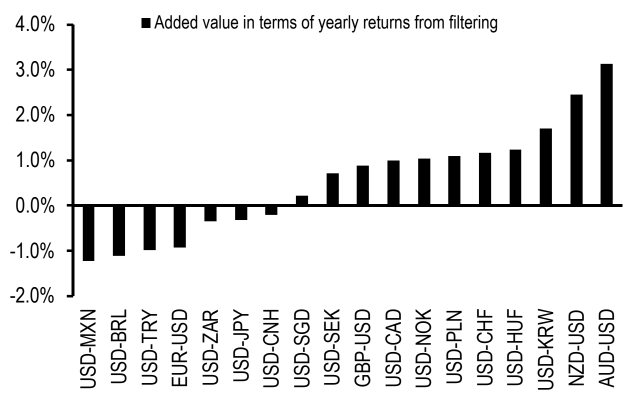
Exhibit 17. The added value (in terms of increase of Sharpe ratio) introduced by the methodology is highest for EM currencies



Source: J.P.Morgan

The second chart (Exhibit 18) displays the extra yearly return generated by filtering. AUD/USD (+3.1%), NZD/USD (+2.5%) and USD/KRW (+1.7%) rank as the top three cases. USD/TRY (-1.0%), USD/BRL (-1.1%) and USD/MXN (-1.2%) are the three bottom cases. We stress that there is no contradiction between the two charts as far as Latam is concerned, as the reduction in vol the strategies enjoy well compensate for the ~1% reduction in yearly returns.

Exhibit 18. The added value (in terms of increase of returns) introduced by the methodology is highest



Source: J.P.Morgan

Aggregated results at a portfolio level

We now display results at the aggregated level, by averaging daily PnLs (converted to a common, USD-base) for the 18 currencies considered. Thanks to the diversification benefits, short-vol strategies are naturally implemented at a portfolio level for systematic trading purposes. Additional work would be required for constructing optimal portfolios from a risk-management standpoint, ideally scaling down attribution to the

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currencies whose PnL is more volatile. With these caveats in mind, the portfolios presented will represent reasonable proxies of a diversified FX short-vol strategy.

Exhibit 19. Performance statistics for the FX short-vol portfolio

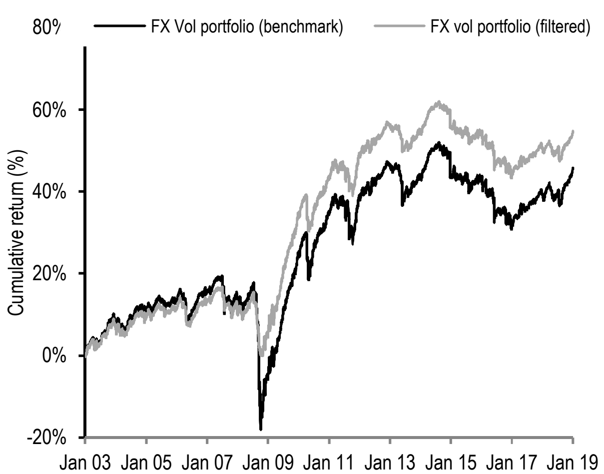
	Since Jan 2003		Since April 2009	
	Benchmark	Filtered	Benchmark	Filtered
Ret	2.8%	3.3%	4.6%	4.5%
Vol	7.5%	5.5%	6.7%	5.5%
Sharpe	0.37	0.60	0.69	0.82
Skewness	-4.1	-3.4	-4.3	-3.2
Kurtosis	41.1	27.6	41.8	24.9
MDD	37.6%	18.6%	21.2%	18.6%
MDD/Vol	5.0	3.4	3.1	3.4

Source: J.P.Morgan

The results of the filtering methodology applied to the FX short-vol portfolio are summarized in Exhibit 19. With data since 2003, the use of the timing indicators for entering the trades largely outperformed the short-vol benchmark. Max drawdown is cut by half, and vol by 30%; as the yearly return is increased by 20%, the Sharpe is up 60% over the benchmark. Higher order moments related to the left-tail of the distribution are also reduced.

