A Quantitative Framework for Cross Asset Style Timing

Machine Learning, Macro and Time-Series models providing views for Portfolio Tilting

Global Quantitative and Derivatives Strategy

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Introducing a Quantitative Framework for Tactical Allocation

We propose a framework for style timing in cross-asset risk premia, which relies on various Machine Learning algorithms to generate views on expected returns. We then incorporate our views for tactical portfolio tilting using the Black-Litterman mechanism.

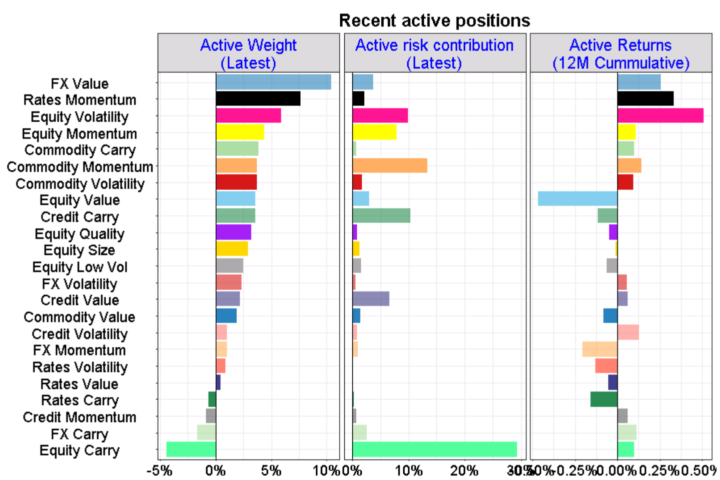
Machine Learning algorithms sniffing through hundreds of predictors: What have the models picked?

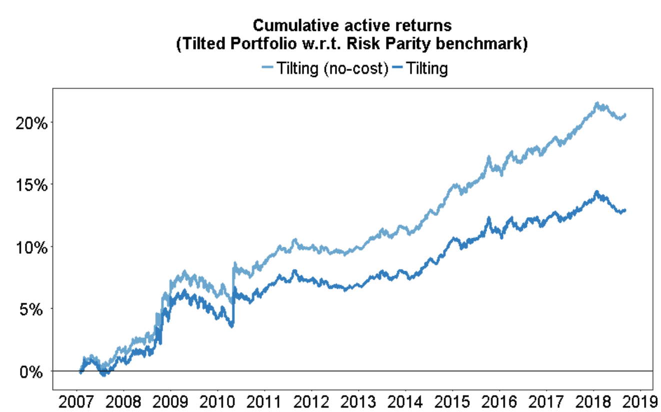
We look at Machine Learning models from basic stepwise selection models, penalized regression models to ensemble models such as Random Forests and Gradient Boosting. Our algorithms sniff through hundreds of predictors ranging from historical returns, macro-economic variables, news sentiment, flows and positioning data to J.P. Morgan surveys. We apply a feature selection procedure to screen for useful predictors, and demonstrate how to use a method called "LIME" to interpret Machine Learning model predictions.

Black-Litterman portfolio tilting based on views

Our model predictions are aggregated into a weighted score which takes into account model correlations. We then apply the Black-Litterman approach to tilt our portfolio with respect to the risk parity benchmark. In terms of active risk, our model suggests an OW in Commodity Momentum, Equity Volatility and Credit Carry, whilst an UW in Equity Carry, FX Carry and Credit Momentum.

Active weights and active returns in our tilted portfolio relative to the risk parity benchmark (left), and cumulative active returns of the tilted portfolio (right)





Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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Systematic Cross-Asset Strategies

- Systematic Strategies Across Asset Classes: Risk Factor: Approach to Investing and Portfolio Management
- Equity Risk Premia Strategies: Risk Factor Approach to Portfolio Management
- Momentum Strategies Across Asset Classes: Risk Factor Approach to Trend Following
- Cross Asset Portfolios of Tradable Risk Premia Indices: Hierarchical Risk Parity: Enhancing Returns at Target Volatility
- Harvesting Volatility Risk Premia With Machine Learning: Volatility Spread Strategy Using Dynamic Linear Model
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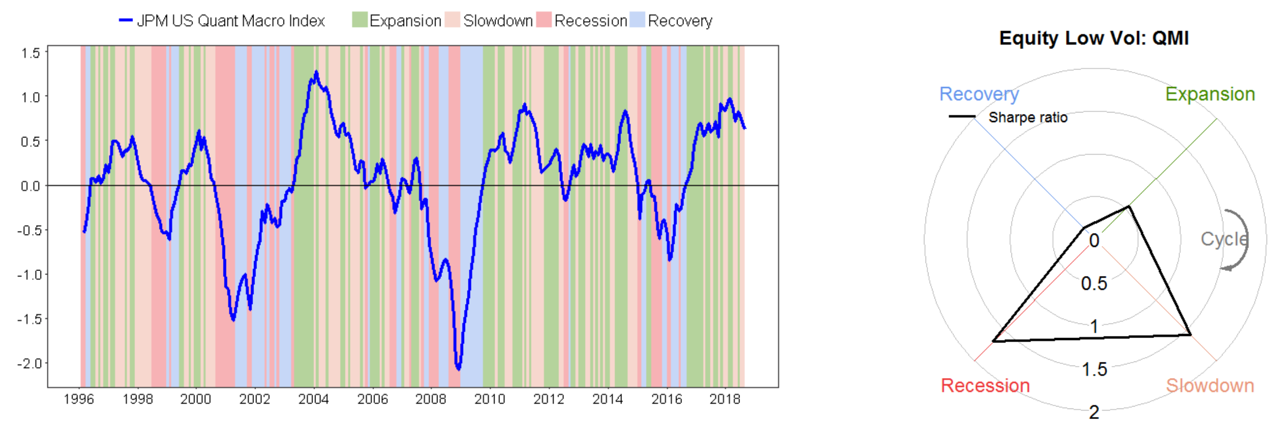
Quantitative Tactical Allocation for cross-asset risk premia

Style timing has always been a hotly debated topic among institutional investors. Intuitively, this is an appealing idea, as we do see evidence that factors (or styles) deliver disparate performance under different macro-economic regimes over the long run. Indeed, our colleagues have developed the Quantitative Macro Indicators (QMI) to time Equity factors. For instance, one might expect stocks with low volatility to outperform volatile stocks in times of recession (Figure 1).

Figure 1: US QMI, and the average performance of the Equity Low Vol Factor under different QMI regimes



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

Having said that, if you have attempted to perform tactical allocation in a systematic way, you probably get a feeling of how hard it is[1]. Asness (2016) uses some simple valuation measures for "contrarian timing", and admit that such timing strategies show weak historical performance.

Whilst most of the timing literature focuses on Equity styles, research on cross assets is relatively scarce, and also mainly focuses on asset class allocations (e.g. GTAA) instead of styles or risk premia (e.g. Blitz et al (2008)). As cross-asset risk premia have become increasingly popular among investors, the question becomes "how to tactically expose to different styles across asset classes".

In this study, we provide a quantitative framework for cross-asset risk premia investors to allocate their portfolios. The idea is simple, but the "backend" analysis is quite heavy due to the number of models and predictors involved. We outline our framework in the next section.

[1] **Note that timing traditional asset classes, or market exposures, is generally easier than timing factors, or risk premia. We have seen that risk premia are less dependent on macro-regimes than asset classes, which is actually one of the appealing characteristics of risk premia.**

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Framework

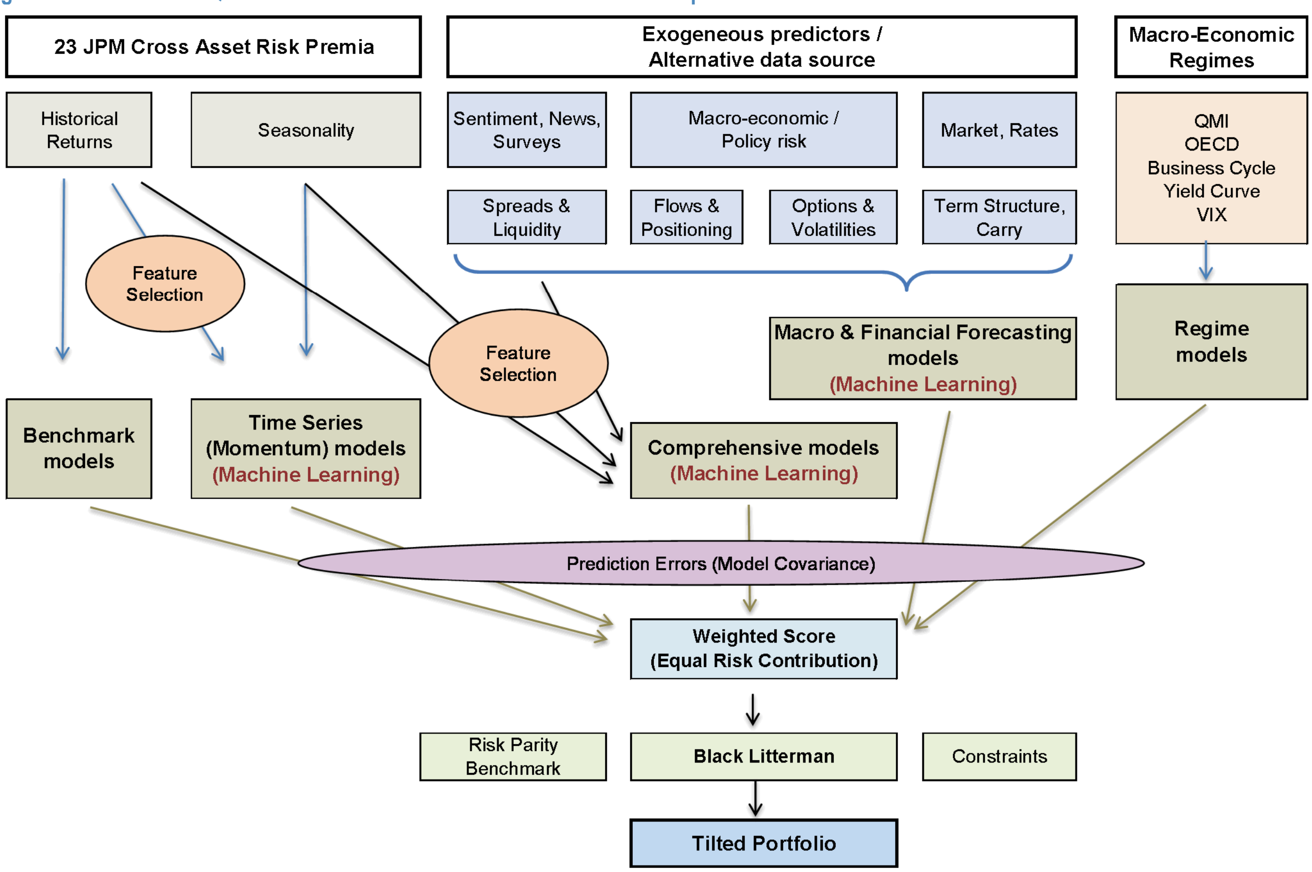
Figure 2 shows our tactical allocation framework. We consider 23 cross-asset risk premia indices (Table 1), and based on their historical returns we have the **Benchmark models** (Past 1-month, 3-year or 5-year averages). We also look at "**Time Series models**" to predict their performance using past returns.

Next, we collect a large number of predictors from macro-economic, sentiment, options, flows and positioning data to "alternative data source" including news and JPM surveys. These features are being selected in our "**Macro & Financial Forecasting models**" based on Machine Learning. By including historical returns in our predictors, we have the "**Comprehensive models**".

Lastly, we estimate macro-economic regimes and use "**Regime models**" to predict returns based on performances within historical macro environment.

With predictions from different models, we use a weighting scheme to estimate an aggregated view for each risk premia, taking into account model correlations. Finally, we apply the Black-Litterman approach to tilt our portfolio away from the risk parity benchmark based on our views (while controlling portfolio risk and active risk).

Figure 2: Framework of Quantitative Tactical Allocation on cross-asset risk premia



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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Throughout our study, we consider a set of J.P. Morgan cross-asset risk premia indices (Table 1) that are relatively "pure and vanilla" in order to give a more representative picture on how various styles have performed[2]. An advantage of considering these tradable indices (rather than prototype research models) is that they are already net of costs[3], and in the implementation we have considered issues such as liquidity constraints and capacity.

Table 1: J.P. Morgan cross-asset risk premia Indices; all indices are net of costs, and we apply t-cost assumptions when we rebalance the indices in our portfolio

Name	Asset	Style	Ticker	Strategy overview
Equity				
J.P. Morgan Equity Risk Premium – Global Pure Value	Equity	Value	JPQFVLW1	L/S strategy on Value factor
J.P. Morgan Equity Risk Premium – Global Pure Quality	Equity	Quality	JPQFQUW1	L/S strategy on Quality factor
J.P. Morgan US Volatility Term Premia Index	Equity	Carry	JPMZVP4G	Systematic long puts on VIX Futures
J.P. Morgan Equity Risk Premium – Global Pure Momentum	Equity	Momentum	JPQFMOW1	L/S strategy on Momentum factor
J.P. Morgan Equity Risk Premium – Global Pure Low Vol	Equity	Low Vol	JPQFLVW1	L/S strategy on Low Vol factor
J.P. Morgan Equity Risk Premium – Global Pure Size	Equity	Size	JPQFSZW1	L/S strategy on Size factor
J.P. Morgan US 5% Mean Reversion Short Volatility Index	Equity	Volatility	JPOSUS5M	Monetize carry between implied and realized volatility through options exposure in S&P (5% notional a day)
Credit				
J.P. Morgan Global Credit Value	Credit	Value	JCREGCV1	Aim to monetize the risk premia between major CDS indices using a fair value spread
J.P. Morgan Credit Global Curve Steepener	Credit	Carry	JCRECVSG	Track performance from a rolling 5s10s steepener on iTraxx Main and CDX IG
J.P. Morgan Global Credit Momentum USD	Credit	Momentum	JCREMOGU	Aim to capture cross-sectional momentum in global credit indices
J.P. Morgan Global HY Short Volatility	Credit	Volatility	JCRESVGH	Aim to monetize the high implied volatility relative to realized volatility in iTraxx Crossover and CDX HY options by selling straddles and delta hedging on a daily basis
Rates				
J.P. Morgan MAST Basket of 3 Index (USD)	Rates	Value	JPMSUBK3	Capture forward rate risk premium in 3-month USD, EUR and GBP Libor 1y forward
J.P. Morgan CarryMax 2 Futures-6 USD Index	Rates	Carry	JCMX2A6U	Capture yield differential in govt. bond futures
J.P. Morgan Helix 3 Index (USD)	Rates	Momentum	JHLXH3US	Capture trends in short-term interest rate markets using money market futures
J.P. Morgan JPVLBTYU Index	Rates	Volatility	JPVLBTYU	Capture value from the implied versus realized volatility of UST10Y Note futures by shorting option strangles and delta hedge
FX				
J.P. Morgan JPFCVA01 Index	FX	Value	JPFCVA01	Capture value in FX pairs in G10 using PPP
J.P. Morgan FX Carry JPFCARB1	FX	Carry	JPFCARB1	Long high yielding currencies and short low yielders on a large universe of currency pairs
J.P. Morgan JMCUFCTA Index	FX	Momentum	JMCUFCTA	Aim to extract the momentum effect from the underlying FX pairs
J.P. Morgan FX Volemont JPVOFX02 Index	FX	Volatility	JPVOFX02	Pure short gamma exposure across 5 USD currency pairs
Commodity				
J.P. Morgan Compendium Fundamental Index	Commodity	Value	JCOPCF	Using momentum on fundamental signals to go long-short commodities
J.P. Morgan Alpha Select II Index	Commodity	Carry	JMABDBSE	Capture commodity curve carry
J.P. Morgan JMCUCCTA Index	Commodity	Momentum	JMCUCCTA	Aim to extract the momentum effect from the underlying commodities
J.P. Morgan Custom JMAB279E Index	Commodity	Volatility	JMAB279E	Monetize the premium between implied and realized volatility with Breakeven Curve filter

Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

[2] **J.P. Morgan offers a large number of tradable cross-asset risk premia indices on our platform, and some of the bespoke risk premia strategies may have specific configurations to meet with clients' investment objectives.**

[3] **We also include assumptions on transaction costs and running fees in the backtests when we rebalance the risk premia portfolio. On average we charge 15 bps (which could vary depending on the liquidity of the indices). We also assume a flat running fee of 20bps per year.**

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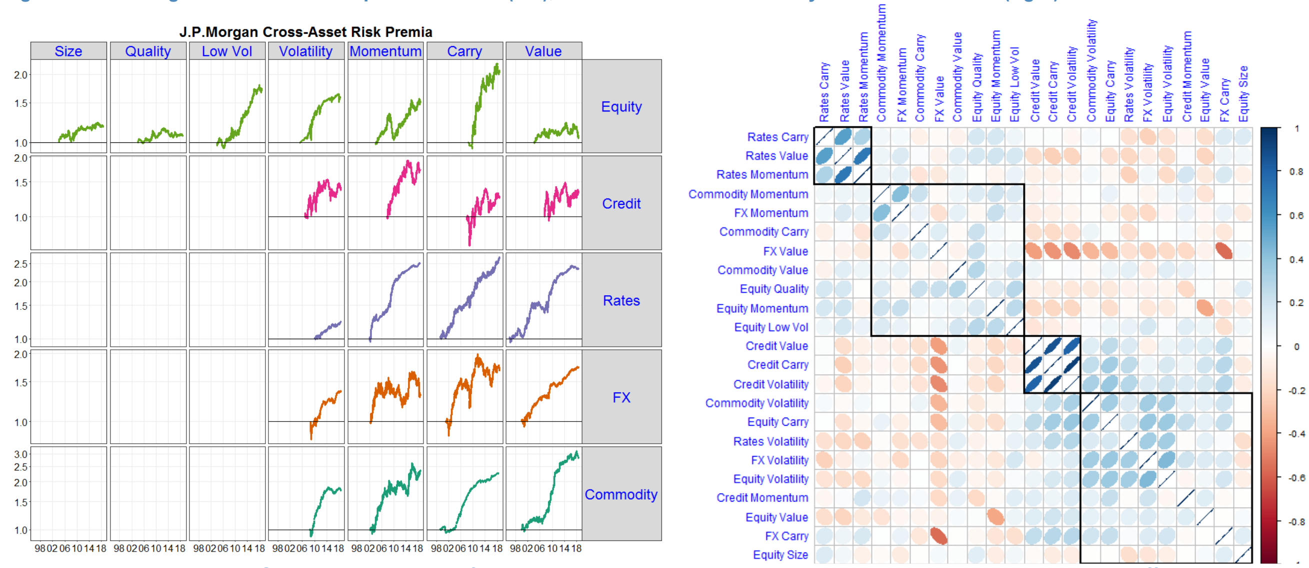
In Figure 3, the left chart shows the cumulated wealth (starting from $1) and the right chart shows the correlation of monthly returns since 2010. Value and Carry risk premia are positively correlated in Rates and Credit, as high-yielding assets tend to be "cheaper". It is interesting to note that FX Value is negatively correlated with many risk premia, especially FX Carry. This is due to the fact that high yielding currencies in G10 tends to be stronger and more expensive, in contrast to the case for EM currencies.

Figure 3: J.P. Morgan cross-asset risk premia indices (left), and correlations of monthly returns since 2010 (right)



The table shows the daily USD returns statistics of these risk premia over whole history; note that the starting dates are different due to data availability: rates start as early as 1996, and volatility risk premia may start as late as 2008

Ticker	Asset	Style	Start date	End date	Ann. Ret.	Ann. Vol.	Shar-pe	Max DD	Hit Ratio	t-stat	Sk-ew	Kurt-osis	Sort-ino	Cal-mer
Equity														
JPQFVLW1	Equity	Value	2004-01-09	2018-09-10	0.3%	3.9%	0.08	14.4%	49.9%	0.4	0.3	3.3	0.01	0.02
JPQFQUW1	Equity	Quality	2004-01-09	2018-09-10	0.5%	2.9%	0.16	9.1%	50.5%	0.7	0.0	3.9	0.02	0.05
JPMZVP4G	Equity	Carry	2008-06-02	2018-09-10	7.5%	11.3%	0.66	14.7%	53.7%	2.2	-0.6	7.2	0.06	0.51
JPQFMOW1	Equity	Momentum	2004-01-09	2018-09-10	2.8%	5.4%	0.51	23.5%	53.5%	2.1	-0.3	1.6	0.05	0.12
JPQFLVW1	Equity	Low Vol	2004-01-09	2018-09-10	3.7%	4.5%	0.82	10.3%	51.5%	3.2	0.1	2.5	0.08	0.36
JPQFSZW1	Equity	Size	2004-01-09	2018-09-10	1.1%	3.6%	0.29	11.5%	50.9%	1.2	-0.2	3.4	0.03	0.09
JPOSUS5M	Equity	Volatility	2005-03-21	2018-09-10	3.7%	5.7%	0.65	15.3%	64.7%	2.4	-3.4	57.6	0.05	0.24
Credit														
JCREGCV1	Credit	Value	2007-07-03	2018-09-10	2.8%	12.2%	0.23	29.0%	51.2%	0.9	0.4	5.0	0.03	0.10
JCRECVSG	Credit	Carry	2008-01-03	2018-09-10	2.4%	12.2%	0.20	29.2%	51.8%	0.8	0.0	3.1	0.02	0.08
JCREMOGU	Credit	Momentum	2007-07-25	2018-09-10	5.4%	9.7%	0.55	24.9%	52.6%	1.9	0.5	7.1	0.05	0.22
JCRESVGH	Credit	Volatility	2006-11-02	2018-09-10	2.9%	10.1%	0.29	22.2%	52.5%	1.1	-0.1	2.6	0.03	0.13
Rates														
JPMSUBK3	Rates	Value	1996-01-02	2018-09-10	3.7%	4.5%	0.82	12.5%	52.9%	4.0	-0.5	6.2	0.07	0.29
JCMX2A6U	Rates	Carry	1999-05-03	2018-09-10	5.0%	10.0%	0.50	12.9%	51.4%	2.4	0.1	2.9	0.05	0.39
JHLXH3US	Rates	Momentum	2002-01-01	2018-09-10	5.5%	4.2%	1.30	7.9%	55.4%	5.3	-0.2	6.7	0.12	0.69
JPVLBTYU	Rates	Volatility	2010-01-05	2018-09-10	2.6%	3.6%	0.71	3.9%	61.9%	2.1	-1.8	10.4	0.06	0.66
FX														
JPFCVA01	FX	Value	2000-01-05	2018-09-10	3.3%	4.5%	0.74	7.8%	52.0%	3.1	-0.4	12.9	0.07	0.42
JPFCARB1	FX	Carry	2001-01-03	2018-09-10	3.2%	9.8%	0.33	28.7%	52.5%	1.5	-0.4	4.1	0.03	0.11
JMCUFCTA	FX	Momentum	2002-04-04	2018-09-10	1.6%	9.4%	0.17	26.0%	48.7%	0.9	-0.1	2.5	0.02	0.06
JPVOFX02	FX	Volatility	2008-08-05	2018-09-10	3.2%	4.6%	0.70	16.5%	59.3%	2.2	-4.5	64.6	0.06	0.19
Commodity														
JCOPCF	Commodity	Value	2000-01-03	2018-09-10	5.9%	6.4%	0.93	10.2%	52.5%	4.0	0.1	3.8	0.09	0.58
JMABDBSE	Commodity	Carry	1999-02-01	2018-09-10	4.4%	3.2%	1.38	9.2%	55.5%	5.9	-0.8	9.0	0.12	0.48
JMCUCCTA	Commodity	Momentum	2002-04-03	2018-09-10	5.2%	10.2%	0.51	21.6%	50.1%	2.2	0.1	2.7	0.05	0.24
JMAB279E	Commodity	Volatility	2008-07-02	2018-09-10	6.0%	4.4%	1.38	9.2%	62.7%	4.3	-2.3	15.0	0.11	0.65

Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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Latest model recommendations

Figure 4 summarizes our latest "score card" for the risk premia. We show the expected returns (weighted) from each of the 5 classes of models. The weighted view is the aggregated prediction from all models.

We highlight OW and UW by considering both the extent of active tilting and their contribution to active risk. Some risk premia (e.g. FX Value) could have a relatively large active weight but still a small active risk due to their low volatilities.