One might question the added value of using a filter for short-vol post Lehman's crash, so in the table, we also measure results since April 2009. The filtered strategy still manages to outperform the benchmark in terms of higher Sharpe ratio (up by 20%) and lower vol (down by 20%), although this time the strategy trails passive short-vol by 0.1% in terms of yearly returns. It is comforting to see that the filter brings value even during strong performances as enjoyed by the benchmark position.

Exhibit 20. Filtering applied to a proxy FX short-vol portfolio



Source: J.P.Morgan

One can gain additional insight by looking at the time series of the vol strategies (Exhibit 20). To a large extent, the long-term added value, in terms of cumulative return, introduced by the filter comes from a reduction of losses at the end of 2008. However, the chart also displays how losses are sharply cut during subsequent drawdown episodes (May 2010, September 2011, June 2013, January 2015, August 2015, June 2016).

Filtering managed to reduce just modestly (14.0% from 15.8%) the structural downtrend suffered by short-vol over the 2015-16 period, mostly attributable to G10 currencies. Since January 2017, the filtered strategy trailed by around 3% the benchmark, as the latter strategy recovered (+11.9%) part of the losses experienced over the past two years, with G10 and EM currencies contributing roughly equally.

To summarize, the approach we have presented relies on diversification and on the use of tactical filters for reducing the drawdowns experienced by short-vol strategies. The possibility of matching the positive long-term returns, while cutting sharply the volatility and the drawdowns, of the benchmark short-vol strategy represents the main value added by the filters. We also stress that, while in this piece we have just focused on FX, the application of the very same methodology to other asset classes would be straightforward.

A proxy for a tactical long-vol strategy

The signals above can naturally trigger tactical long-volatility trades; we consider to buy, on a daily basis, the fraction of maximum (Vega) notional which corresponds to the reduction from the 100% allocation for the short-vol strategy. In other words, we scale up long-vol trades by the proportion by which we have reduced short-vol trades. As commented earlier, compared to what was done in previous studies, here we don't try to build an optimal long-vol portfolio across different currencies at any point in time, but rather to consider long-vol trades, on a currency-by-currency basis, over time.

We start by showing results after aggregating all such long-vol strategies over the different currencies (Exhibit 21). We see from the chart that the occasional positive jumps as experienced by the strategy come at the cost of significant PnL-bleed over time. It is worth pointing out that given the wide vol premia found on short-dated options, a more realistic analysis of long-volatility trades would suggest considering longer-dated instruments, where the time-decay is less punitive than on the 1M maturity considered in this piece.

With these considerations in mind, we see that the tactical strategy manages time-decay more gently than the long-vol benchmark. As introduced earlier, higher

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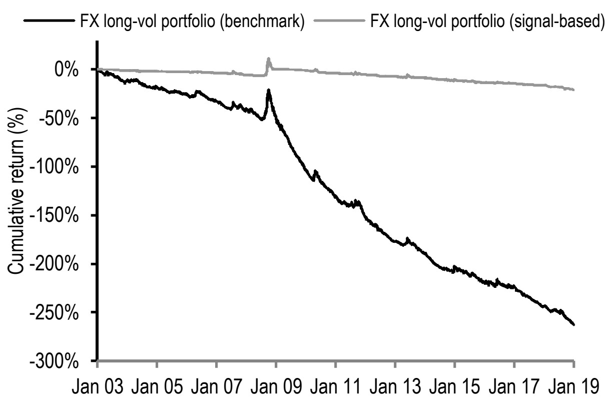
(and positive) skewness (7.1 vs 3.8) and Kurtosis (195 vs 40), features that vol buyers are eager to pay for, for both hedging and high-leverage speculative strategies, point favourably to the filtered strategy over the long-vol benchmark. Intuitively, in absence of trading costs, the PnL of this long-vol strategy should correspond to the difference of filtered vs passive short-vol strategies overviewed earlier (in practice, trading costs introduce an asymmetry between long- and short-vol positions).

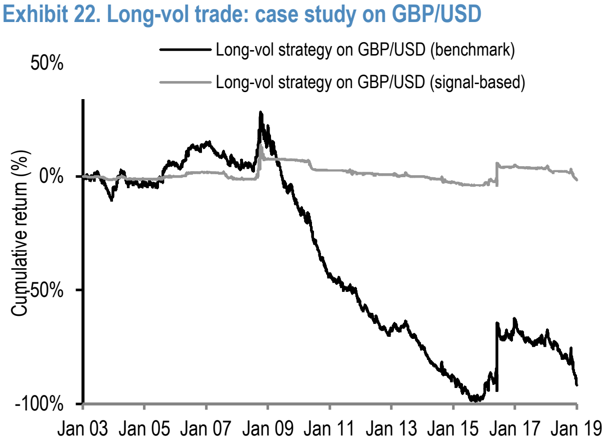
Exhibit 21. Using the filters for triggering long-vol trades helps reducing the time decay of long-volatility positions



Source: J.P.Morgan

The case study on GBP/USD (Exhibit 22) possibly highlights more clearly the value of the methodology than for the portfolio case, especially over the 2016 EU referendum episode.

Exhibit 22. Long-vol trade: case study on GBP/USD



Source: J.P.Morgan

We have already commented that with the rules chosen above, risk-off signals are activated up to 15% of the time (see for instance Exhibit 2). The reason for that was the goal of matching the long-term returns of the short-vol benchmark while allowing the possibility of an aggressive scaling down during market stress episodes. This implies that, when applied to long vol trades, the earlier rules might not trigger enough signals for being meaningful to vol buyers in practice.

For a more active long-vol trading strategy (i.e., for trading more often), one could consider for instance reducing the value of the z-scores above which trade-off signals are activated. Another option regards the use of a non-linear algorithm whereby positions are scaled down more aggressively than by the fraction of activated risk-off signals. A more general possibility would be that of relying on a Machine Learning (ML) algorithm for aggregating the signals. Some flavor of the latter technologies, in the context of short-vol strategies, is presented in the following (and final) section.

Using Machine Learning for the aggregation of the trading signals

In this section, we explore the use of a Machine Learning (ML) algorithm for aggregating the trading signals used in the short-volatility filtering strategy. This section is not meant to be a comprehensive or extensive review of the uses of Machine Learning applied to trading strategies. Instead, it is intended as a way of giving the reader a quick taste for the possible applications of ML in this space. An overview of ML techniques applied to FX vol trading was carried out in a previous piece (*Big Data and AI strategies, Enhancing FX Volatility Trading with Machine Learning*, Cheng et al).

The purpose of using a ML algorithm in this case is to be able to learn from the past interplay between the aforementioned trading signals and the PnL of the short-volatility strategy. This will potentially allow us to find patterns in the data that cannot be captured by the fixed trading rules described in the previous sections. In order to test this proposition, we first selected an algorithm that fitted the data structure and qualities. We then divided the data into training and testing sets, and created a rolling (daily) recalibration methodology. Finally, we compared the results to the benchmark short-volatility strategy and drew some conclusions.

The way we decided to approach the problem of combining the trading signals using Machine Learning, was by setting it up as a supervised ML classification problem. That is, using the trading signals for a given date as features (input variables), we try to predict (classify or label) whether the short-volatility strategy entered on that same date would have a positive PnL at expiry or not. This is a binary classification problem, since it has two possible labels: positive PnL or negative PnL. The structure of the data – a limited amount