Figure 4: Recommendation and score card for the cross-asset risk premia; aggregated forecast is obtained by summing the forecasts from 5 classes of models

Overweight	Details / Remarks	Model views
Commodity Momentum	The model is increasing the OW in the recent months	+ve: Aggregated model prediction is the highest across all risk premia +ve: Historically performance in Q4 tends to be positive
Equity Volatility	The model has been OW since the volatility spike in early February	+ve: The time-series models indicate a 1M trend (positive trend, positive impact) +ve: The time-series models indicate a 12M reversal (negative trend, positive impact) -ve: Historical performance in Q3 is negative
Credit Carry	The model suggests OW, although it seems to be scaling down the exposure in recent months	+ve: Model predictions are quite positive +ve: Models show a strong 1M trend (positive trend, hence a positive impact) -ve: Models show that a stronger US Dollar maybe negative for returns
Underweight	**Details / Remarks**	**Model views**
Equity Carry (Volatility Carry)	The model suggests a relatively large UW. Most of the decrease in the position is due to portfolio optimization effect	-ve: Aggregated model perdiction is relatively low -ve: Performance used to be poor during volatility spikes
FX Carry	The model is slightly UW in the past few months	-ve: Model predictions (esp. the Macro & Financial forecasting models) are quite negative +ve: Higher oil prices maybe positive for returns
Credit Momentum	The model just turns UW recently, switching from OW in 2017	-ve: The current "Bear Flattening" yield curve regime tends to be very negative for Credit Momentum

	Aggregated Forecast (bps)	Aggregated Forecast / Volatility	Model Forecasted Returns (bps)					Notional (x 100) (5% Vol Target)				Risk (%)		
			Benchmark	Economic Regime	Macro & Financial Forecasting	Time Series	Comprehensive	Risk Parity	Tilted Portfolio	Active Tilting	Active Tilting / Volatility	Vol	Portfolio Risk Contribution	Active Risk Contribution
Equity Value	-10.3	-0.08	-1.3	1.3	-1.4	-4.6	-4.3	18.0	21.6	3.6	0.8	4.5	4.6	3.0
Equity Quality	13.1	0.17	0.9	2.7	3.1	2.5	3.9	29.9	33.1	3.2	1.2	2.7	4.0	0.9
Equity Carry	8.5	0.03	7.1	4.7	-3.7	11.6	-11.2	7.6	3.2	-4.5	-0.4	11.3	0.6	29.3
Equity Momentum	70.7	0.41	-6.1	6.5	22.2	20.9	27.3	13.2	17.5	4.4	0.7	6.0	5.4	7.9
Equity Low Vol	54.6	0.42	4.9	7.9	13.1	18.1	10.6	18.2	20.8	2.5	0.6	4.6	4.4	1.5
Equity Size	11.4	0.11	-1.4	0.8	0.1	10.3	1.6	23.2	26.2	2.9	0.8	3.5	4.2	1.3
Equity Volatility	21.9	0.15	1.4	3.3	4.8	9.5	3.0	12.6	18.5	5.9	1.2	4.9	4.1	9.9
Credit Value	24.9	0.08	2.9	8.5	13.3	-10.4	10.6	7.5	9.7	2.2	0.2	10.8	5.4	6.7
Credit Carry	30.7	0.13	7.3	3.5	4.3	14.7	0.9	10.1	13.7	3.6	0.4	8.3	6.4	10.4
Credit Momentum	37.3	0.14	-1.1	-2.0	25.6	9.9	4.8	8.9	8.0	-0.9	-0.1	9.3	2.7	0.7
Credit Volatility	62.5	0.26	3.9	0.0	17.0	15.7	25.8	10.0	11.1	1.0	0.1	8.4	4.3	0.9
Rates Value	27.7	0.51	-0.8	6.3	7.1	4.4	10.8	47.9	48.3	0.4	0.2	1.9	4.1	0.0
Rates Carry	37.1	0.17	4.8	7.5	14.6	11.0	-0.8	12.8	12.2	-0.6	-0.1	7.4	4.0	0.2
Rates Momentum	35.8	0.70	2.0	6.6	11.8	9.9	5.6	51.2	58.9	7.7	4.3	1.8	5.4	2.1
Rates Volatility	14.6	0.18	2.6	3.7	1.7	6.9	-0.3	32.4	33.3	0.9	0.3	2.9	4.5	0.1
FX Value	37.8	0.75	1.9	5.0	12.0	8.1	10.8	45.4	55.8	10.4	6.0	1.7	4.6	3.8
FX Carry	-15.1	-0.06	5.7	3.3	-15.9	3.4	-11.6	11.6	9.9	-1.7	-0.2	8.8	3.7	2.5
FX Momentum	-11.7	-0.05	-3.9	2.9	-6.6	-1.1	-2.9	9.3	10.3	1.0	0.1	8.7	3.9	0.9
FX Volatility	7.8	0.09	3.6	1.1	-0.3	8.3	-5.1	27.6	30.0	2.4	0.8	3.1	4.4	0.6
Commodity Value	57.9	0.35	1.4	7.5	7.3	21.2	20.5	14.1	16.0	1.9	0.3	5.8	4.2	1.4
Commodity Carry	33.7	0.55	1.9	10.0	7.3	7.3	7.2	46.9	50.8	3.9	1.8	2.1	5.6	0.8
Commodity Momentum	99.2	0.38	0.4	16.1	39.1	18.3	25.3	8.0	11.7	3.7	0.4	9.2	5.6	13.4
Commodity Volatility	22.4	0.24	-2.5	1.7	14.7	1.5	6.9	24.4	28.1	3.7	1.1	3.3	4.1	1.7

Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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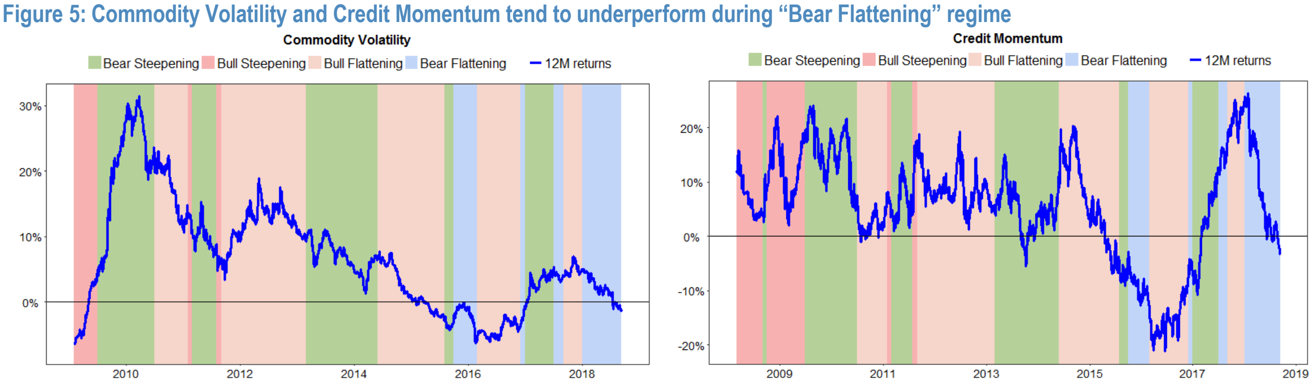
Formulating views on expected returns

Macro-economic regime-based expectations

The first approach to predict returns is a traditional one which relies on the identification of the current or forthcoming macro-economic regimes. The most typical are the Growth and Inflation regimes, which have been applied in our Cross-asset regime investing model.

Macro regimes tend to give a smoother view that is supposed to stay for an extended period of time. We find that some risk premia, e.g. Commodity Volatility and Credit Momentum, tend to be affected by the movement of the yield curve. They both underperform during "Bear Flattening", i.e. when interest rates increase and the yield curve flattens (Figure 5).

Figure 5: Commodity Volatility and Credit Momentum tend to underperform during "Bear Flattening" regime



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

Another interesting regime is the business cycle: Many investors have recently been concerned if the US economy has finally reached the late cycle, and if the current second-longest expansion since WWII will end soon. One may try to identify the stage of the business cycle by looking at the recession probability, say in 1-year horizon. Our fundamental cross-asset strategists have applied a rotation model based on recession probabilities, and find that an active Equity/Bond portfolio outperforms the 60/40 benchmark by 70-200bps per annum.

For the purpose of historical analysis, we use the NBER recession dates to define recessions. Unfortunately, for risk premia returns which are only available since 1996, there are only 2 recession periods in US: The 2000 dot-com bubble and the 2008 GFC. Early-cycle of expansion is the first 12 months following the end of the recession, and Late-cycle is the 12 months before the start of the recession. Dates between Early-cycle and Late-cycle are labelled as Mid-cycle. We have real-time daily recession probabilities since October 2016, and hence from that onwards we use the levels of recession probabilities to gauge the cycles – ideally we hope to be able to detect inflection points at real time.

We look at some popular regimes monitored by investors, defining them in a rather heuristic manner[4] (Figure 6):

- **Economic growth**: JPM US Quant Macro Indicator (QMI), OECD Total Leading Indicator
- **Business Cycle**: US recession probability in 1 year, historical NBER recession dates[5]
- **Interest rates:** US Treasury yield curve (10Y vs 2Y) and rates changes (10Y)
- **Volatility:** VIX (5-year rolling z-score)

Figure 6: Macro regimes heuristic definitions; we mainly define regimes based on levels and changes of some indicators

OECD CLI MoM Change

	OECD Regime	Negative	Positive
OECD CLI Level	Negative	Recession	Recovery
	Positive	Slowdown	Expansion

US QMI MoM Change

	QMI Regime	Negative	Positive
US QMI Level	Negative	Recession	Recovery
	Positive	Slowdown	Expansion

Yield Curve Slope (US 10Y over 2Y)

	Yield Curve Regime	Flatten / Invert	Steepen
Interest Rate (US 10Y)	Rising	Bear Flattening	Bear Steepening
	Falling	Bull Flattening	Bull Steepening

VIX change (z-score)

	VIX Regime	Negative	Positive
VIX Level (z-socre)	Negative	Risk Taking	Risk Building
	Positive	Market Normalize	Vol Spike

Historical	12M after Recession	In-between	12M before Receesion	NBER Recession
US Recession Probability	P < 5%	5% < P < 35%	35% < P < 70%	P > 70%
Business Cycle	Early-cycle	Mid-cycle	Late-cycle	Recession

Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

For each risk premium, we look at the returns across periods within the same regime. To prevent results being distorted by extreme performance over short-lived regimes (e.g. a regime lasting for only a few months), we weight the returns with the length of the regime.

The average historical returns conditional on the latest regime (e.g. slowdown based on US QMI) will be used as the prediction for returns in the next month. Figure 7 shows the latest regimes based on end of August data, and Figure 8 plots the historical macro regimes.

Figure 7: Latest macro regimes based on month-end indicators

Regime	Indicator	Latest Indicator	Latest Indicator (1M chg)	Latest Regime
QMI	US QMI Level	0.63	-0.04	Slowdown
OECD	OECD CLI (over 100)	-0.35	-0.11	Recession
Business Cycle	US Recession Probability	24.2%	1.0%	Mid-cycle
Yield Curve	US 10Y - US 2Y (3M avg)	0.31	-0.08	Bear Flattening
VIX	VIX 5-year z-score	-0.44	0.02	Risk building

Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

[4] On the other hand, we may use Hidden Markov Models (HMM) to estimate the regimes. An example is to estimate low, mid and high volatility regimes, e.g. Peng at al (2018)

[5] For Business Cycle, we do have some look-ahead bias as the NBER recessions dates can only be determined after the turning points have observed. However, we follow Normand and Edgerton (2018) here and only use the recession probability since it is live in 2016

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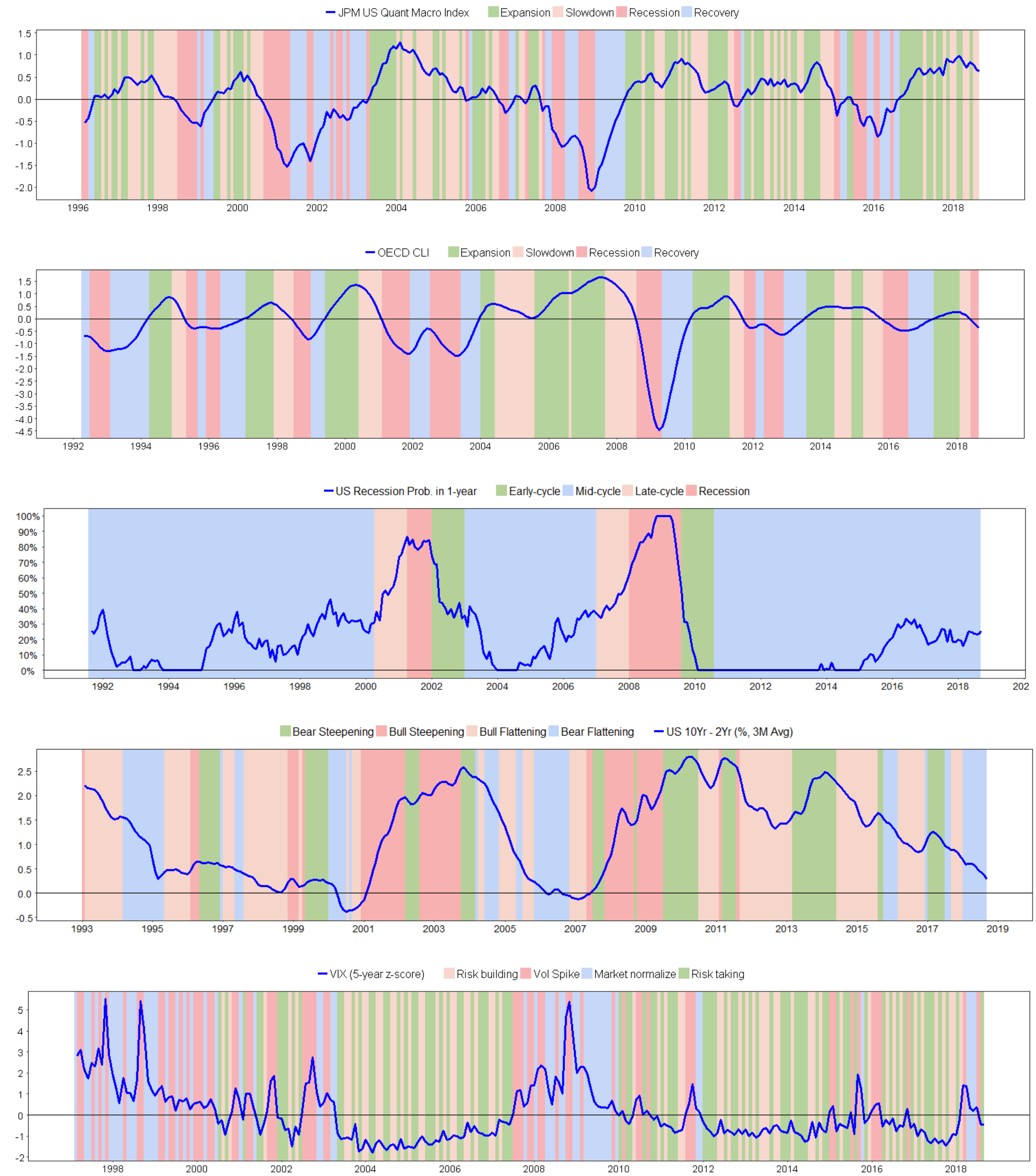
Figure 8: Macro regimes: Growth/recession regimes based on US QMI and OECD CLI; Business cycles based on recession probabilities (and historical NBER dates); yield curve regimes based on US 10Yr and US 2Yr; and VIX regimes based on rolling 5-year z-scores of VIX levels



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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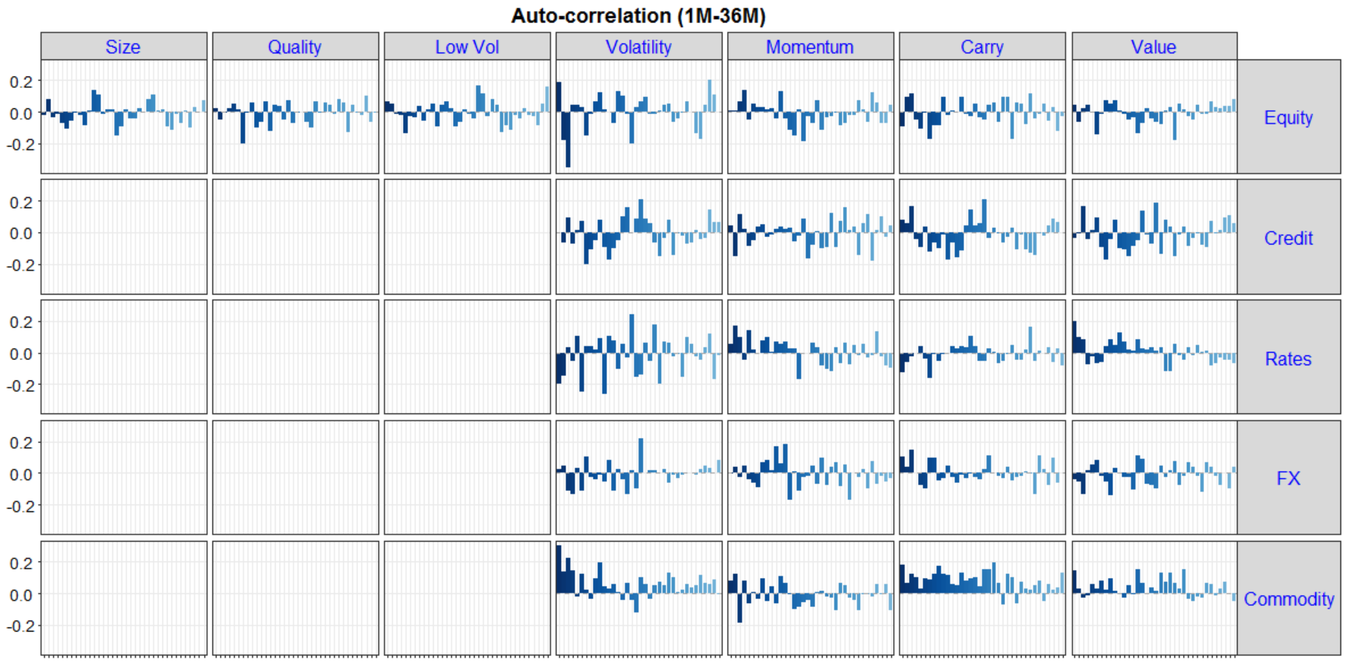
Time-series models exploiting returns patterns

Moskowitz et al (2011) find that time-series momentum, i.e. trend following, is a remarkably consistent and profitable strategy for each of the 58 liquid investments including equity indices, currencies, commodities and sovereign bonds. Historical returns in general contain information which helps to predict future performance, although its efficacy could differ across assets (e.g. trend following in EM FX tends to be more profitable than G10 FX (Ilmanen 2011)) and lookback windows (e.g. for Equities one might consider 12M-1M to remove short-term reversal effects, but for other asset classes 12M gives stronger results (Asness et al 2012)). We have actually designed a robust trend-following system across asset classes, which is able to diversify across lookback windows and improve risk-adjusted performance (Tzotchev et al (2018)).

Autocorrelations

To estimate whether return patterns are trending or mean-reverting, Figure 9 shows the autocorrelations of risk premia returns at various lags from 1 month (darker blue) to 36 months (lighter blue). Positive autocorrelations indicate trending behavior: Commodity Carry and Commodity Volatility are amongst the risk premia with the most persistent trends at a short horizon of 1-3 months. Short-term reversal patterns (i.e negative autocorrelations) are observed in Rates Carry, Rates Volatility and FX Value.

Figure 9: Autocorrelations of risk premia returns from 1 month (darkest blue) to 36 months (lightest blue). Commodity Carry and Commodity Volatility are amongst the risk premia with the most persistent trends at a short horizon of 1-3 months; short-term reversal patterns are observed for Rates Carry, Rates Volatility and FX Value



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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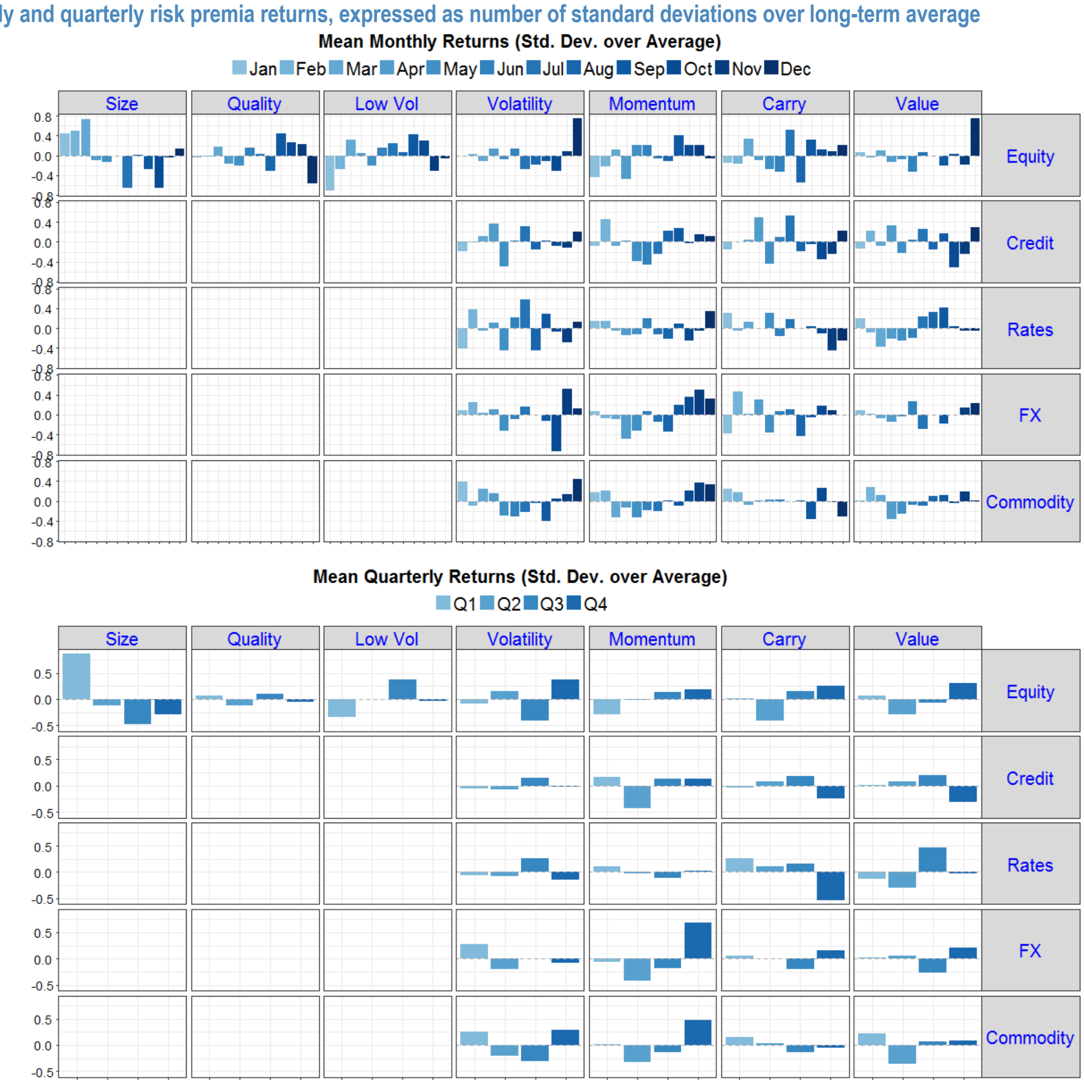
Seasonality

We can also unveil interesting patterns when we look at seasonality of returns. One of the most commonly studied patterns is the January effect, which could partly be explained by higher risk appetite at the beginning of the year. Ilmanen (2011) finds that small caps, volatile stocks, high-yield credits and many risk-taking carry strategies tend to outperform in January.

In Figure 10, we show the mean monthly returns (upper chart) and quarterly returns (lower chart) of each risk premia, expressed as the number of standard deviations over long-term average. We see that Equity Size indeed outperforms in January (and also for Q1). Equity Low Vol underperforms in January, which reaffirms that volatile stocks tend to perform better at the beginning of the year. Equity Value and Volatility have significantly higher returns in December compared to the rest of the year. FX Momentum and Commodity Momentum both outperform towards the end of the year in Q4, whilst Rates Carry in general suffers. We will include a quarterly dummy to capture seasonality in returns in some of our models.

Figure 10: Average monthly and quarterly risk premia returns, expressed as number of standard deviations over long-term average



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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We consider various "***Time-series based (Momentum)***" models, together with benchmarks including the **Naïve** forecast (past 1M returns), and simple averages using **past 3-year** and **past 5-year** monthly returns.

AR(1)
A simple autoregressive model using only one lagged term, i.e. past 1M returns r_t:

$$r_{t+1} = \alpha + \beta r_t + \varepsilon_{t+1}$$

Linear Model
A simple linear model using 3 predictors (past 1M, 3M and 12M returns) to forecast next 1M returns:

$$r_{t+1} = \alpha + \beta_1 r_{t,1M} + \beta_2 r_{t,3M} + \beta_3 r_{t,12M} + \varepsilon_{t+1}$$

LASSO
We fit a linear model with L1 regularization to shrink the magnitude of the coefficients. By tuning the penalty parameter, we obtain a sparse set of coefficients out of a large number of predictors.

Stepwise Selection
A simple, efficient statistical approach that iteratively adds predictors to a linear model. At each step, the predictor that gives the most additional improvement (e.g. in terms of RMSE or R-squared) to the existing model is added. We can tune the maximum number of predictors to be included in the final model.

Random Forest
Random Forest is a popular Machine Learning algorithm that uses an ensemble of decision trees to make predictions. As a single decision tree has high variance (i.e. predictions differ dramatically with a small change in data), it is better to use bagging to fit many decision trees with different bootstrapped samples, and aggregate the predictions to reduce variance. Random Forests improves the bagging procedure by building less correlated decision trees, where the trick is to only consider a random subset of predictors to split a node when "growing" a decision tree.

Gradient Boosting Machine (GBM)
GBM is another ensemble model which builds a sequence of decision trees to fit the data. Starting from a constant model, the algorithm attempts to improve the fit by adding a decision tree (or some other weak learners) to the existing model at each iteration, so as to explain the residuals from the last model. This is the "boosting" procedure, and the final model is a series of additive decision trees. The model is usually estimated via an optimization routine called "Stochastic Gradient Descent".

Extreme Gradient Boosting (XGBoost)
XGBoost is conceptually similar to GBM, except that it is implemented to make the model more robust (via regularization) and improves the running speed (memory optimization, cache-line optimization). It is a winning algorithm on Kaggle, and we have also applied it in our Global Equity Value Strategy.

We use a rolling window to estimate the models every year, and predictions are obtained every month end. For some more details on the estimation of these models, please refer to the Appendix.

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Machine Learning models using macro, financial and technical data

Apart from using macro-regimes and historical returns to predict risk premia, we can also look at many other predictors that might drive performance. Examples include market variables, options data, risk metrics, sentiment measures and surveys. Before digging into a large number of predictors, we first select some variables where investors closely monitor. Movements in these variables (e.g. US Dollar, yield and volatility) could likely drive returns in asset classes and risk premia:

Linear Model

We first consider a simple linear model with a constant set of predictors $F_t^{(j)}$:

$$r_{t+1} = \alpha + \sum_j \beta_j F_t^{(j)} + \varepsilon_{t+1}$$

where $F_t^{(j)}$ are factors including 1M returns in S&P 500, WTI Crude Oil and the US Dollar Index, together with 1M change of the VIX, high yield spread, US 3M rates and the slope of the yield curve (estimated as US 10Y over US 2Y). Despite being simple, such a linear model could sometimes beat complicated Machine Learning models, and they are also much easier to interpret.

More predictors for our Machine Learning models

With the vast amount of public information available to investors, it would be too constrained to limit ourselves to a small set of predictors. As such, we firstly curate a large number of possible features, where we will feed them into different Machine Learning models (e.g. Random Forests, GBM) to predict risk premia returns. We also create a number of variations (e.g. 3M average, 1M change) of each feature, hence the total number of predictors (not including historical returns) goes beyond 1000. In practice, it is not ideal to include highly correlated predictors into the Machine Learning models, and we also expect some predictors maybe more relevant for a particular risk premia (e.g. yield curves for Credit and Rates). As such, we use a ***feature selection algorithm*** to pre-select a subset of predictors before every model calibration. In simple terms, the selection procedure involves two steps:

- Fit a bagged CART[6] and collect the top predictors based on variable importance
- Within the top predictors, we remove those which are highly correlated

We use R's caret package for our feature selection procedure (Kuhn 2009).

In Figure 11 to Figure 13, we provide the details for about 200 predictors that we collect for our Machine Learning models. We look at their average levels (or returns for some market variables) over the past 1M, 3M and 12M, and we estimate their changes over various lookbacks. This leads to over 1000 predictors in our pool.

Using these predictors, we run 5 Machine Learning models: Stepwise, LASSO, Random Forest, GBM and XGBoost. The "***Macro & Financial Forecasting***" versions do not include returns, and the "***Comprehensive***" versions consider all macro and financial predictors, as well as historical returns across risk premia.

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[6] **CART stands for Classification And Regression Tree**

These predictors are grouped into 7 categories in Figure 11 to Figure 13:

1. **Macro-economic variables:** Growth, Inflation, Policy uncertainty
2. **Sentiment & surveys:** News sentiment, J.P. Morgan investor surveys
3. **Market variables:** Asset class performances, currencies, rates, valuation
4. **Spreads & liquidity:** Credit / High-yield spreads, swap spreads
5. **Flows & positioning:** Bond fund & ETF flows, speculative positioning in futures
6. **Options & volatilities:** Implied volatility, VRP (Implied vs Realized vol), Skew
7. **Term structures & carry:** Futures term structures, commodity carry, FX carry

For each risk premia, we show groups of predictors that are selected by our top models in the Appendix.

Figure 11: Predictors for Machine Learning models: Macro-economic variables, sentiment and surveys

Macro-economic Variables	Ticker / Source	Details
Growth		
ADS Business Condition	ADS BCI Index	Aruoba-Diebold-Scotti (ADS) Business Conditions Indices is designed to track real business conditions at daily frequency using a Dynamic Factor Model and Kalman Filter
Global Economic Activity Surprise	JPEASIGL Index	
DM Economic Activity Surprise	JPEASIDM Index	JPM EASI indices are designed to capture economic activity surprises
EM Economic Activity Surprise	JPEASIEM Index	
US Economic Activity Surprise	JPEASIUS Index	
China Economic Activity Surprise	JPEASICN Index	JPM Quant Macro Indicators (QMI) are monthly indices developed to time equity styles based on business cycles
JPM US QMI	JPM	
JPM EU QMI	JPM	JPM Forecast Revision Indices (FRI) are weekly indices that track changes in the JP Morgan forecast of real GDP growth over the coming four quarters
JPM GEM QMI	JPM	
JPM Japan QMI	JPM	
Global GDP Forecast Revision	JPM	
DM GDP Forecast Revision	JPM	
EM GDP Forecast Revision	JPM	
JPM Global GDP Nowcast Bias	JPM	
Recession Probability in 1 Year	DataQuery	
Inflation		
US Inflation Surprise	CSIIUSD Index	The Citi Inflation Surprise Indices measure price surprises relative to market expectations. A positive reading means that inflation has been higher than expected and a negative reading means that inflation has been lower than expected.
G10 Inflation Surprise	CSIIG10 Index	
EM Inflation Surprise	CSIIEM Index	
China Inflation Surprise	CSIICNY Index	
Policy Uncertainty		
Global Economic Policy Uncertainty	EPUCGLCP Index	Economic Policy Uncertainty (EPU) is an index to guage uncertainty based on newspaper coverage frequencies of particular phrases that combine variations of "economic uncertainty" with keywords such as "legislation", "regulation" or "Fed" (for US). (Baker et al 2016)
US Trade Policy Uncertainty	EPUCTRAD Index	
US Monetary Policy Uncertainty	EPUCMONE Index	
US Economic Policy Uncertainty	EPUCCUSM Index	
EU Economic Policy Uncertainty	EPUCCEUM Index	
China Economic Policy Uncertainty	EPUCNCHM Index	
Sentiment & Surveys	**Ticker / Source**	**Details**
Sentiment		
JPM Equity Sentiment	JPMEQGSI Index	JPM Equity Sentiment is a weekly indicator to gauge sentiment in Equities
US Composite Consumer Sentiment	DataQuery	
US Composite Manufacturing Sentiment	DataQuery	Our economists compile various versions of composite sentiment for US
US Composite Non-manufacturing Sentiment	DataQuery	
Conference Board Consumer Confidence	CONCCONF Index	High-frequency daily sentiment is derived from a sentiment analytics provider called RavenPack to capture sentiment in different contexts. Using RavenPack's taxonomy system that automatically tags news stories to various topics and groups such as economy, employment, inflation, Initial offerings, etc. By removing news stories that are fact-based, we can focus on articles that contain sentiment on outlook and expectations that are more forward-looking
University of Michigan Consumer Sentiment	CONSSENT Index	
EU Consumer Confidence	EUCCEMU Index	
Business & Consumer Confidence	RavenPack	
US Employment Sentiment	RavenPack	
Economic Outlook	RavenPack	
Inflation Outlook	RavenPack	
Equity Outlook	RavenPack	
IPO Sentiment	RavenPack	
Commodity Sentiment	RavenPack	
Corporate Credit Sentiment	RavenPack	
Sovereign Credit Sentiment	RavenPack	
JPMorgan Survey		
Corporate Bond Weight	JPM	Our credit strategists issue a monthly survey to credit investors and ask about their positions on corporate bond (UW / Neutral / OW), cash levels (Low / Mid / High) and spread outlook (Positive / Neutral / Negative), and construct diffusion indices to gauge the changes.
Cash Position	JPM	
Spread Outlook	JPM	
JPM China Sentiment	JPM	Our China strategists aggregate responses from analyst surveys on sector outlook and sector sentiment in China

Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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Figure 12: Predictors for Machine Learning models: Market variables, spreads & liquidity, flows and positioning

Market Variables	Ticker / Source	Details
Asset Class Performances		
S&P 500	SPX Index	Measure market performance in different asset classes
MSCI DM	NDDUEAFE Index	
MSCI EM	NDUEEGF Index	Look at 1M, 3M and 12M cumulated returns
WTI Crude Oil	USCRWTIC Index	
S&P GSCI	SPGSCI Index	Consider 1M vs 3M and 3M vs 12M crossovers of the average price levels
Gold	XAUUSD Curncy	
Global Inflation-linked debt	LF94TRUU Index	
iTraxx Europe 5Yr	ITRXTE5I Index	
iTraxx Crossover 5Yr	ITRXTX5I Index	
CDX IG 5Yr	CDXTIL15 Index	
CDX HY 5Yr	CDXTHL15 Index	
Currency		
US Dollar	DXY Curncy	Look at 1M, 3M and 12M cumulated currency returns
EUR	EUR Curncy	
JPY	JPY Curncy	Consider 1M vs 3M and 3M vs 12M crossovers of the average price levels
Asian currency	ADXY Curncy	
EM currency	MXEF0CX0 Index	
Rates		
G7 and Eurozone Gerneric 3M	Bloomberg	Collect 10Y over 3M gerneric government rates for the G7 countries (US, Canada, UK, France, Germany, Italy, Japan) and the Eurozone as a proxy for rates carry
G7 and Eurozone Gerneric 10Y	Bloomberg	
G7 and Eurozone Gerneric 10Y over 3M	Bloomberg	
US 2Yr	USGG2YR Index	Carry is a major driver of returns (Koijen et al 2013)
US 10Yr over 2Yr	See above	
USD Libor	US0003M Index	
EUR Libor	EE0003M Index	
GDP Libor	BP0003M Index	
Fed Target Rate	FDTR Index	
US 3M10Y Forward Swap Rate	USFS0C10 Curncy	
Valuation		
S&P 500 Price-to-Earnings	Bloomberg	
US Value P/E over Growth P/E	Bloomberg	Look at valuation metrics of US market (CAPE and P/B)
DM P/E over EM P/E	Bloomberg	
S&P 500 Price-to-Book	Bloomberg	Also consider the valuation spreads between styles (Value vs Growth) and markets (DM vs EM)
US Value P/B over Growth P/B	Bloomberg	
DM P/B over EM P/B	Bloomberg	Valuation spreads between asset class (Equity vs Bond) is estimated as the ratio between the earnings yield of US equities and the US 10-year yield
Equity-Bond Premia	Bloomberg	
Spreads & Liquidity	**Ticker / Source**	**Details**
Credit Spread		
Credit Spread A	CSI A Index	The JULI index is the JP Morgan US Liquid Index, an index of High Grade US corporate bonds
Credit Spread BBB	CSI BBB Index	
High Yield Spread	CSI BARC Index	JPM EMBI indices track the fixed income performance in EM markets
US High Grade Spread z-score	JULIZ Index	
JPM EMBI Global Spread	JPEIGLSP Index	
JPM EMBI+ Sovereign Spread	JPEIPLSP Index	
US IG CDS spread	CDX IG CDSI GEN 5Y	
US HY CDS spread	CDX HY CDSI GEN 5Y	
US HY over IG CDS spread	See above	
EU IG CDS spread	ITRX EUR CDSI GEN 5Y	
Liquidity		
Ted Spread	BASPTDSP Index	Ted spread is the difference between 3M Eurodollar (interbank loan) and 3M Treasury Bill ("riskless" government loan), which may proxy funding liquidity.
US 2Yr swap spread	USSP2 Index	
US 10Yr swap spread	USSP10 Index	Swap spread may proxy the liquidity in the treasury market
Flows & Positioning	**Ticker / Source**	**Details**
Fund Flow		
EU IG Bond Inflow	JPM, EPFR	Bond Fund Flow data are weekly data provided by EPFR.
EU HY Bond Inflow	JPM, EPFR	
US HG Bond Fund Flow	JPM, EPFR	For EU IG and HY Bond Funds, we look at the net Inflow in terms of % of AUM
US HY Bond Fund Flow	JPM, EPFR	
EM Bond Fund Flow	JPM, EPFR	For US IG and HY Bond Funds, and EM Bond Funds, we look at the net flow in dollar terms
US Equity ETF Flow	JPM, Bloomberg	
UK Equity ETF Flow	JPM, Bloomberg	Equity ETF flows may gauge the sentiment of retail investors
Eurozone Equity ETF Flow	JPM, Bloomberg	
Japan Equity ETF Flow	JPM, Bloomberg	
EM Equity ETF Flow	JPM, Bloomberg	
Speculative Positions		
S&P 500 Spec Position	Bloomberg, CFTC	Speculative positions are estimated as the net positions (long contracts minur short contracts) in the non-commercial category of the Commitments of Traders reports, scaled by open interest
MSCI EM Spec Position	Bloomberg, CFTC	
VIX Spec Position	Bloomberg, CFTC	
WTI Crude Oil Spec Position	Bloomberg, CFTC	
Brent Crude Oil Spec Position	Bloomberg, CFTC	
Gold Spec Position	Bloomberg, CFTC	

Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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Figure 13: Predictors for Machine Learning models: Options data, Volatilities, term structures and carry

Options Data & Volatility	Ticker / Source	Details
Implied Volatility		
VIX	VIX Index	We consider cross asset implied volatilities to monitor risk-off regimes in various asset classes
V2X	V2X Index	
MSCI EM Vol	VXEEM Index	
MOVE	MOVE Index	MOVE index measures the weighted average of implied volatility on 1M Treasury options
Oil Vol	OIV Index	
Gold Vol	XAUUSDV1M Curncy	VTRAC-X is the J.P. Morgan volatility tracker of expected price volatility in CDS markets for a rolling 30 day expiry, based on quoted option prices
JPM EU IG Vol	VTRXEIP Index	
JPM EU HY Vol	VTRXEHP Index	
JPM EU Fin Vol	VTRXEFP Index	
JPM US IG Vol	VTRXUIP Index	
JPM US HY Vol	VTRXUHP Index	
HY Vol	VXHYG Index	
JPM Global FX Vol	JPMVXYGL Index	
JPM G7 FX Vol	JPMVXYG7 Index	
JPM EM FX Vol	JPMVXYEM Index	
EURUSD 1M Vol	EURUSDV1M Curncy	
USDJPY 1M Vol	USDJPYV1M Curncy	
US 10Yr Vol	TYVIX Index	
USD Libor Swaption Vol	USSV0C5 Curncy	
VRP (Implied vs Realized Volatility)		
S&P 500 VRP	Bloomberg, DataQuery	Volatility Risk Premia (VRP) is the difference between implied volatility (IV) and realized volatility (RV). This is a popular "contrarian" timing signal across all asset classes. IV measures market expectation of future volatility and typically goes up much more than RV during risk-off scenarios. In many cases, subsequent returns is higher as the market has overreacted.
STOXX 50 VRP	Bloomberg, DataQuery	
NIKKEI 225 VRP	Bloomberg, DataQuery	
Oil VRP	Bloomberg, DataQuery	
Gold VRP	Bloomberg, DataQuery	
EURUSD VRP	Bloomberg, DataQuery	
USDJPY VRP	Bloomberg, DataQuery	
iTraxx Main VRP	DataQuery	
iTraxx Crossover VRP	DataQuery	
CDX IG VRP	DataQuery	
CDX HY VRP	DataQuery	
Volatility Skew & Hedge Ratio		
S&P 500 Skew	SKEW Index	SKEW Index is calculated from S&P 500 OTM options and typically ranges from 100-150. A value of 100 means that the distribution of S&P 500 log-returns are normal. If the value increases, the probability of tail risk increases
EURUSD Risk Reversal	EURUSD25R1M Curncy	
USDJPY Risk Reversal	USDJPY25R1M Curncy	
EURJPY Risk Reversal	EURJPY25R1M Curncy	
iTraxx Main 3M Skew	DataQuery	Volatility skew measures the differences of implied volatility between OTM call options and put options of the same maturity. It may proxy sentiment and risk appetite
iTraxx Main 3M Skew	DataQuery	
CDX IG 3M Skew	DataQuery	
CDX HY 3M Skew	DataQuery	Risk reversals are options strategies based on volatility skew
CBOE Equity Put/Call	PCUSEQTR Index	Equity Put/Call ratio can proxy risk appetite and the extent of hedging
Term Structures & Carry	**Ticker / Source**	**Details**
Term Structures & Carry		
EURUSD ATM Vol 1Y-3M	Bloomberg	We look at volatility slope in FX and Credit
USDJPY ATM Vol 1Y-3M	Bloomberg	
iTraxx Main 3M-1M Calendar Skew	DataQuery	VIX carry and other Commodity carry is estimated from the term structure of the futures, using the first and second contracts. Carry is negative if the term structure is in Contango, and positive if the term structure is in Backwardation.
iTraxx Crossover 3M-1M Calendar Skew	DataQuery	
VIX Carry	Bloomberg	
Brent Crude Oil Carry	Bloomberg	
WTI Crude Oil Carry	Bloomberg	Carry is a major driver of returns (Koijen et al 2013)
Gasoline Carry	Bloomberg	
Natural Gas Carry	Bloomberg	
Gold Carry	Bloomberg	
Copper Carry	Bloomberg	
Aluminum Carry	Bloomberg	
FX Carry		
JPY/USD Carry	JPYUSDCR Index	We look at the returns of FX carry trades, i.e. borrowing the short currency to fund buying the long currency and earning interest. For notational convenience, we always short USD here.
GBP/USD Carry	GBPUSDCR Index	
EUR/USD Carry	EURUSDCR Index	
CAD/USD Carry	CADUSDCR Index	
AUD/USD Carry	AUDUSDCR Index	Carry is a major driver of returns (Koijen et al 2013)
NZD/USD Carry	NZDUSDCR Index	
CHF/USD Carry	CHFUSDCR Index	
G10 Carry Trade Index	FXCTG10 Index	

Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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Evaluating model predictions

In the last sections, we use different models to predict risk premia returns based on regimes, historical returns and predictors from macro-economic variables, sentiment, volatilities to flows and positioning data. Here we analyze their overall performance, hoping to gain some insights on “which models to recommend”. Whilst we admit that traditional measures such as RMSE and R-squared may give us some idea of the goodness of fit, they may not be the best metrics to reflect how good the model is when one utilizes its predictions in a systematic strategy. As our objective is to have positive and consistent PnL, we derive evaluation metrics that are more relevant for a trading signal (i.e. our forecasts) $y_{t+1|t}$ that attempts to predict returns r_{t+1}:

- **Hit ratio:** Proportion of correct signs in the predictions
- **Profit (per risk):** We assume a simple strategy that long one unit if $y_{t+1|t} > 0$, and short one unit if $y_{t+1|t} < 0$. The PnL of this strategy after T periods is $PnL(T) = \sum_{t=0}^{T-1}\left(sign\left[y_{t+1|t}\right] \times r_{t+1}\right)$. We define profit per risk as $E[PnL]/\sqrt{Var[PnL]}$
- **Profit scaled (per risk):** We also want the magnitude of our prediction to be proportional to the outcome. Hence we modify the above strategy and long $\left|y_{t+1|t}\right|$ unit if $y_{t+1|t} > 0$, and short $\left|y_{t+1|t}\right|$ unit if $y_{t+1|t} < 0$. We then define profit scaled (per risk) similarly as above: $E[PnL]/\sqrt{Var[PnL]}$
- **Profits for long & short legs:** We want to know whether the profits are from the long positions or the short positions, or ideally both
- **PnL when correct or wrong:** We want to know the expected profit (or loss) when our prediction is correct (or wrong)
- **Sensitivity:** We evaluate how the signal can classify the signs of the returns. As risk premia tend to deliver more positive returns than negative returns, we define sensitivity as the proportion of correct calls for negative returns, as given by values in a confusion matrix (left chart). For models that always give positive predictions (e.g. some regime-based ones), sensitivity will be zero

		# of Outcome	
		Negative	Positive
# of Prediction	Negative	A	B
	Positive	C	D

Sensitivity = A / (A+C)

In Figure 14, we show the hit ratios (upper chart) and the profit scaled per risk (lower chart) for each risk premia. We find that:

- It is not always true that complicated models could beat naive benchmarks, e.g. simple historical returns give reasonable forecasts for Equity Value and Equity Low Vol
- Value risk premia are more successfully predicted by time-series models exploiting momentum and reversal patterns
- Macro & financial forecasting models may also perform well without using any information in historical returns (e.g. for Equity Quality)
- Higher hit ratios do not always translate to higher profit: It is more important to "hit" when the magnitude of returns is large. An example is Equity Volatility: Using Business Cycle regime as prediction gives high hit ratio (77%), but when we apply it to a trading strategy, the simple Linear Macro model delivers the largest profit consistently

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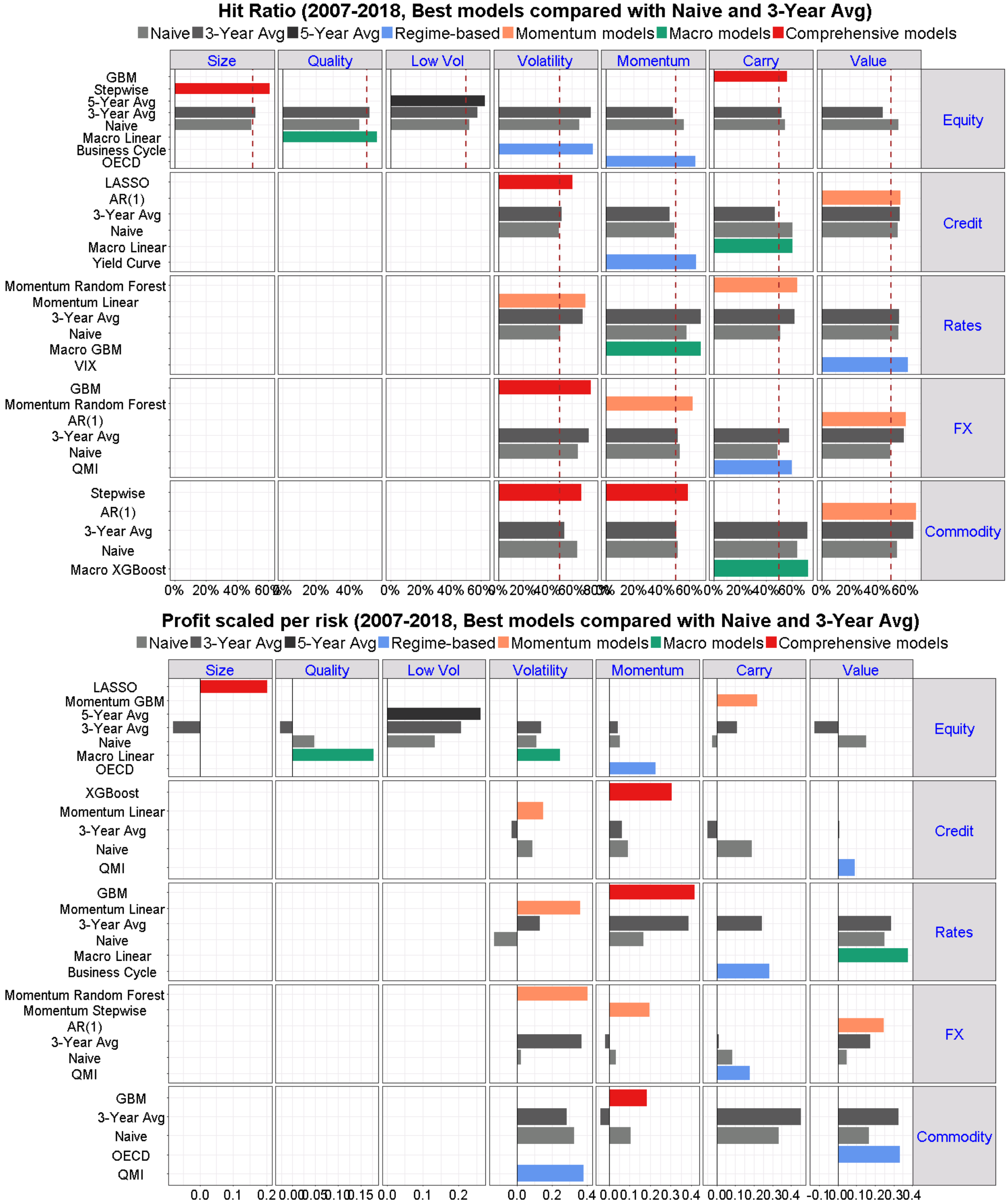
Figure 14: Hit ratios (top) and profit scaled per risk (bottom) of the best models, compared with naive and 3Yr average forecast (2007 – 2018); the dotted line corresponds to a hit ratio of 50%



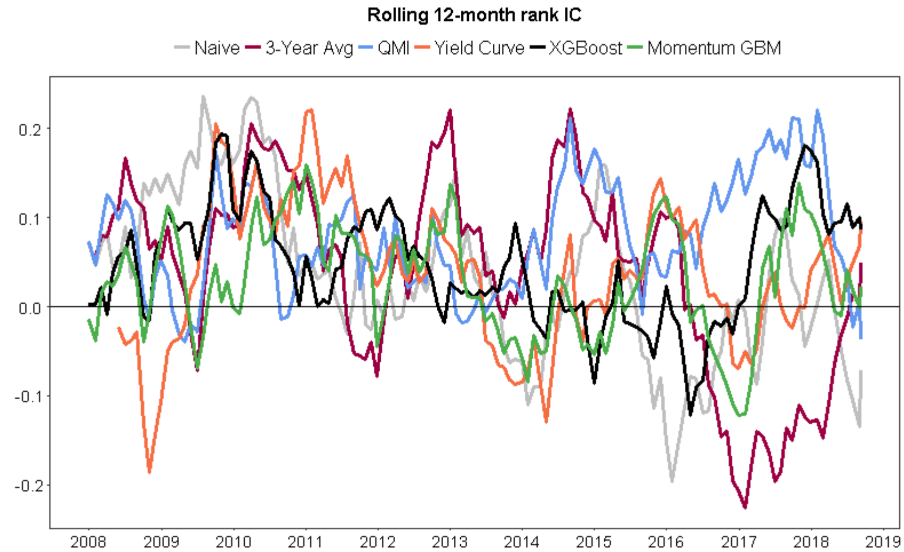
Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

Rank Information Coefficient

It might be a bit dizzy to look at so many different models, which could even perform differently for each risk premia. If we are only allowed to pick a single model across all risk premia, which one would we prefer?