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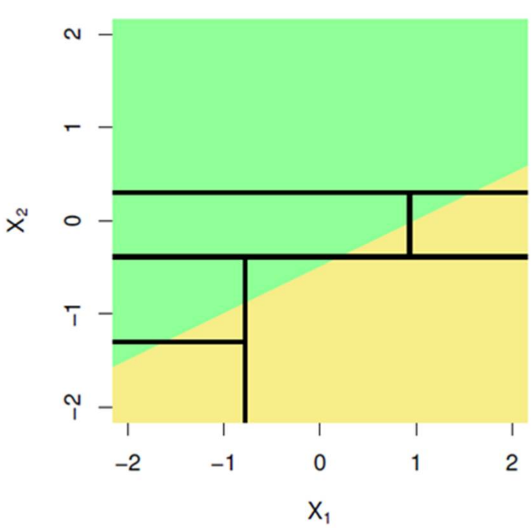
(<4000) of labeled non-text data samples – as well as the nature of the problem suggested that a Random Forest (RF) classification algorithm could be a good candidate for the matter at hand. Further, the RF algorithm does not usually overfit, and its basis – decision trees – are easy to interpret and explain.

Indeed, decision trees are the building blocks of RF algorithms. In simple terms, the idea behind a decision tree algorithm is to branch out (divide) the training data set into different subsets. The division is based on the different permutations of the values of the input variables (the trading signals, in this case). The objective is to find the permutations that give the best prediction of the target variable (the PnL of the strategy in this exercise). This branching exercise is done one input variable at a time, starting with the input variable that has the best ability to predict the value of the target variable (or label) – see Exhibit 23. Note that the order of the variables by which the data is branched out matters, making it a permutation exercise rather than a combinatorial one. The ultimate goal of this algorithm is to create a decision model – one that mirrors how data was branched out – that is able to predict the value of a target variable based on the value of the input variables, when applied to a testing set.

Exhibit 23. Example of the division of a data set under the Random Forest algorithm



Source: J.P.Morgan

Decision trees are a popular method of Machine Learning classification. They are robust and produce intuitive models. However, they overfit training sets, i.e. they have low bias, but high variance. Random forests are a way of averaging decision trees, trained on different parts of the same training set, with the goal of reducing the variance. The different parts of the training sets are selected by bootstrapping samples. The aggregation of the decision trees in order to find a final classification is done by tree averaging/voting. This methodology comes at the expense of a small increase in the bias and some loss of interpretability, but generally greatly boosts the performance of the final model.

Exhibit 24. Mean return, volatility and risk-adjusted return obtained when applying the Random Forest algorithm to the different currency pairs

Asset	Strategy	Ret	Vol	Sharpe	MDD	MDD/Vol
EUR-USD	Filtered	8.1%	7.6%	1.07	13%	1.7
EUR-USD	Passive	8.8%	8.2%	1.07	14%	1.7
GBP-USD	Filtered	1.4%	9.4%	0.15	37%	4.0
GBP-USD	Passive	2.9%	11.7%	0.25	50%	4.3
USD-JPY	Filtered	6.9%	9.4%	0.73	25%	2.6
USD-JPY	Passive	7.5%	10.9%	0.69	26%	2.4
USD-CHF	Filtered	0.4%	14.1%	0.03	40%	2.9
USD-CHF	Passive	-3.7%	26.7%	-0.14	83%	3.1
USD-CAD	Filtered	2.9%	6.1%	0.47	13%	2.1
USD-CAD	Passive	2.3%	7.8%	0.30	18%	2.3
USD-NOK	Filtered	1.8%	8.2%	0.22	31%	3.8
USD-NOK	Passive	1.8%	11.7%	0.15	48%	4.1
USD-SEK	Filtered	1.6%	8.1%	0.20	20%	2.5
USD-SEK	Passive	1.8%	9.7%	0.19	24%	2.5
AUD-USD	Filtered	5.9%	7.8%	0.76	22%	2.8
AUD-USD	Passive	4.5%	10.4%	0.43	29%	2.7
NZD-USD	Filtered	2.5%	8.7%	0.29	26%	3.0
NZD-USD	Passive	1.0%	11.5%	0.08	37%	3.2
USD-BRL	Filtered	13.8%	15.7%	0.88	28%	1.8
USD-BRL	Passive	13.3%	16.3%	0.81	28%	1.7
USD-MXN	Filtered	10.0%	12.8%	0.78	41%	3.2
USD-MXN	Passive	11.0%	13.2%	0.83	41%	3.1
USD-ZAR	Filtered	5.9%	13.7%	0.43	54%	3.9
USD-ZAR	Passive	4.0%	15.6%	0.26	72%	4.6
USD-PLN	Filtered	3.3%	9.7%	0.34	49%	5.1
USD-PLN	Passive	2.4%	11.8%	0.20	68%	5.7
USD-HUF	Filtered	-2.6%	9.5%	-0.27	76%	8.0
USD-HUF	Passive	-4.0%	11.7%	-0.34	103%	8.9
USD-KRW	Filtered	9.0%	8.0%	1.12	32%	3.9
USD-KRW	Passive	9.0%	9.0%	1.00	40%	4.4
USD-SGD	Filtered	3.1%	4.7%	0.68	12%	2.6
USD-SGD	Passive	3.3%	5.4%	0.61	12%	2.2
USD-TRY	Filtered	11.5%	14.0%	0.82	40%	2.9
USD-TRY	Passive	12.0%	14.4%	0.83	40%	2.8