We try to look at how the model predictions could help us rank the risk premia, i.e. whether higher predictions correspond to higher 1-month-ahead returns. Figure 15 shows the rank Information Coefficient (IC) of the models. We find that regime-based predictions, especially the US QMI, show good ranking ability. Predictions based on past 3-year average returns did a good job in ranking the risk premia before 2016, but in the recent years the performance is poor. The XGBoost model shows good ranking ability in the past 2 years, just followed by the QMI regime-based predictions.

Figure 15: Rank IC and the distribution of hit ratios for each model. Positive rank IC means that the model predictions tend to be positively correlated to the rank of the 1M-ahead returns



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

Hit ratios, profits and sensitivity

Another measure to gauge average model performance is to look at the hit ratios. In Figure 16, we show the distributions of hit ratios across risk premia, sorted by their median values. Interestingly, regime-based model (VIX, OECD) gives the highest hit rates, followed by the simple linear Macro model. Gradient Boosting Machines (GBMs) perform well, especially for the time series version only based on historical returns.

The AR(1) model in general do not have the highest hit ratios, but we see from the right chart that it "***hits at the best times***" such that average profit is highest. GBMs (whatever version it is) also tend to deliver higher profits than most other models. Linear models (Stepwise, LASSO) in general perform poorly and have the lowest hit ratios and profit.

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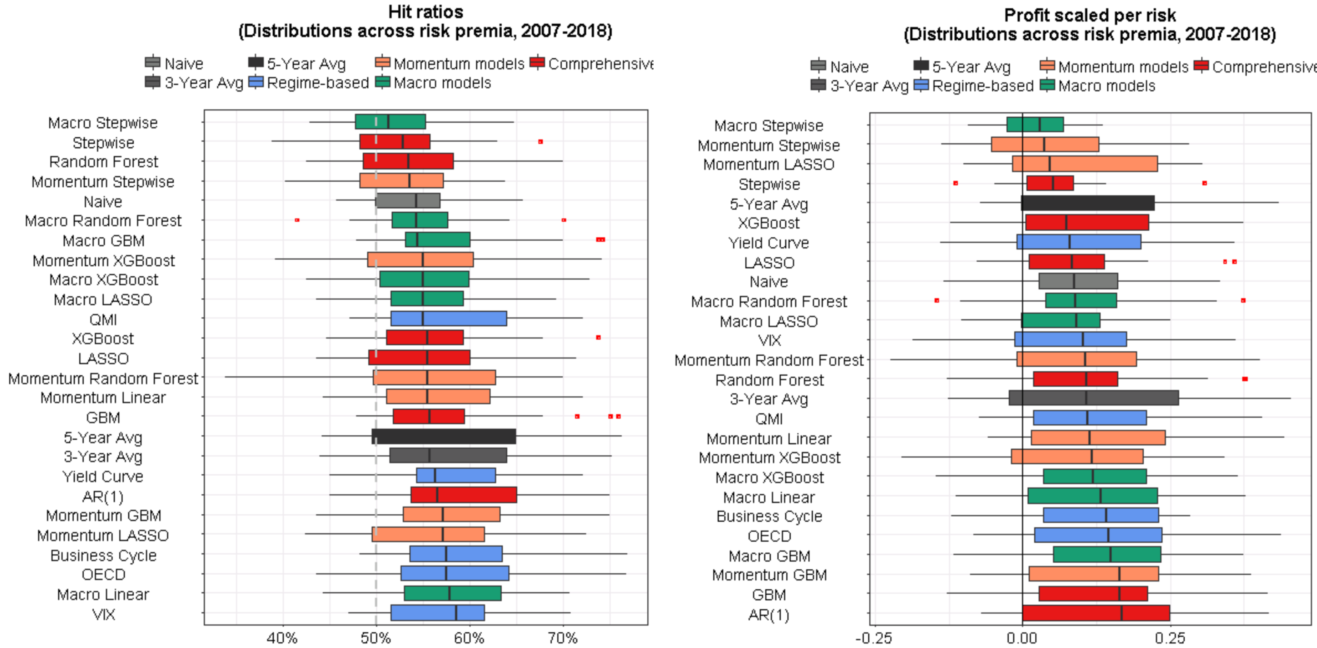
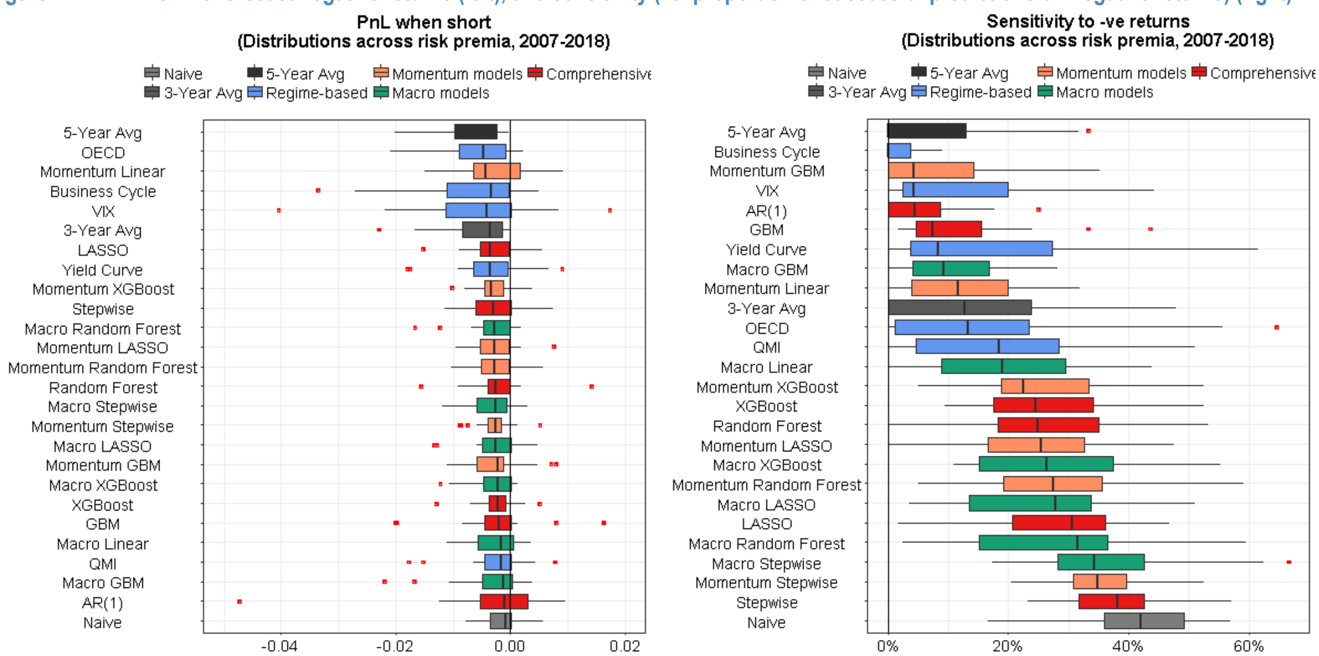
Figure 16: Hit ratios (left) and profit scaled per risk (right) distributions



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

Figure 17 illustrates how well the models perform conditional on negative predictions (left), and how often the models are successful in predicting negative returns. We note that macro-based models (especially Stepwise) tend to be more sensitive to negative returns, and some of the models with high hit rates (AR(1), GBM) actually do not always give negative predictions.

Figure 17: PnL when we forecast negative returns (left), and sensitivity (i.e. proportion of successful predictions on negative returns) (right)



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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Weighting across model predictions

Instead of relying on a single model prediction, we attempt to combine them to get a weighted score for decision making and portfolio construction[7]. We look at:

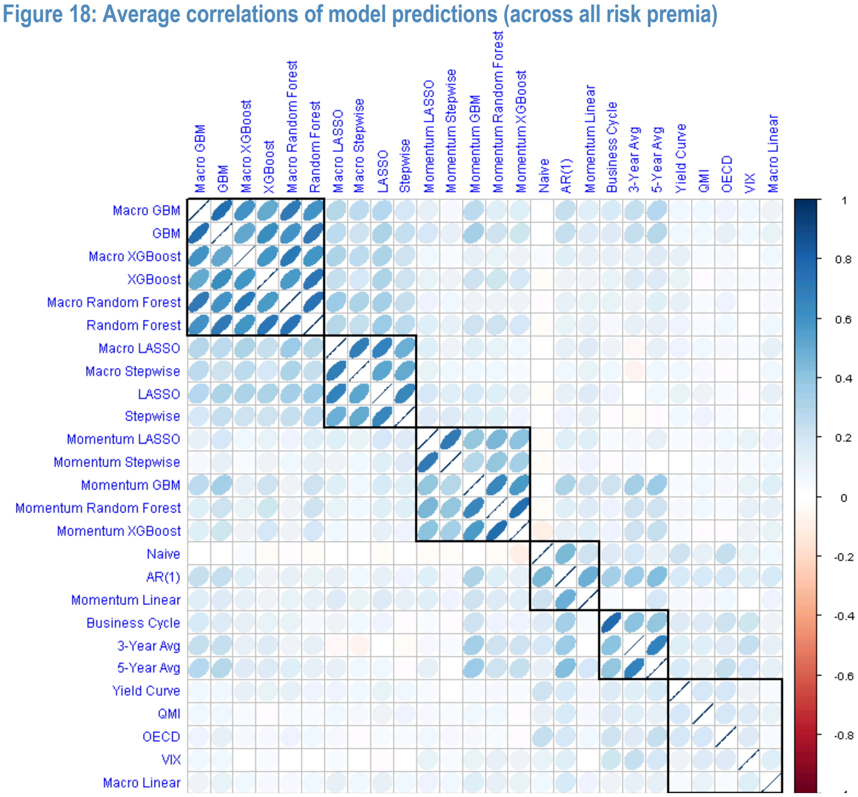
Equal weight: Simple average of all model predictions

Equal Risk Contribution (ERC): A drawback of equal-weighting all the models is that it will be affected by the number of "similar" models we include into the pool. For instance, predictions from purely time-series based models are highly correlated (Figure 18). A better approach is to assign equal risk budget to the models[8]. This can take care of the correlations and scale down their weights if predictions are correlated. Also, models with large variances will have smaller weights. We solve for the model weights w which satisfy the usual criteria of equal risk budget:

$$w_i(\Omega w)_i = w_j(\Omega w)_j \quad \forall \; models \; i, j$$

where Ω is the matrix that quantifies model covariance.

Figure 18: Average correlations of model predictions (across all risk premia)



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

[7] Creating a weighted score from all model predictions is not the only way to decide on portfolio construction. Another possible way is to apply Meucci (2008)'s opinion pooling approach to estimate the expected returns based on all the views. Note that the Black-Litterman approach cannot handle such scenario with multiple predictions of the same risk premia, due to issues in multi-collinearity.

[8] Instead of allocating weights across assets, we allocate weights across models

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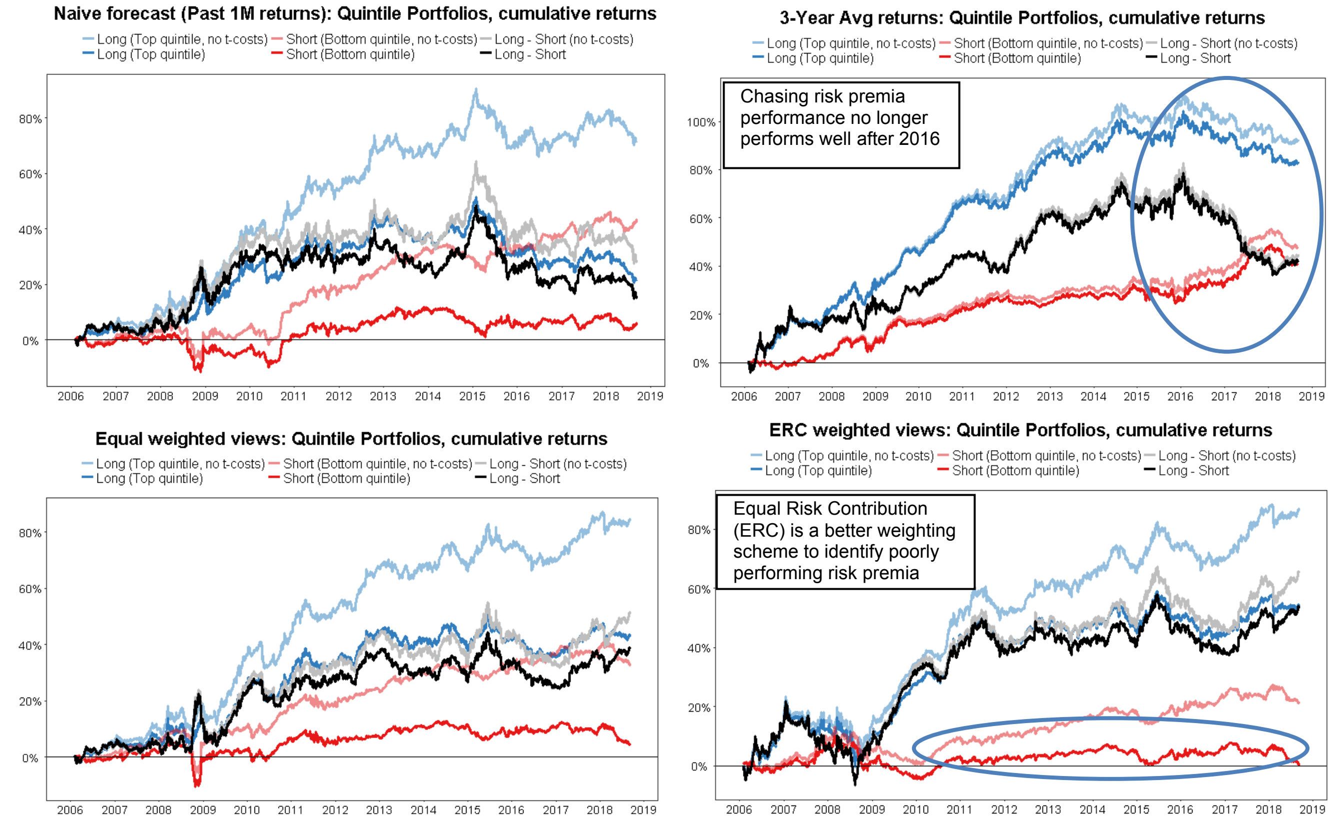
In Figure 19, we show the cumulative returns by sorting the 23 risk premia into 5 portfolios (i.e. quintiles), based on different scores. We start with the benchmarks (Naïve and 3-year average returns) and find that both have decent predictive power on risk premia performance. An interesting observation is that a "structural break" seems to have occurred around 2016, where chasing risk premia performance is no longer a profitable strategy.

On the lower panel in Figure 19, we show the results using a weighted score based on all model predictions. We find that using an ERC weighting scheme that accounts for model correlations (bottom right) can improve the ranking ability of the weighted score, compared with the equal-weighted version (bottom left).

Figure 19: Cumulative returns of risk premia portfolios ranked by different scores: Naïve forecast (top left), 3-year average returns (top right), Equal-weighted scores from all models (bottom left) and ERC weighted scores from all models (bottom right)



Portfolios (After cost)	Start date	End date	CAGR	Vol	Sharpe Ratio	t-stat	Skew	Kurt	Max Drawdown	Hit Ratio	Sortino Ratio	Calmer Ratio
Naïve forecast (Past 1M returns)												
Top Quintile	2006-02-01	2018-09-07	1.5%	5.9%	0.25	1.01	-0.28	2.56	20.6%	51.3%	0.02	0.07
Bottom Quintile	2006-02-01	2018-09-07	0.4%	4.6%	0.09	0.41	0.15	7.94	13.7%	50.9%	0.01	0.03
3-Year average returns												
Top Quintile	2006-02-01	2018-09-07	4.7%	5.4%	0.88	3.20	-0.18	4.30	11.0%	53.2%	0.08	0.43
Bottom Quintile	2006-02-01	2018-09-07	2.6%	3.8%	0.70	2.56	0.31	3.82	6.0%	51.4%	0.07	0.44
Equal-weighted score (from all models)												
Top Quintile	2006-02-01	2018-09-07	2.8%	5.4%	0.51	1.91	-0.32	3.15	10.7%	52.6%	0.05	0.26
Bottom Quintile	2006-02-01	2018-09-07	0.3%	4.2%	0.08	0.35	-0.15	11.4	15.0%	52.5%	0.01	0.02
Equal Risk Contribution (ERC) weighted score (from all models)												
Top Quintile	2006-02-01	2018-09-07	3.3%	6.0%	0.55	2.08	-0.28	4.03	18.4%	51.7%	0.05	0.18
Bottom Quintile	2006-02-01	2018-09-07	0.0%	3.5%	0.01	0.10	-0.07	4.21	13.3%	50.8%	0.00	0.00

Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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Tilting our portfolio: The Black-Litterman approach

As we have combined the predictions from all models, the next question is: How can we apply these weighted predictions for tactical allocation? First, let us start from a pure risk-based portfolio as a benchmark, assuming that we do not have any views.

Risk Parity benchmark

In "Cross Asset Portfolios of Tradable Risk Premia Indices", we show that risk premia are in general lowly correlated and constitute good buildings for portfolios. Hence, we use a "naïve" risk parity portfolio as our benchmark here, which simply allocates weights inversely proportional to the volatility of the risk premia:

$$\omega_j \propto \sigma_j^{-1}$$

Simple rule-based tilting

Without any optimization, we could apply a simple rule-based tilting depending on the views. We look at a case study using the rule as in Figure 20, which simply rank the risk premia and increase (decrease) the risk parity weight by a constant scale.

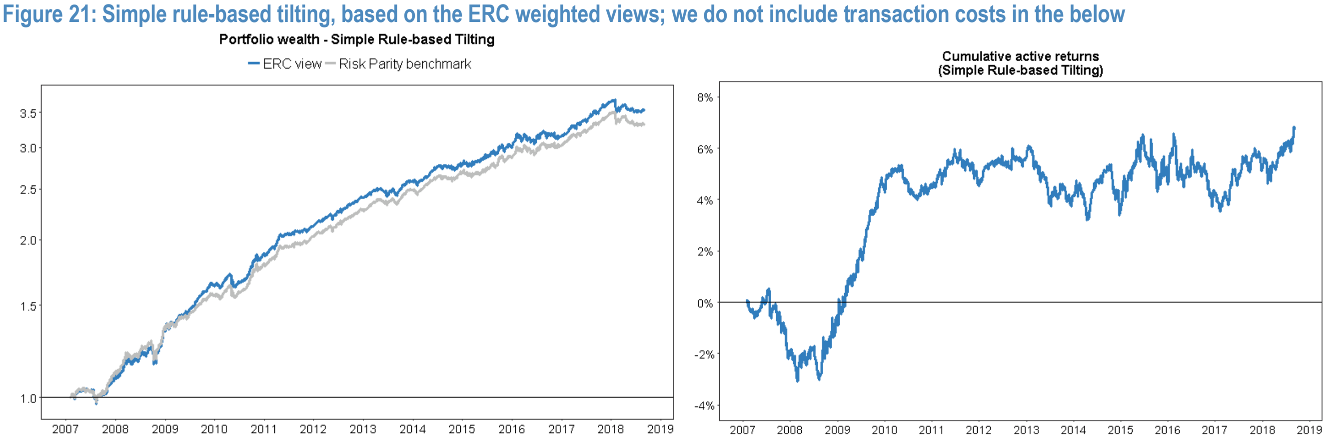
Figure 20: Simple rule-based tilting

	Top 20%	2	3	4	Bottom 20%
Weight Multiplier	1.5	1.25	1	0.75	0.5

Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

We find that such a simple tilting yields a small outperformance before cost, and is mainly driven by the period 2009-2010.

Figure 21: Simple rule-based tilting, based on the ERC weighted views; we do not include transaction costs in the below



	Start date	End date	CAGR	Vol	Sharpe Ratio	t-stat	Skew	Kurt	Max DD	Hit Ratio	Sortino Ratio	Calmer Ratio
Risk Parity benchmark	2007-02-01	2018-09-07	10.5%	5.3%	1.99	6.66	-0.68	5.93	8.2%	58.0%	0.18	1.28
Rule-based Tilting	2007-02-01	2018-09-07	11.1%	5.6%	1.98	6.59	-0.67	5.92	8.5%	58.0%	0.17	1.31
Active Risk			**Active returns**	**Active risk**	**IR**	**t-stat**	**Skew**	**Kurt**	**Max DD**	**Hit Ratio**	**Sortino Ratio**	**Calmer Ratio**
			0.5%	1.5%	0.36	1.28	0.04	3.65	3.6%	51.1%	0.03	0.15

Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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Black Litterman tilting

Another way is to apply the Black-Litterman framework to tilt the risk parity portfolio based on our views[9]. This is a Bayesian way to quantify how our prior belief would change conditional on our views. The prior distribution of returns could be implied from the portfolio holdings in various ways.

In the traditional Black-Litterman approach, one usually starts from the market portfolio that is Mean-Variance Optimal (MVO). Here, we instead start from the risk parity portfolio. At first sight, this poses a question of how to obtain implied returns from a risk-based portfolio: After all, they should have "no views" since they are not dependent on expected returns. Nevertheless, one could show that the risk parity portfolio is optimal (i.e. corresponds to the portfolio with maximum Sharpe ratio) when asset pairwise correlations are constant and all assets have the same Sharpe ratio (Maillard, Roncalli and Teiletche (2010), Roncalli (2014)).

Taking the assumption that correlations across risk premia are zero, it follows that holding the risk parity portfolio implicitly reflects a view that the Sharpe ratios of the risk premia are equal[10]. Implied returns of the risk parity portfolio are then given by

$$\mu_j^{implied} = E[Sharpe\,] \times \sigma_j \quad \forall\, risk\ \ premia\ j$$

We use this implied returns as our prior, and then apply the Black-Litterman mechanism to obtain the posterior returns based on our views[11]. We then obtain our tilted portfolio by maximizing the posterior expected returns, subject to portfolio risk constraints (5%) as well as active risk constraint (2%)[12].