Source: J.P.Morgan

For our test, we used the Random Forest classifier function in the *Sklearn* package in the *Python* computing language. We also created a rolling recalibration methodology, which allows to re-calibrating the RF model every day during the period considered, thus incorporating the previous day's data into the algorithm's training set. We found this feature to greatly increase the performance of the model versus calibrating just once. The period considered for the test was April 2009 to January 2019. For training of the RF algorithm, we also used data going back to January 2004. As for the currencies considered, we used 17 currency pairs (the same as in previous sections except USD/CNH, because of a lack data for some periods considered in the model).

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The results show that the RF algorithm clearly adds some value. The risk-adjusted returns were higher than the benchmark's in 14 out of 17 currency pairs, as can be seen in Exhibit 24. Further, the Sharpe ratio, when averaged across currencies, improved by 20%, from 0.43 to 0.51. This improvement comes from an almost 19% reduction in the volatility of the strategy – from a 12.1% to a 9.8% annualized daily volatility. The average annualized return across currencies was also increased by almost 10%, from 4.6% to 5.0%. The benefits of the strategy do not stop there; the (negative) skewness was also reduced by 9.6%, as was the Kurtosis, which was reduced 12.3%. More importantly, the max drawdown was reduced significantly -- almost 24% -- from 43%, to a more manageable 33%. Finally, the trading signal of the strategy was active in 77.3% of the days.

At the portfolio level (by averaging all currencies except CNH since April 2009, for being consistent), the RF algo introduced manages to outperform the agnostic equal allocation as introduced earlier (Exhibit 25) on the main metrics (yearly return, vol. Sharpe ratio, max drawdown), which is a very encouraging result.

Exhibit 25. Since April 2009, the ML-based allocation outperforms the equal-allocation to the signals at the portfolio level

	Since 2009	
	ML	**Linear**
Ret	5.0%	4.7%
Vol	5.6%	5.7%
Sharpe	0.90	0.81
Skewness	-3.2	-3.2
Kurtosis	28.8	25.2
MDD	-17.2%	-20.9%
MDD/Vol	-3.1	-3.6

Source: J.P.Morgan

The results above appear promising and would definitely call for additional research, which we aim to cover in future pieces. It would be adequate to test different ML algos and come up with a comparative assessment about which one works best, and whether ML brings sufficient added value for replacing the agnostic equally weighted allocation of the signals, as reviewed above. The ML-based selection of the variables in the final allocation process (which we do here with RF) could be compared with more traditional selection techniques, such as the one which ranks the variables by performance, as measured by the marginal improvement in terms of Sharpe ratios vs the benchmark.

Additionally, it would be tempting to explore other non-linear functions of the original variables as features in the ML algo(s), thus feeding the model with more information than the binary trading signals introduced earlier. For instance by inputting the z-score value itself: this would naturally remove the arbitrary choice of a fixed threshold for the activation of the signals.

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