Figure 22 shows the backtest of the resulting portfolio (blue), compared with the risk parity benchmark (black). We show performances before cost (lighter lines) and after cost (darker lines) to show the impact[13]. We find that tilting the risk parity portfolio has delivered some positive active returns (about 1.6% per year) at a slightly higher level of portfolio risk (5.8% vs 5.3% in the benchmark). Active returns have been most significant around the period 2008-2009. Overall, active outperformance is quite consistent throughout 2011-2018. We note that currently the active portfolio has experienced some drawdown, but in terms of magnitude it is comparable to the one around 2016.

---

[9] **Whilst the Black-Litterman approach is a popular framework to incorporate views (most commonly in terms of returns) into risk-based portfolios, one could also consider risk measures that include expected returns, e.g. downside risk and expected shortfall (Roncalli (2014)). Martellini et al (2014) applies this idea and look at a "conditional" risk parity strategy that is more adaptive to economic environment such as rising rates.**

[10] **Jurczenko and Teiletche (2015) also applies this property to look at active risk-based portfolios that are more adaptive to macro-economic regimes.**

[11] **For more details on the Black-Litterman mechanism, please refer to the Appendix.**

[12] **We solve for the tilted portfolio numerically by defining our objectives and imposing constraints.**

[13] **Our experience shows that transaction costs have quite a significant impact on returns, especially for our tilted portfolio which has higher turnover. We cope with this by smoothing our portfolio weights with a rolling 3-month average.**

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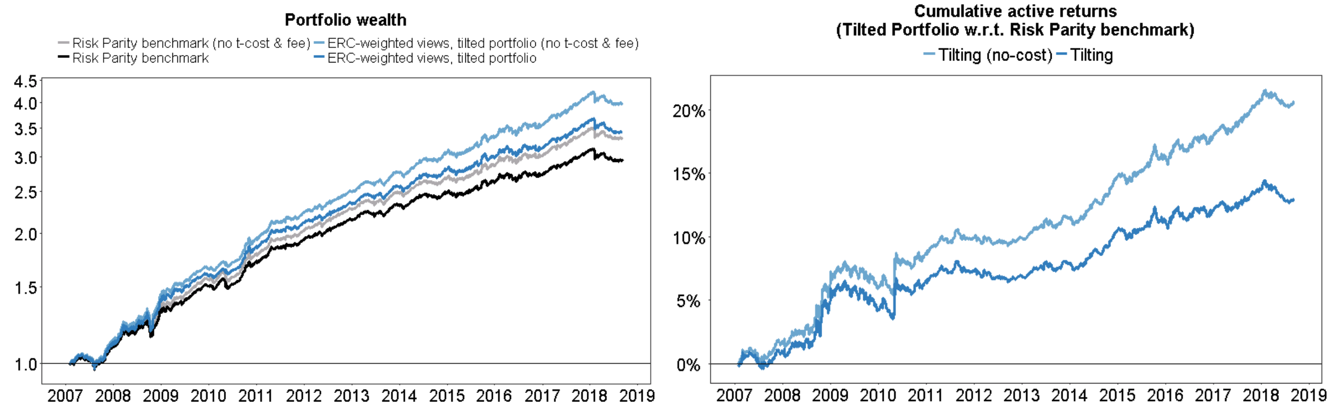
Figure 22: Portfolio wealth (left) and cumulative active returns (right) for the tilted portfolio; the table shows the daily USD returns statistics; for backtests after costs and fees, we apply an average t-cost assumption of 15bps (which may differ across risk premia due to liquidity) and an annual running fee of 20bps



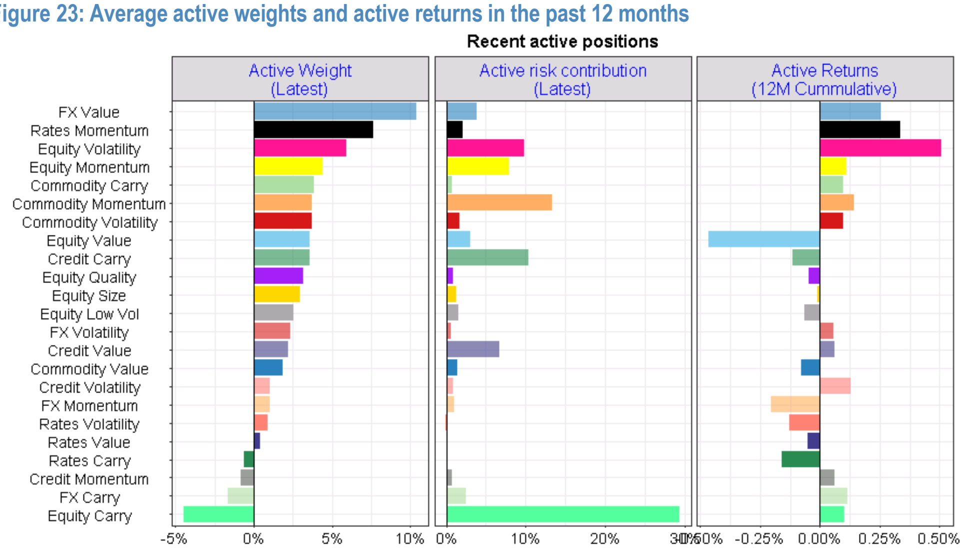
	Start date	End date	CAGR	Vol	Sharpe Ratio	t-stat	Skew	Kurt	Max DD	Hit Ratio	Sortino Ratio	Calmer Ratio
No costs												
Risk Parity benchmark	2007-02-01	2018-09-10	10.5%	5.3%	1.99	6.65	-0.69	5.94	8.2%	57.8%	0.18	1.28
Black-Litterman Tilting	2007-02-01	2018-09-10	12.2%	5.8%	2.11	6.99	-0.48	4.47	9.2%	57.1%	0.19	1.32
With costs and fees												
Risk Parity benchmark	2007-02-01	2018-09-10	9.4%	5.3%	1.78	6.00	-0.69	5.95	8.3%	57.1%	0.16	1.13
Black-Litterman Tilting	2007-02-01	2018-09-10	10.8%	5.8%	1.86	6.23	-0.48	4.48	9.3%	56.3%	0.17	1.16

Active Risk	Active returns	Active risk	IR	t-stat	Skew	Kurt	Max DD	Hit Ratio	Sortino Ratio	Calmer Ratio
No costs	1.6%	1.4%	1.09	3.79	1.20	17.09	2.5%	53.7%	0.11	0.64
With costs and fees	1.0%	1.4%	0.70	2.45	1.17	16.74	2.9%	52.1%	0.07	0.35

Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

In Figure 23, we analyze recent active weights and active returns so as to understand which positions (OW or UW) are contributing to the active performance relative to the risk parity benchmark. We see that in the past 12 months, OW in FX Value, Equity Volatility and Rates Momentum have delivered the highest returns. Latest UW in Equity Carry contributes to large active risk due to its high volatility.

Figure 23: Average active weights and active returns in the past 12 months



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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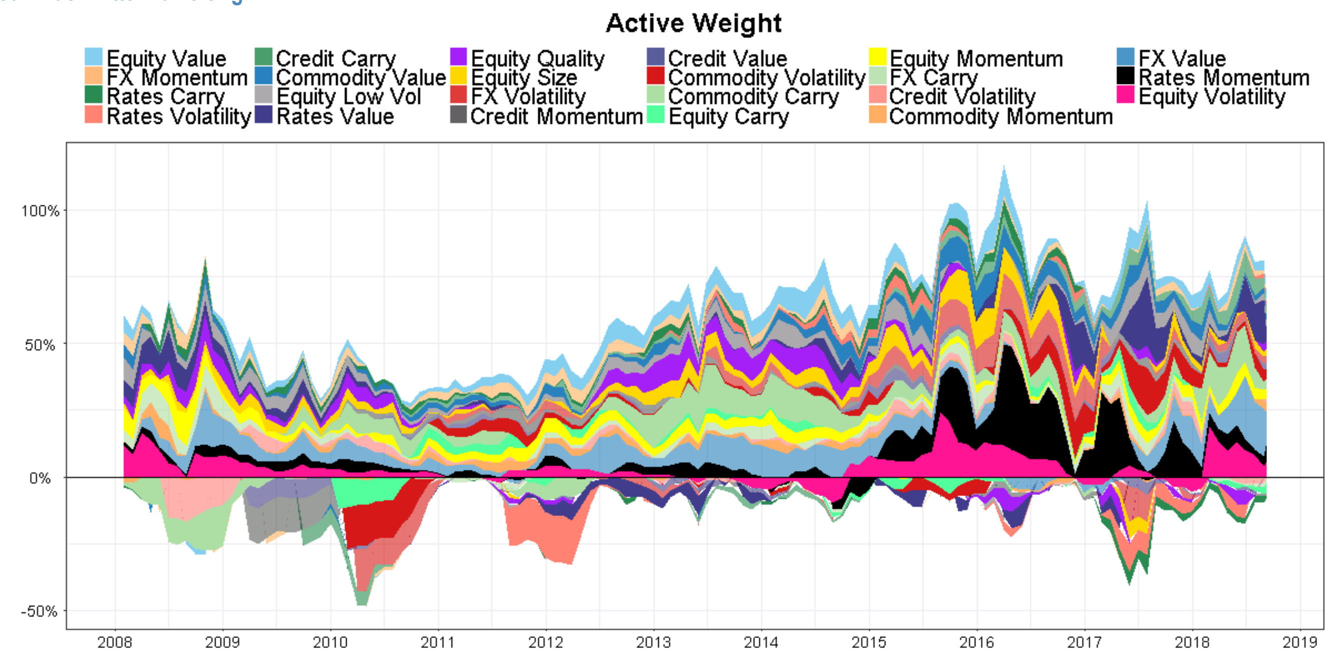
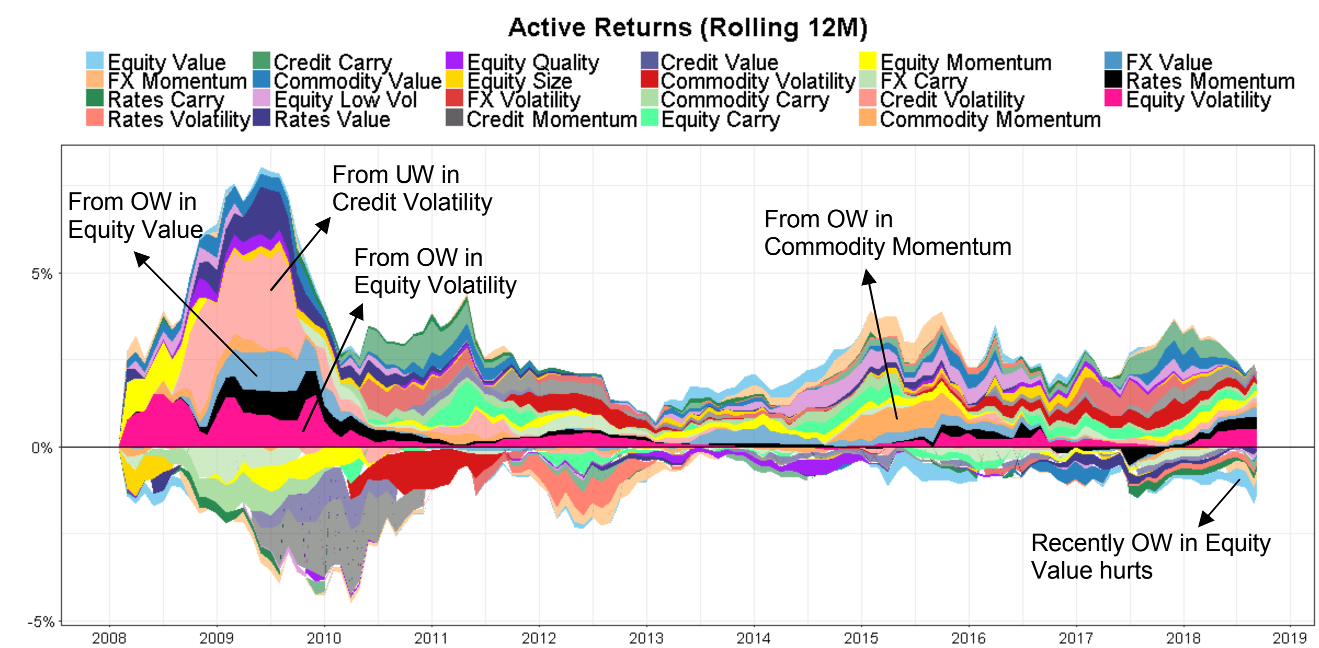
Figure 24 shows the time-varying active weights and rolling 12-month active returns for each risk premia. We note that the active weights have a positive bias, which could be possible as the tilted portfolio is utilizing some of the negative correlations for diversification purposes (whilst keeping the portfolio risk at a similar level). Interestingly, around 2008-2010, large positive active returns have been obtained by UW positions in Credit Volatility and OW positions in Equity Volatility.

Figure 24: Active performance in the past 12 months (top), active weights (middle) and active returns (bottom) of the risk premia, based on our Black-Litterman tilting





Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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Latest views and predictions

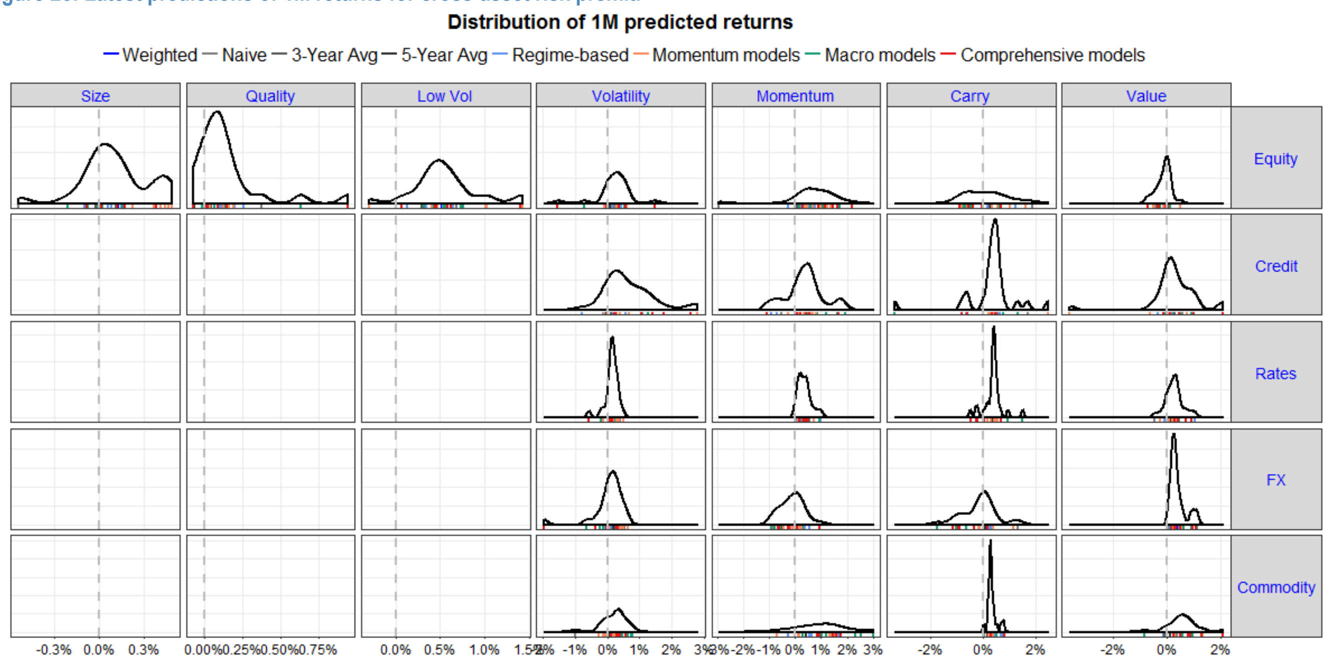
In the following sections, we summarize the performance and model predictions for each risk premia. Sorted by recent hit ratios, we list the "top" models and show their predictive statistics (e.g. PnL, RMSE) together with the long-only "model-free" version as a reference. Amongst the top models, we highlight some of their predictors sorted by the absolute coefficients, i.e. more important variables will be shown on top. To understand if the predictor is contributing positively or negatively to the predicted returns, we also show the latest value (rolling 12-month z-score indicators) next to the coefficients. For some linear models, we output the t-statistics[14] to show the significance of the coefficients.

Extracting insights from Machine Learning models

How do we show the coefficients for the top predictors in the ensemble Machine Learning "black-box" such as Random Forest, GBM and XGBoost? We use the approach known as [Local Interpretable Model-Agnostic Explanations (LIME)][15]. The idea is to use a simple linear model to explain what the model is doing around our latest data (i.e. locally).

Figure 25 shows the distributions of the latest predicted returns across all risk premia.

Figure 25: Latest predictions of 1M returns for cross-asset risk premia



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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[14] **We only use these t-statistics to get a sense of relative importance across the predictors. The values are likely inflated due to autocorrelations in the data, and we have not made any adjustments.**

[15] **The approach is based on the paper "Why Should I Trust You?" (Ribeiro et al 2016), and we have used it to explain our Machine Learning predictions in the Global Value strategy (Lau et al 2018)**

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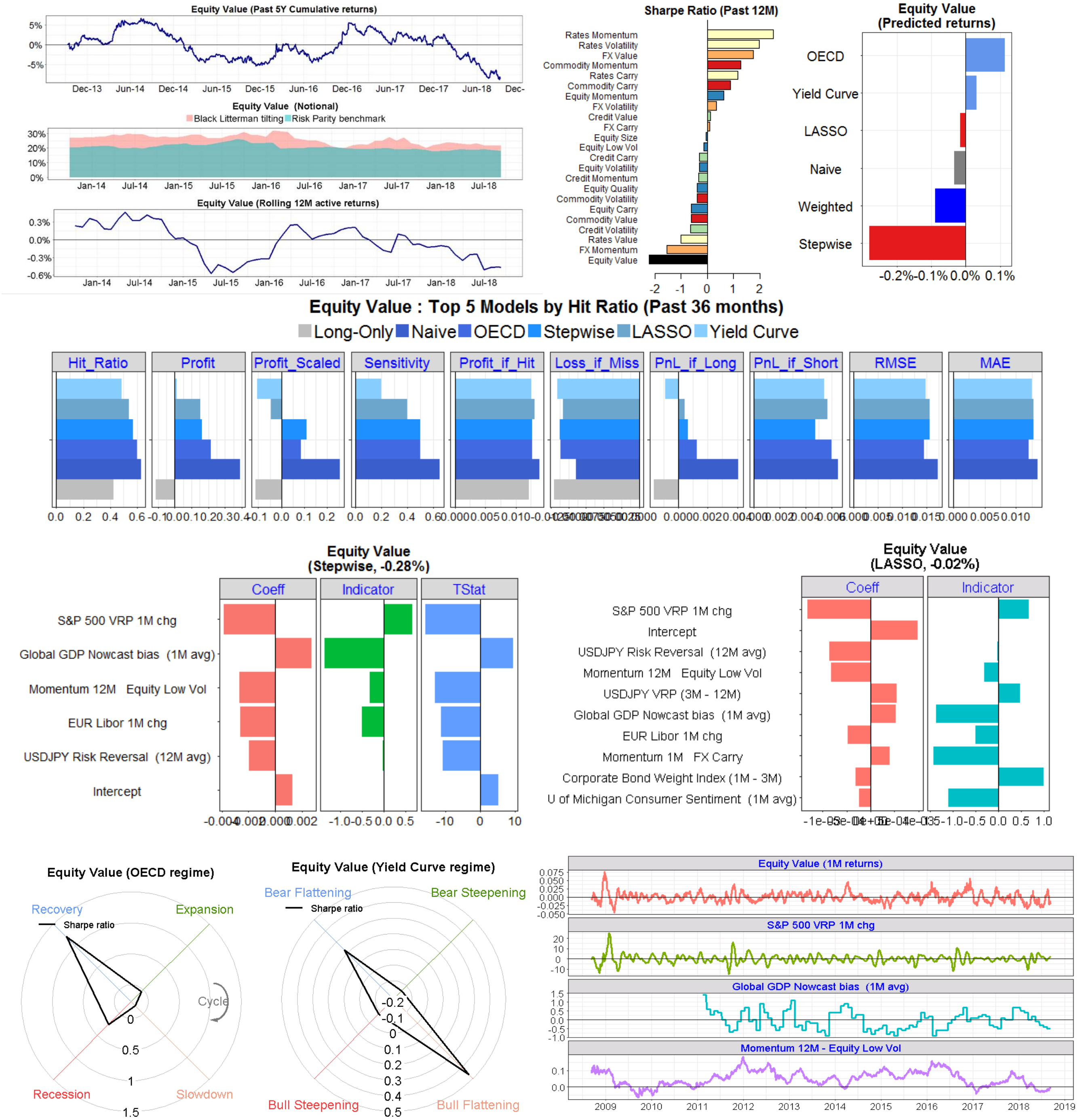
Equity Value

Figure 26: Equity Value is the worst performing risk premia over the past year. The Naive forecast based on past 1M returns deliver the highest hit ratio despite its larger forecast errors. Most predictions are negative, except for the regime-based models. The current recession OECD regime gives positive predictions, but Equity Value used to perform much better during recovery. The Stepwise model and the LASSO model both suggest that an increase in VRP (IV vs RV) in S&P 500 could hurt returns. If the JPM Global GDP Nowcast drops below the reported number, Equity Value may underperform. Our Black-Litterman model suggests a small OW in Equity Value



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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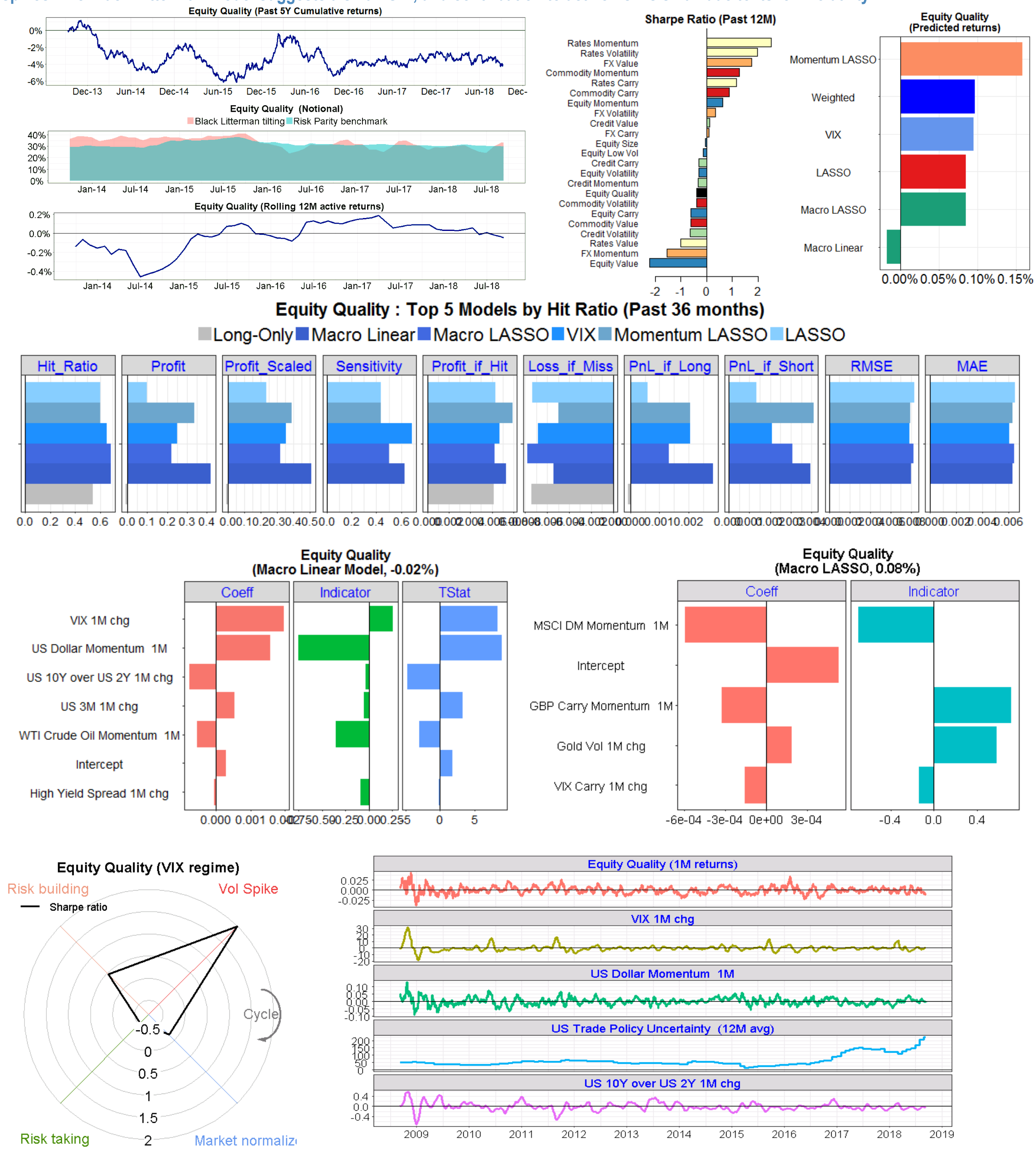
Equity Quality

Figure 27: Equity Quality has a negative Sharpe ratio in the past year. The Macro Linear model gives the highest hit ratio and profit, and is the only top model that gives a negative prediction. Equity Quality tends to perform better when VIX increases, the US Dollar strengthens, or when DM equities are down. The VIX regime model shows the same picture, i.e. returns are higher during “risk-off” episodes such as volatility spikes. The Black-Litterman model suggests a small OW, and contribution to active risk is small due to its low volatility



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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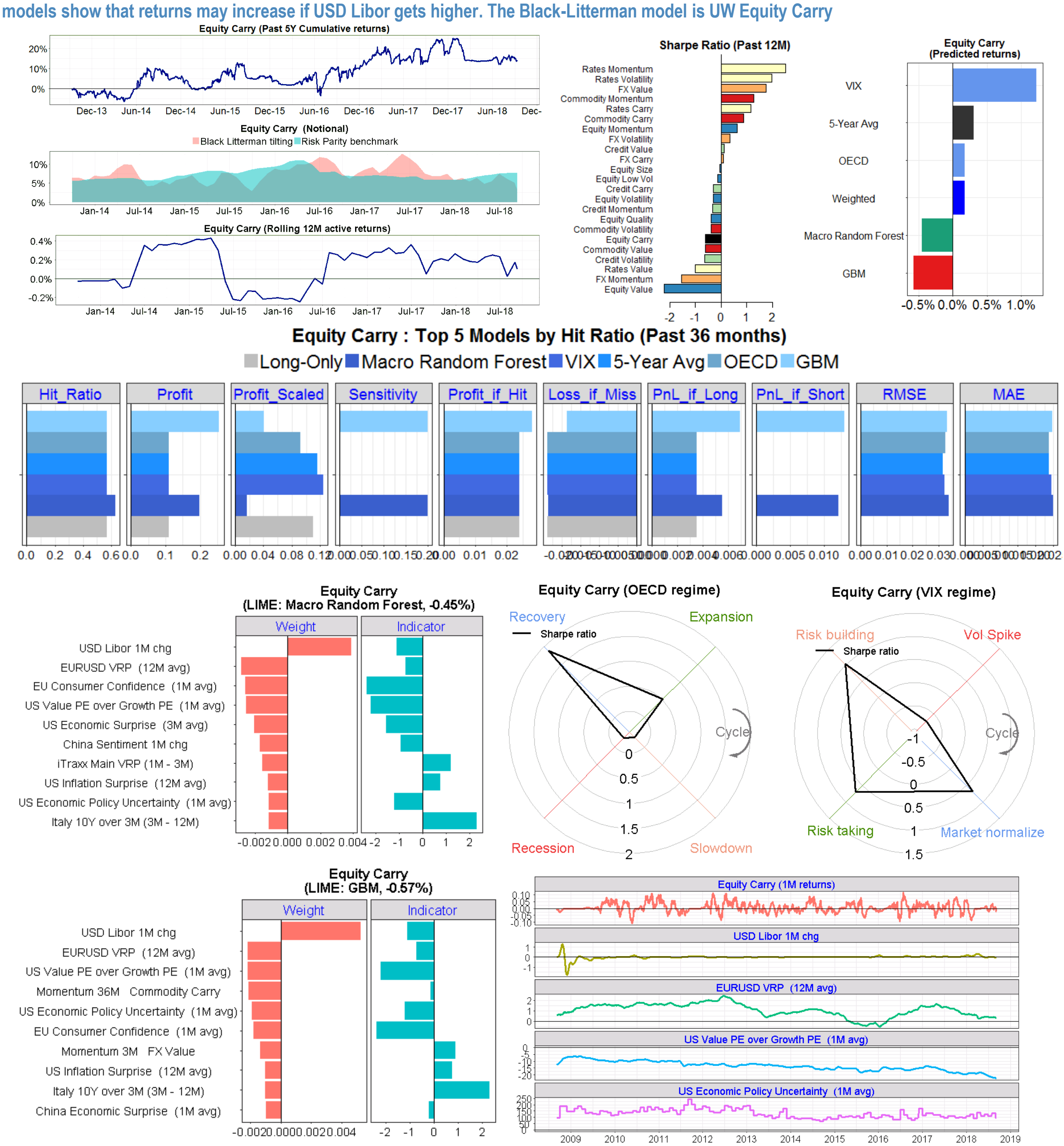
Equity Carry

Figure 28: Equity Carry has negative returns this year since our risk premia is designed to extract carry on Volatility, and the vol spike in early February has hurt performance (which can be seen in the VIX regime model). Typically the risk premia performs better during recovery regimes, and poorly in the current OECD regime of recession. The Machine Learning models (Macro Random Forest and GBM) are more sensitive to scenarios of negative returns, whilst other regime-based models or the simple 5-year average forecasts are always positive. The models show that returns may increase if USD Libor gets higher. The Black-Litterman model is UW Equity Carry



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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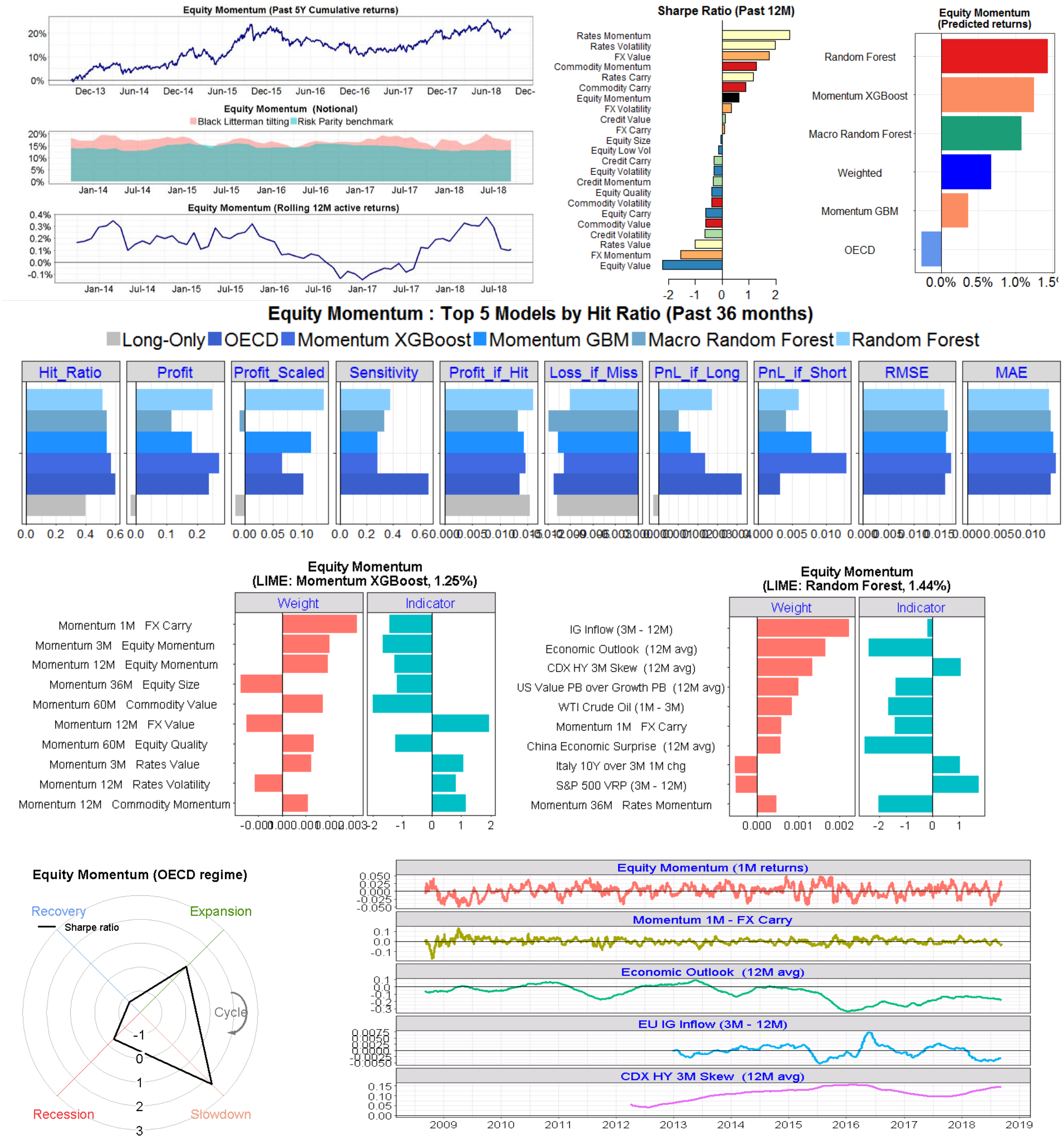
Equity Momentum

Figure 29: Equity Momentum performs relatively well in the past year, despite some drawdowns in June and July. Expected returns are negative under the current OECD recession regime. However, other top Machine Learning models predict positive returns. The time-series based XGBoost and GBM models both indicate quite a strong positive relationship between Equity Momentum and FX Carry. The Random Forest model shows that an increase in EU IG bond fund inflow or an improvement in economic outlook sentiment is supportive for Equity Momentum. The Black-Litterman model has been OW in Equity Momentum in the past year



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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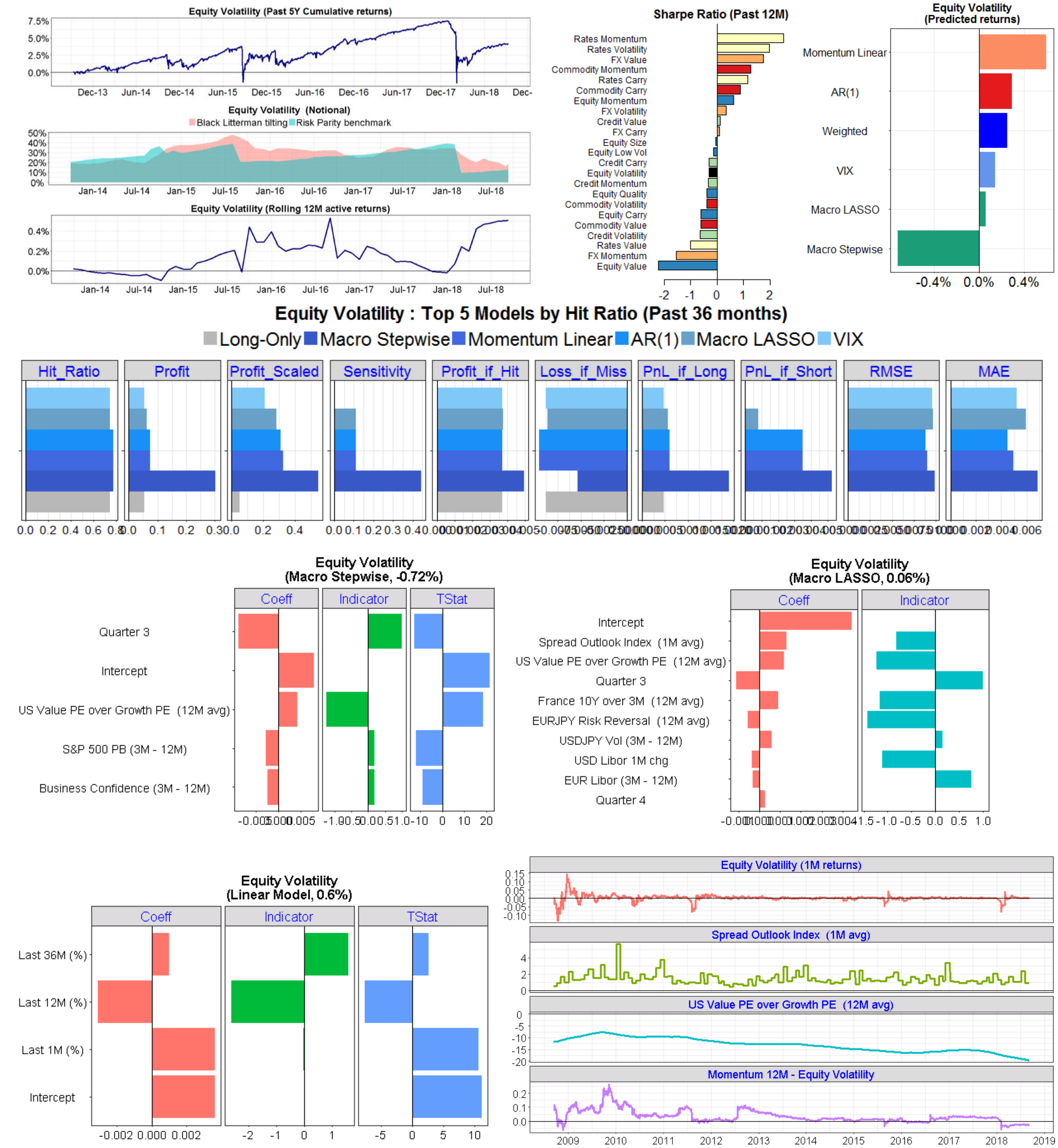
Equity Volatility

Figure 30: Equity Volatility suffered a large drawdown in early February, and its past 12M returns is negative. The Macro Stepwise model gives high hit rate and a significantly higher profit than other models, partly due to its ability to predict negative returns. The model predicts negative returns, driven by poor historical performance in Q3 and a cheaper Value versus Growth stocks. More negative spread outlook may also hurt performance. The time-series models indicate a 1M trend and a 12M reversal. Since the volatility spike in February, the Black-Litterman model has been OW in Equity Volatility



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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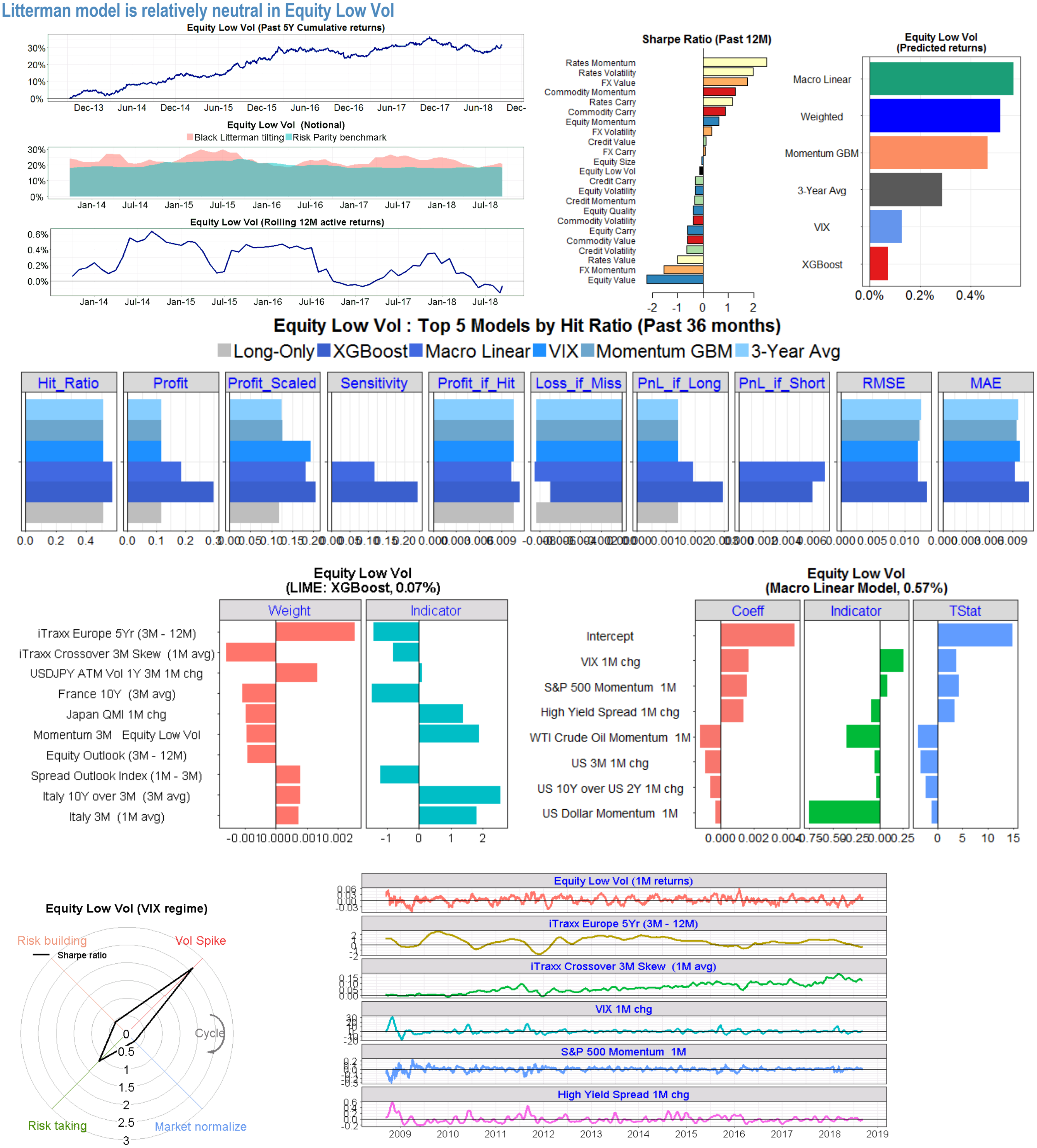
Equity Low Vol

Figure 31: Equity Low Vol is flattish in the past year. Model predictions are overall positive, where the XGBoost model shows some positive relationship with credit returns (iTraxx Europe). Although the Linear Macro model is mainly dominated by the positive intercept, an increase in VIX may be positive for Equity Low Vol returns. Prediction is slightly positive under the current “risk building” VIX regime. The Black-Litterman model is relatively neutral in Equity Low Vol



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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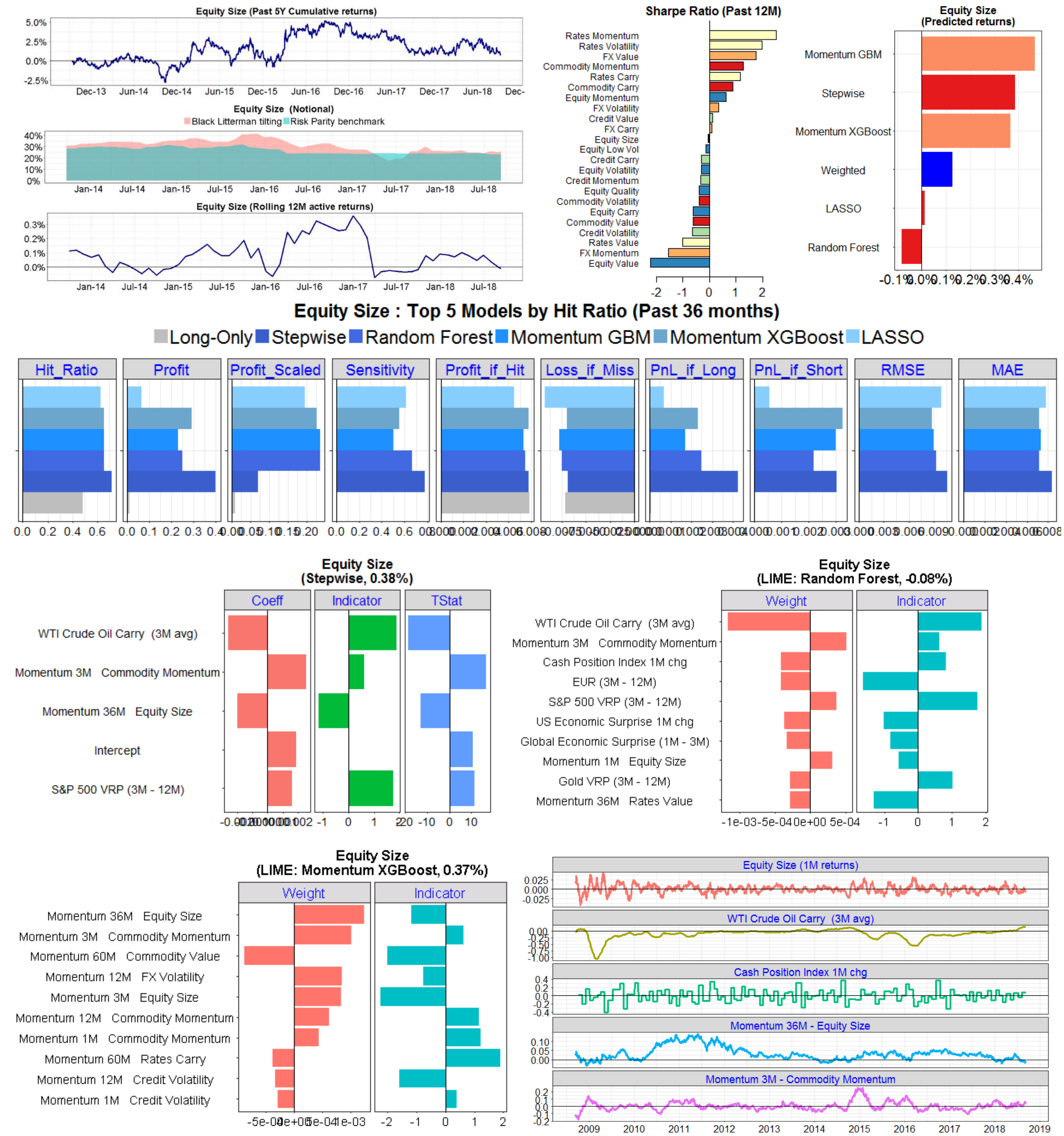
Equity Size

Figure 32: Equity Size is slightly down in the past year. Our model predictions are quite disperse: The Random Forest models are slightly negative, whilst the time-series based boosting models and the Stepwise model are positive. The models show that a higher oil carry or an increase in investors' cash position could be negative for Equity Size. The positive trend in Commodity Momentum may contribute to higher returns in Equity Size. The Black-Litterman model is relatively neutral in Equity Size



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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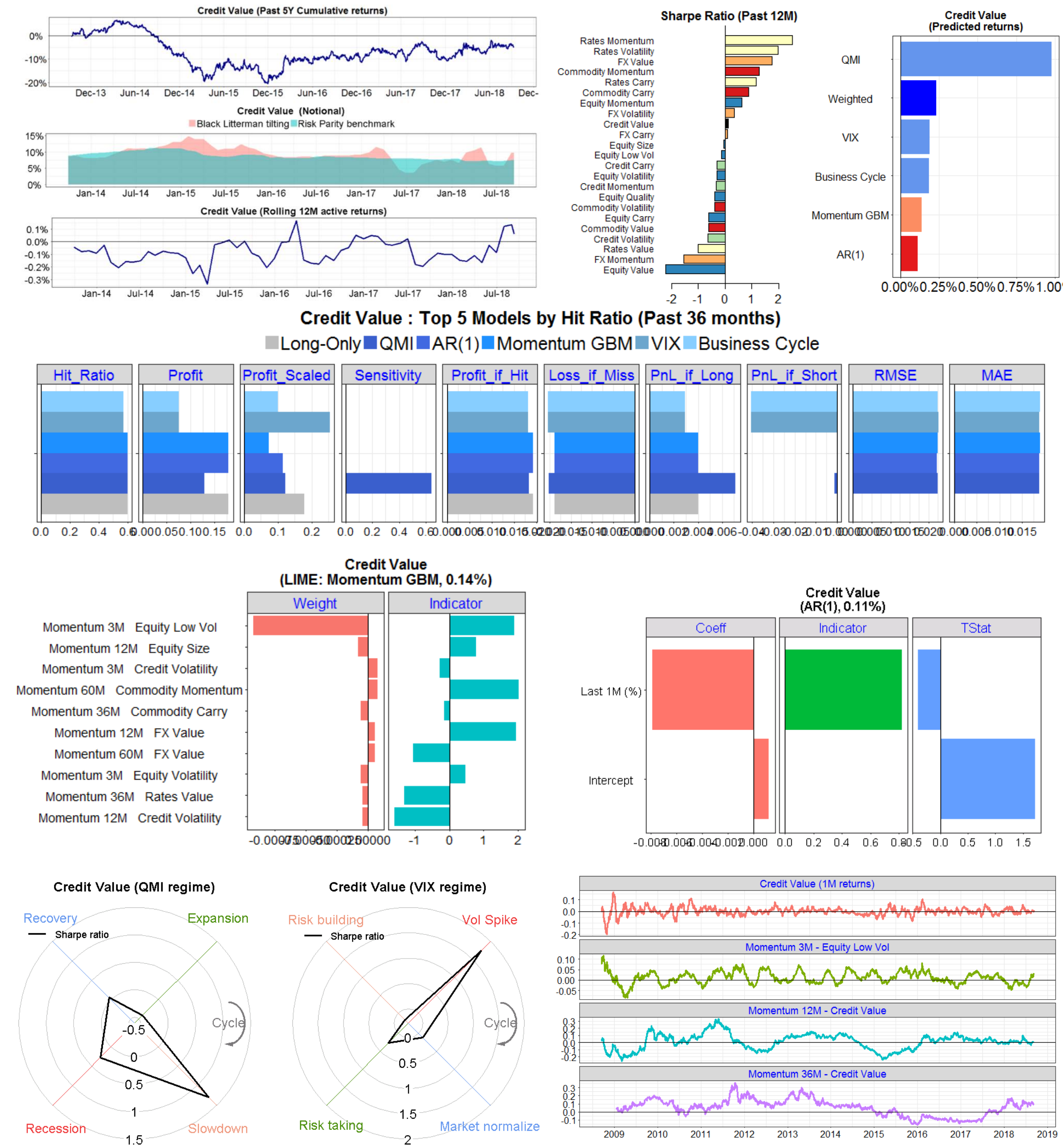
Credit Value

Figure 33: Credit Value has been flattish in the past few months. A simple long-only approach will have a decent hit ratio close to 60%, and we actually struggle to find a significantly better model. The current QMI slowdown regime tends to be quite positive for Credit Value, but models are not so optimistic. The Momentum GBM model indicates that Credit Value tends to perform worse when Equity Low Vol goes up. The AR(1) model does not have a significant coefficient and is dominated by the positive intercept. The Black-Litterman model recently turned OW in Credit Value



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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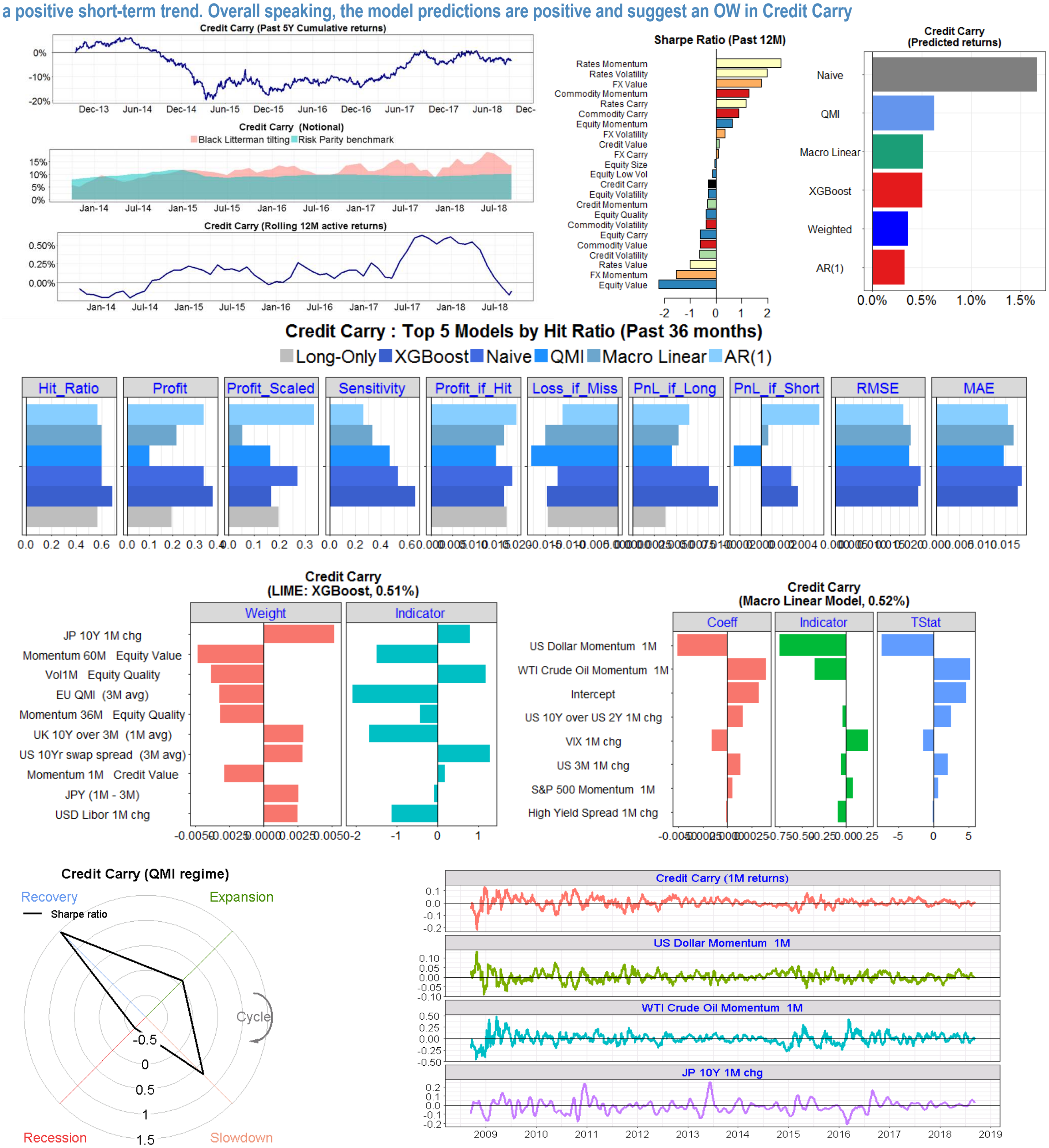
Credit Carry

Figure 34: Credit Carry is slightly down in the past 1 year. The XGBoost model gives the highest hit ratio and gives a positive prediction due to an increase in JGB 10Y and the negative past 5-year performance of Equity Value. The Macro Linear model shows that a recent weakness in the USD has boosted returns in Credit Carry, but it is off-set by a drop in oil price. The latest QMI regime (slowdown) corresponds to a decent positive performance in Credit Carry. The AR(1) model gives a highly significant and positive coefficient (not shown below), indicating a positive short-term trend. Overall speaking, the model predictions are positive and suggest an OW in Credit Carry



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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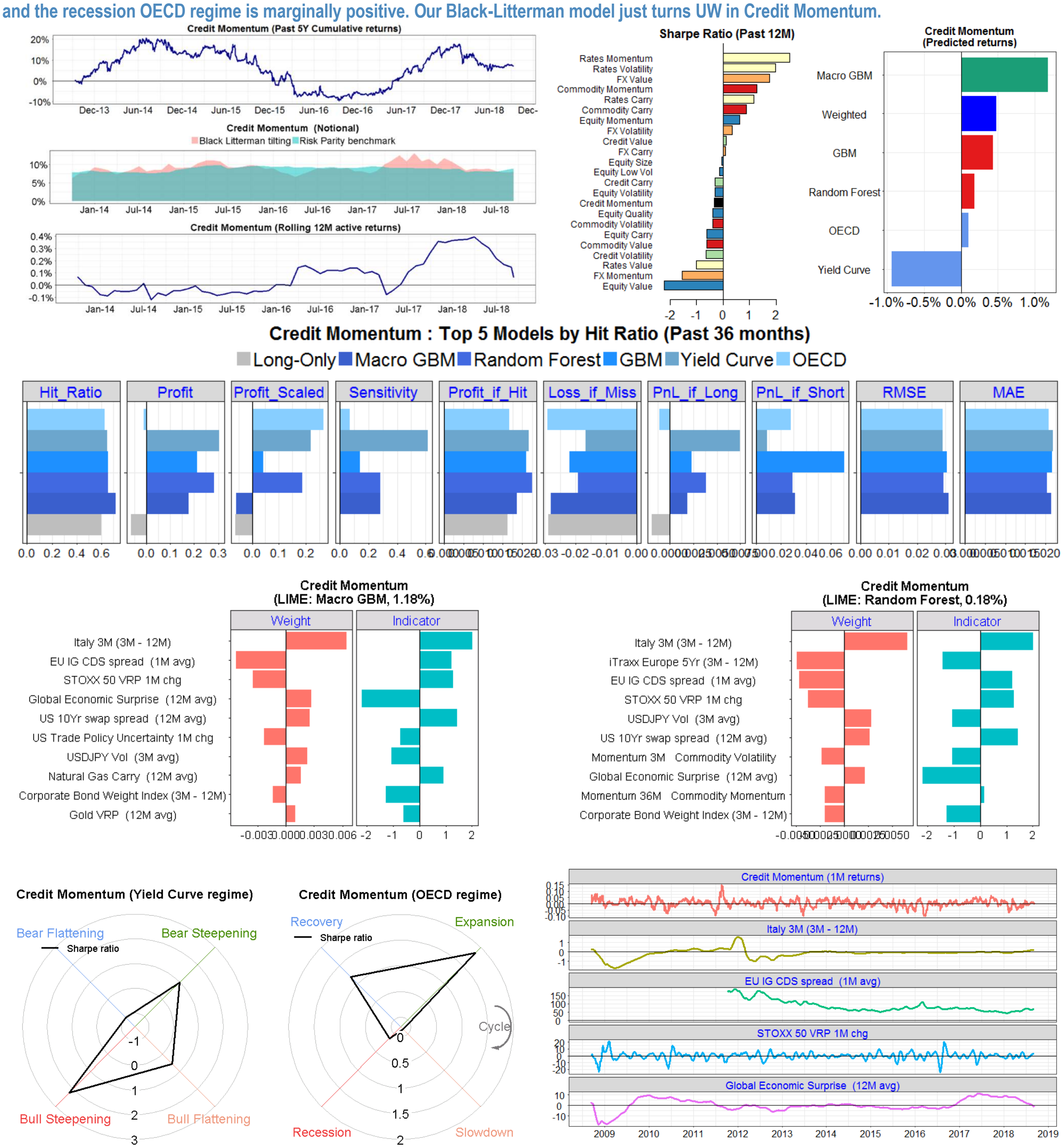
Credit Momentum

Figure 35: Credit Momentum is slightly down in the past year. The Macro GBM model and the Random Forest model both highlight a positive correlation between returns and an increase in 3M rates in Italy. However, there are headwinds including a higher IG CDS spread, an increasing STOXX 50 VRP and a negative global economic surprise. The current VIX regime (risk building) is negative for Credit Momentum, and the recession OECD regime is marginally positive. Our Black-Litterman model just turns UW in Credit Momentum.



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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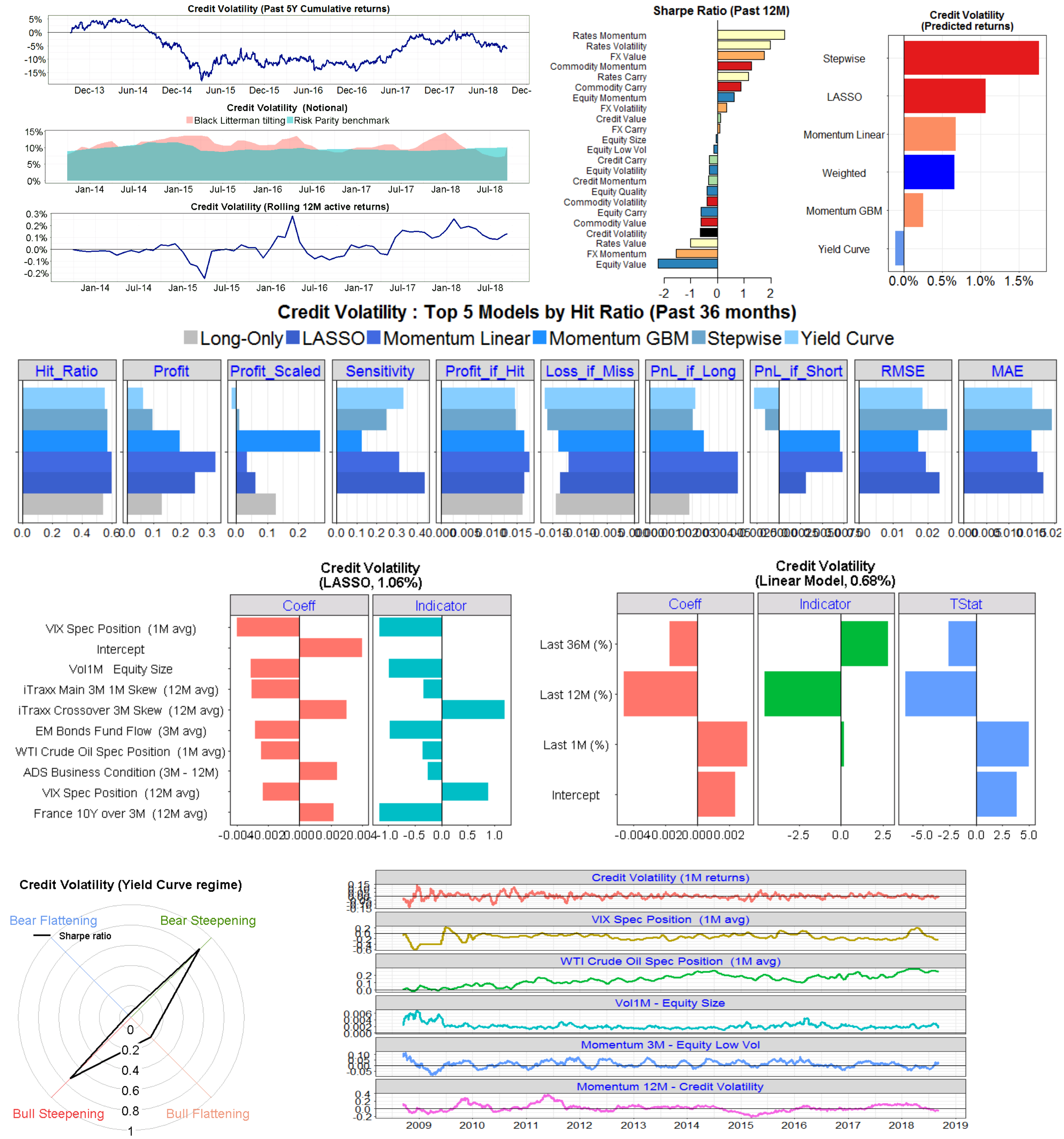
Credit Volatility

Figure 36: Credit Volatility had performed negatively in the past 12 months. Model predictions for next 1M returns are overall positive, except for the yield curve regime (currently in "Bear Flattening") which predicts negative 1M performance. The LASSO model shows that Credit Volatility tends to perform well when there are more net short speculative positions in VIX. From the Linear Momentum model, we see evidence of 1M trend and 12M reversal. Credit Volatility also seems to be negatively correlated with Equity Low Vol (from the GBM model not shown below). The Black-Litterman model just turned OW in Credit Volatility.



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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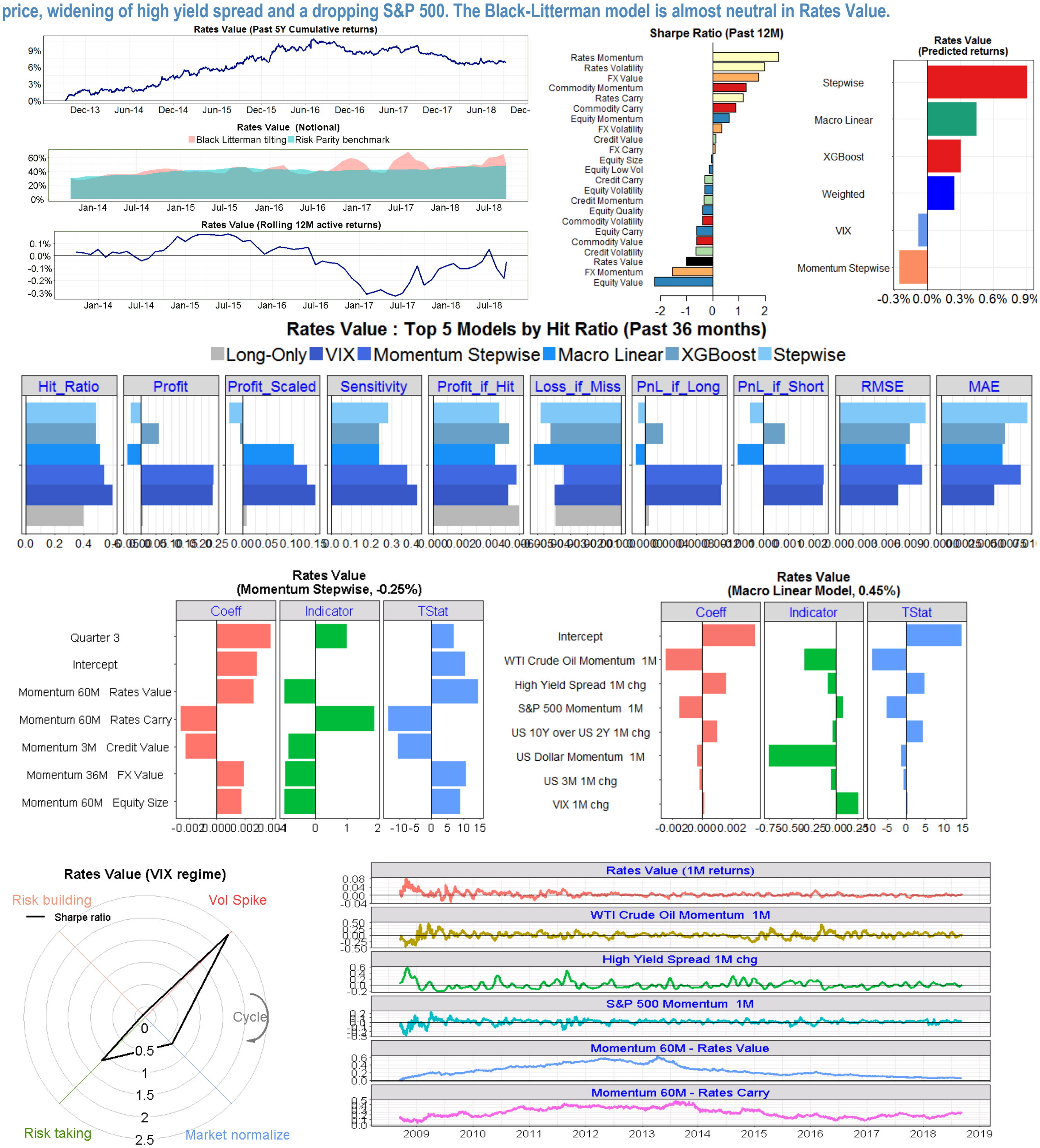
Rates Value

Figure 37: Rates Value performed poorly in the past 12 months, with a Sharpe ratio ranking in the bottom amongst all risk premia. The current VIX regime (risk-building) gives a negative 1M returns, and the Momentum Stepwise model is also negative. Although Q3 has historically performed better, the model indicates a strong 5-year trend which is negative as of latest. The Linear Macro model is dominated by the positive intercept, and apparently Rates Value performs better under "risk-off" regimes (which can also be seen in VIX regime): lower oil price, widening of high yield spread and a dropping S&P 500. The Black-Litterman model is almost neutral in Rates Value.



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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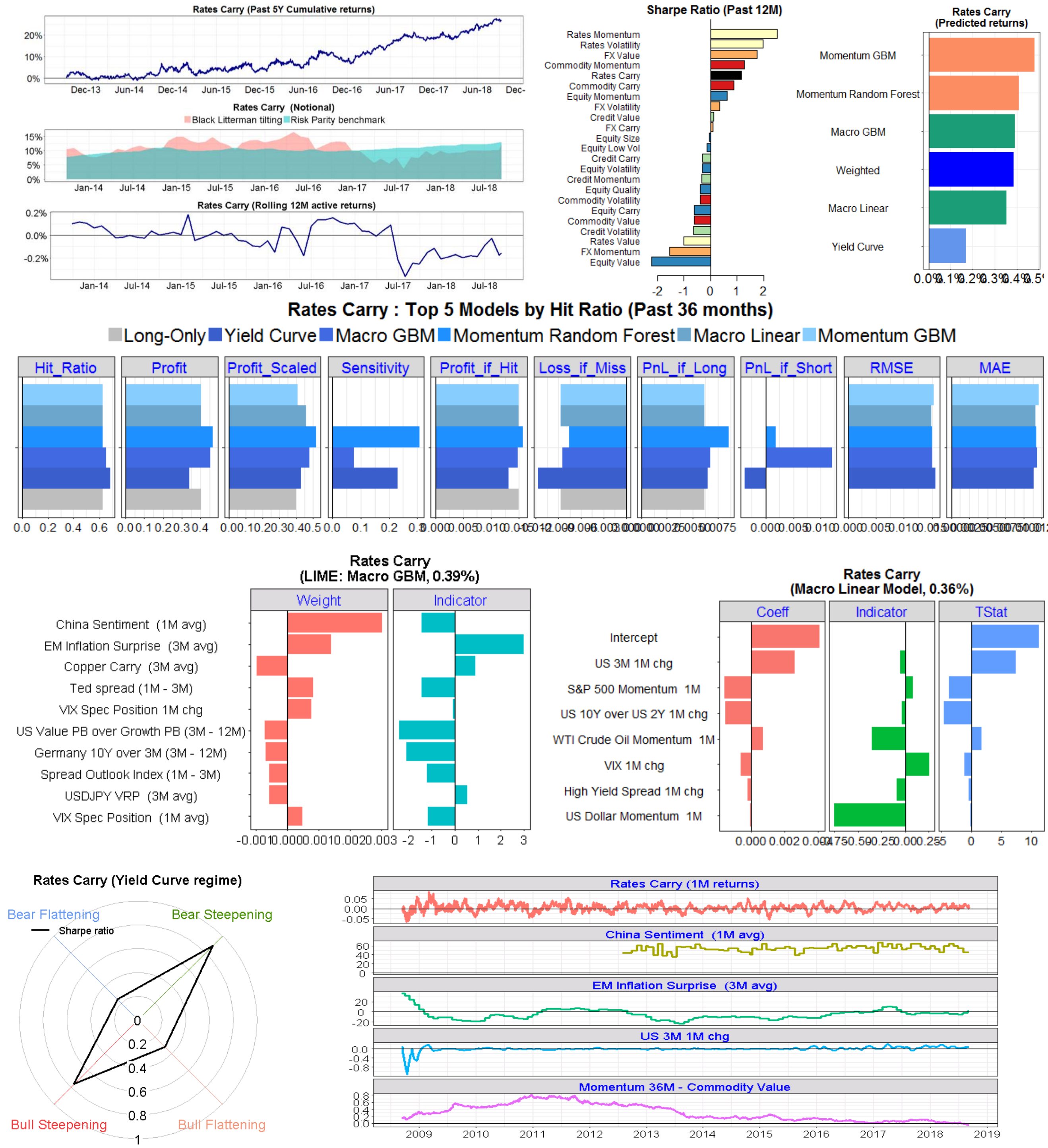
Rates Carry

Figure 38: Rates Carry has delivered a high Sharpe ratio in the past year. The yield curve regime predictions have the highest hit rate recently, which gives a modest positive return under the current "Bear Flattening" regime. The Macro GBM model shows strong positive correlation with China sentiment and EM inflation surprise. The Momentum Random Forest model (not shown below) finds a negative relationship between Rates Carry and Commodity Value. The Linear Macro model is again dominated by the positive intercept, and shows that an increase in US 3M rates may be positive for Rates Carry. However, the Black-Litterman model is UW in Rates Carry.



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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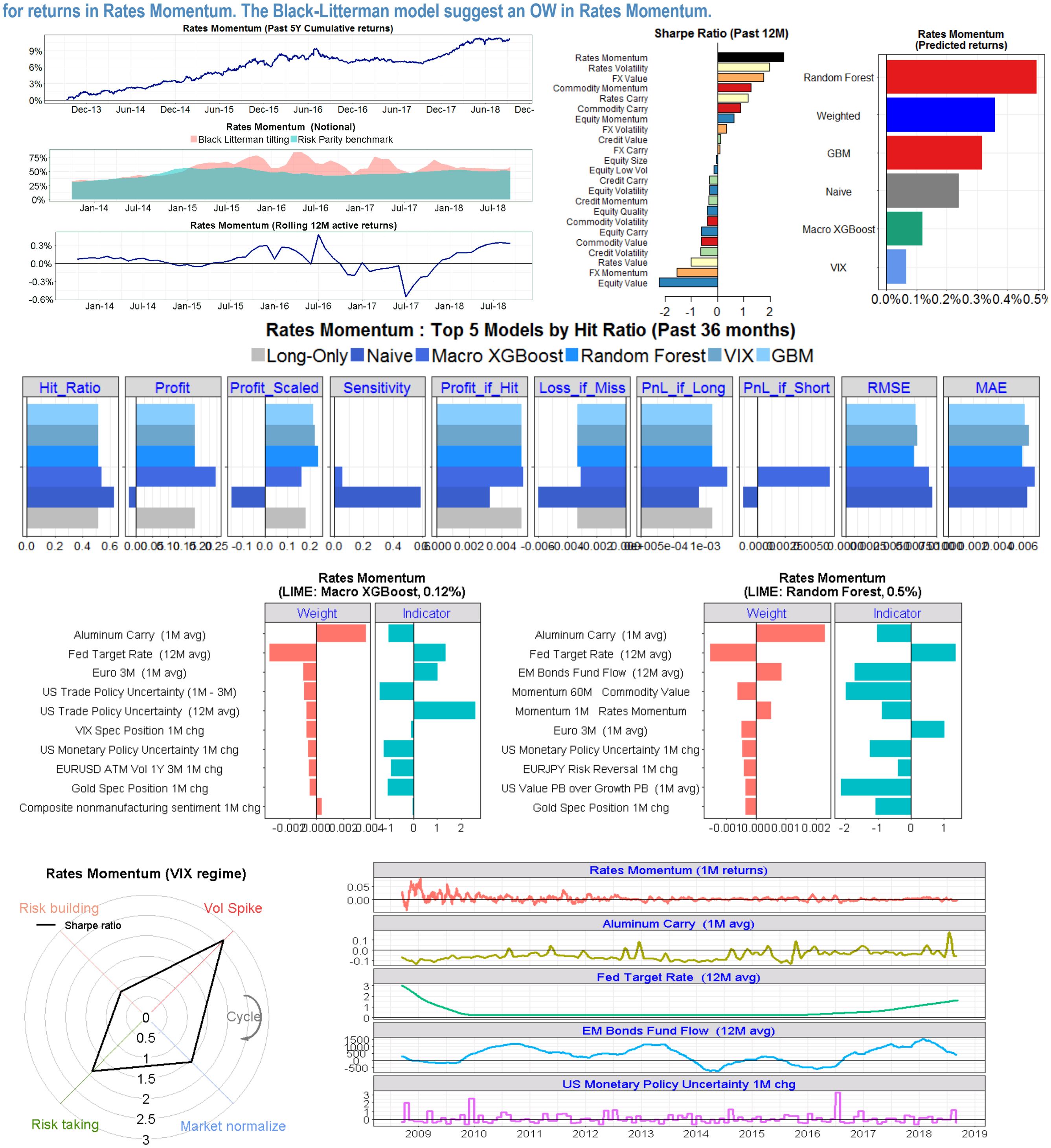
Rates Momentum

Figure 39: Rates Momentum is the top performing risk premia in the past 12 months, giving a Sharpe ratio around 2. Interestingly, the Naïve forecast using past 1M returns gives the highest hit rate in the past 3 years, although it may not hit at the best times (i.e. profit is negative). The Macro XGBoost model, the Random Forest model and the GBM model all select similar top features, showing that a lower carry in Aluminium and a higher Fed target rate could both hurt returns. We also note that a decrease in US monetary policy risk seems to be positive for returns in Rates Momentum. The Black-Litterman model suggest an OW in Rates Momentum.



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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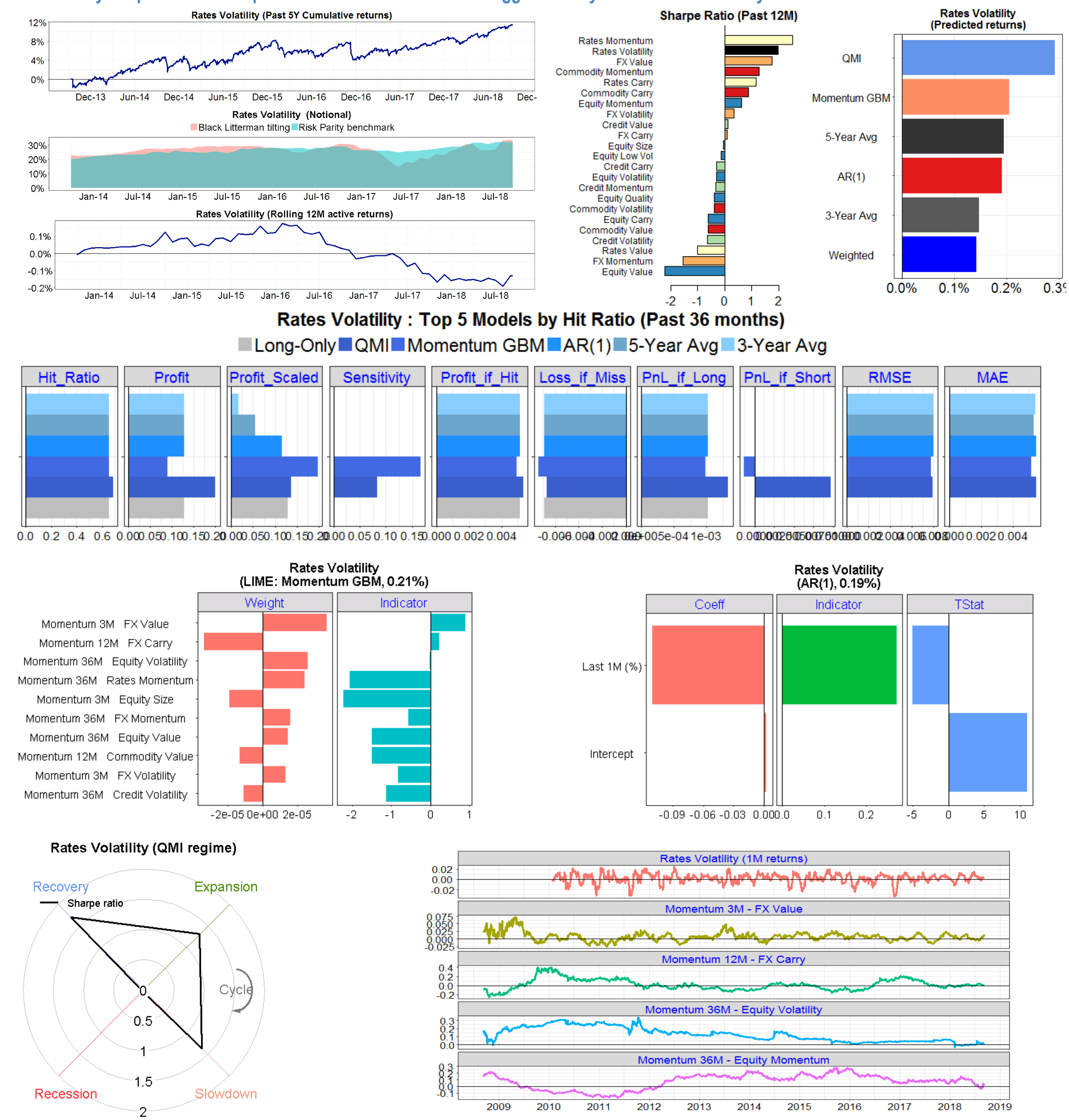
Rates Volatility

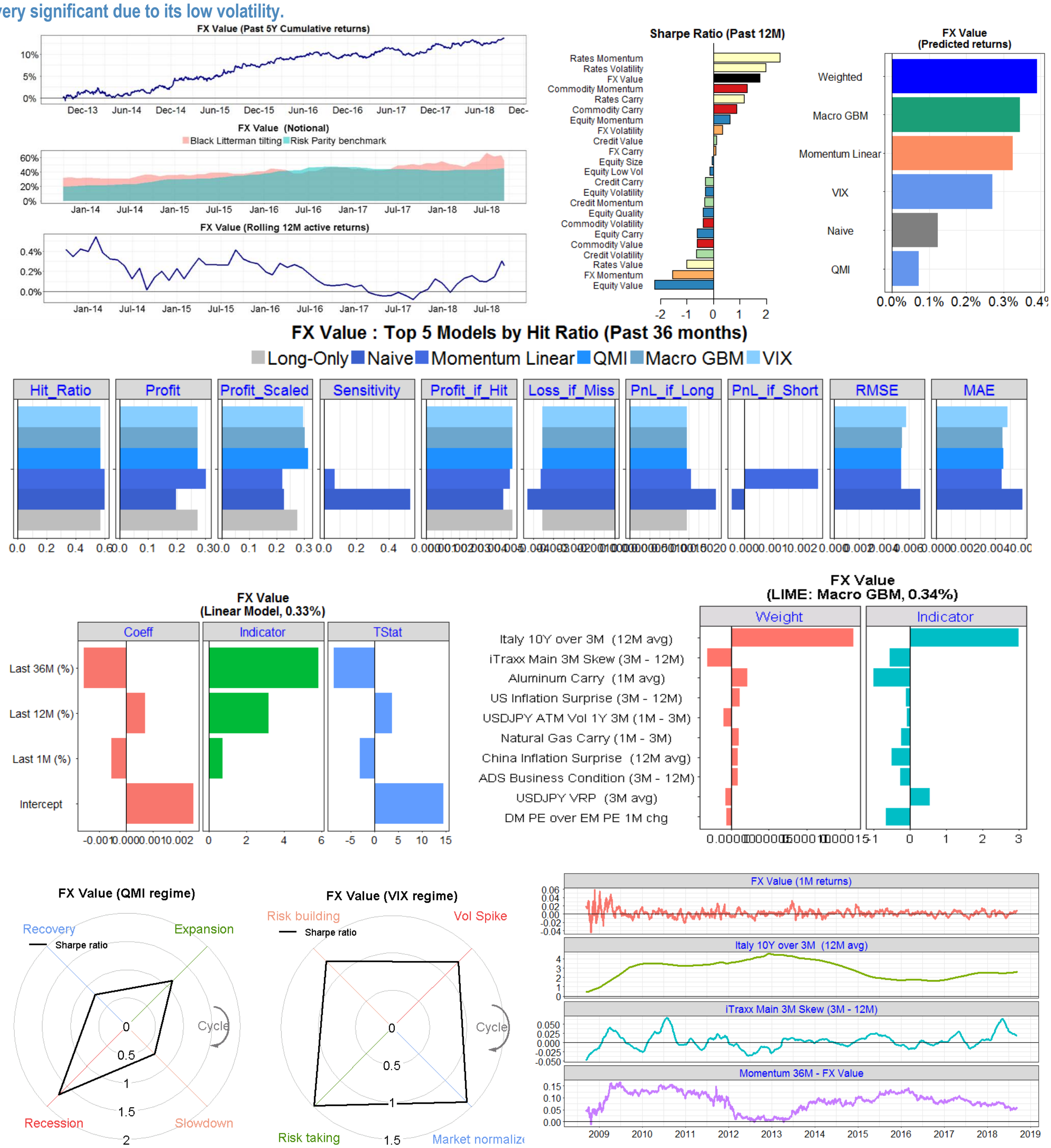
Figure 40: Rates Volatility follows Rates Momentum as the second-best performing risk premia in the past year. As in the case for Commodity Carry, a simple long-only strategy would have performed decently, just beaten by the QMI regime model, which gives quite a positive prediction under the current slowdown regime. Hit ratios across other "time-series based" models are similar. The Momentum GBM model shows a positive correlation between Rates Volatility and FX Value. The simple AR(1) model indicates some effect of 1M reversal, but still it is dominated by the positive intercept. The Black-Litterman model suggests a tiny OW in Rates Volatility.



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

FX Value

Figure 41: FX Value is one of the top risk premia with relatively low volatility and delivering a very positive Sharpe Ratio last year. Note that a long-only model will also give a decent hit ratio in this case. The Linear Momentum model is largely dominated by the positive (and significant) intercept, followed by a long-term reversal. The Macro GBM model is mainly determined by the yield curve in Italy, where a steepening of the curve will likely boost returns. For the regime-based models, the QMI slowdown regime suggests small 1M returns, whilst the current VIX regime (risk building) is more positive. Our Black-Litterman model suggests quite a large OW in FX Value, but active risk is not very significant due to its low volatility.



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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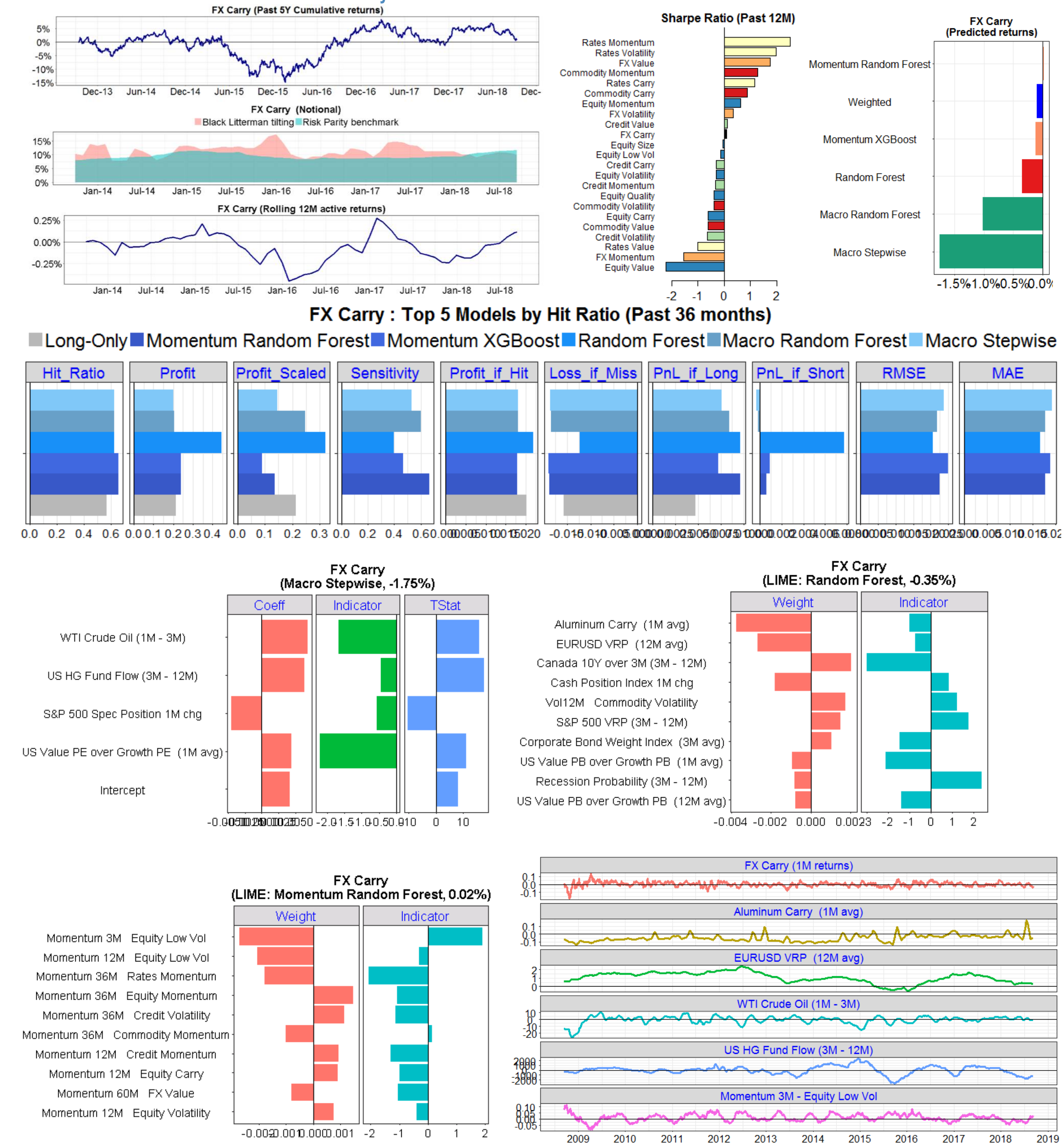
FX Carry

Figure 42: FX Carry delivers a marginally positive Sharpe ratio in the past 12 months. Among the top models, predictions for next 1M returns are in general negative. The Random Forest models occupy the top spots based on recent hit ratios. Interestingly, the "Comprehensive" version using all predictors has higher profit and lower errors compared with the "Momentum" or "Macro" versions. FX Carry tends to be negatively correlated with Equity Low Vol. A decreasing VRP (IV vs RV) in EUR/USD and higher oil price seem to be positive for FX Carry. Our Black-Litterman model indicates an UW in FX Carry.



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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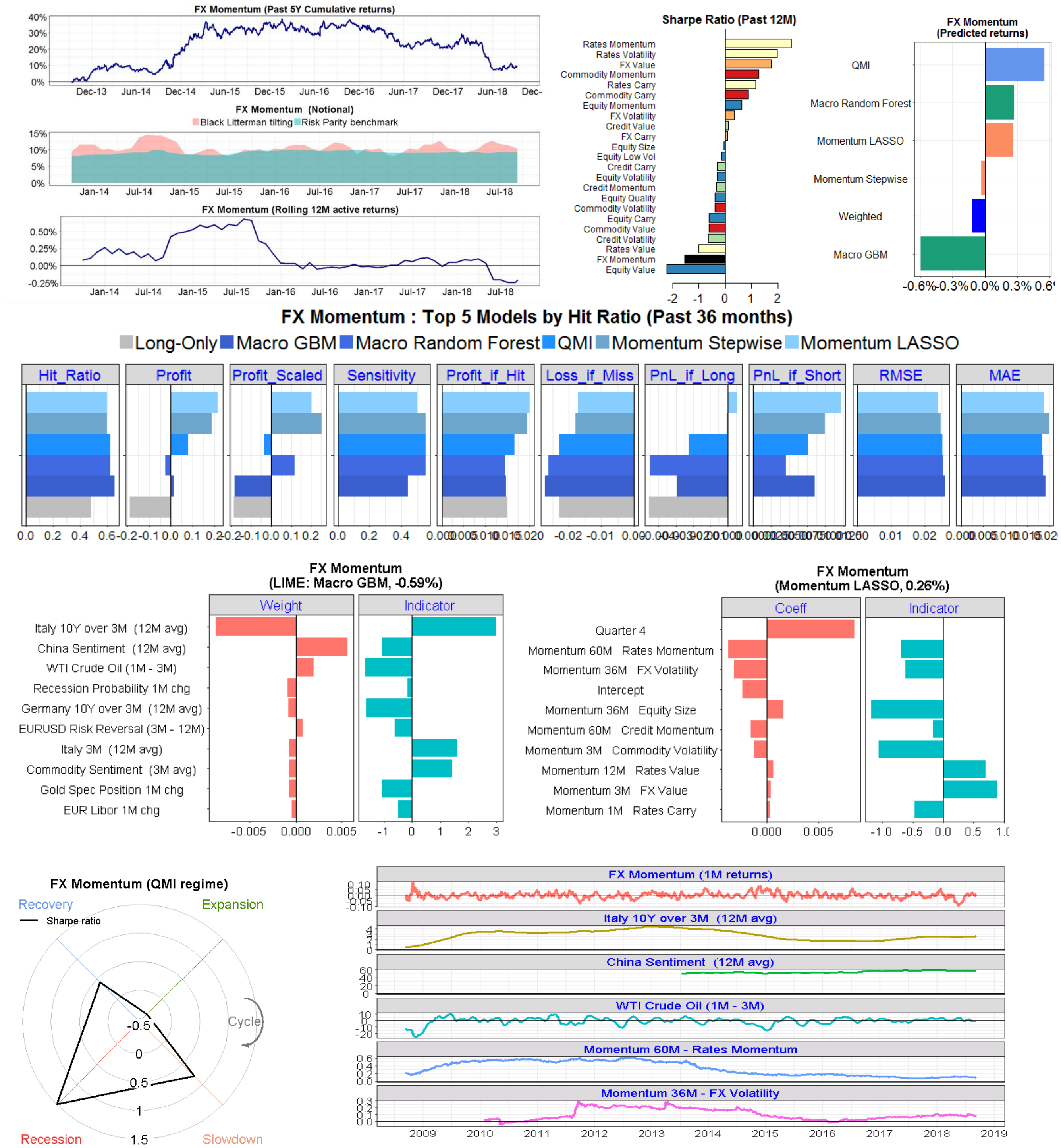
FX Momentum

Figure 43: FX Momentum has suffered a large drawdown early this year, making it the second worst performing risk premia after Equity Value. The Macro GBM model (with top hit ratio) suggests a negative 1M returns at -59bps, driven largely by the steepening yield curve in Italy, deteriorating sentiment in China and a negative oil momentum. The momentum LASSO model is positive due to poor long-term performances in Rates Momentum and FX Volatility. The QMI regime (Slowdown) predicts quite a positive return. The Black-Litterman model suggests a small OW in FX Momentum.



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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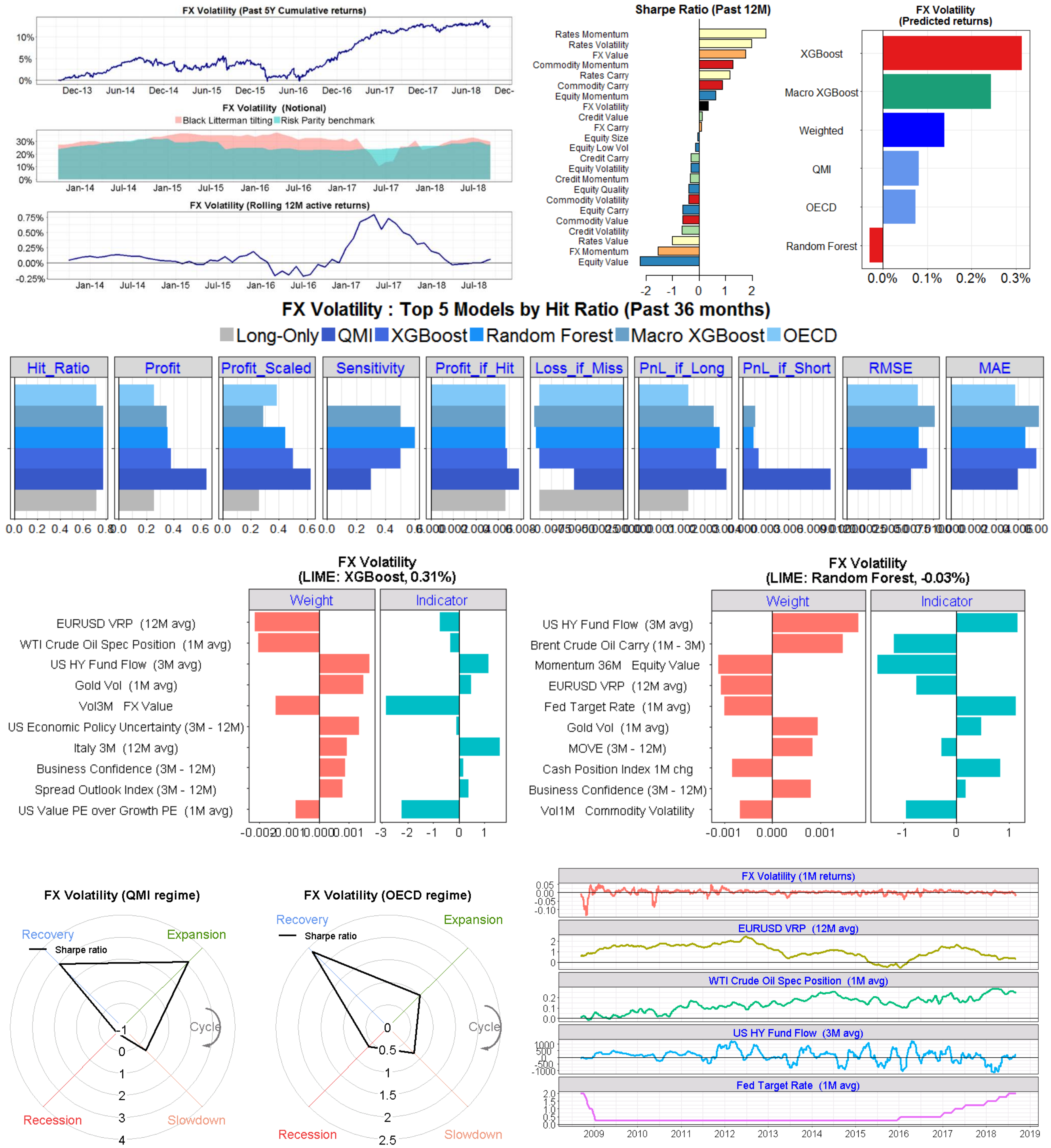
FX Volatility

Figure 44: FX Volatility delivered a small positive Sharpe ratio in the past 12 months. Both the QMI regime (Slowdown) and OECD regime (Recession) point towards a modest positive 1M returns. The XGBoost model suggests positive returns driven by a falling VRP (IV vs RV) in EUR/USD, an increasingly net short position in oil and a higher inflow into US high yield funds. The Random Forest model is more neutral, as a drop in carry in oil and an increase in the Fed target rate may hurt returns. Our Black-Litterman model suggests an OW in FX Volatility.



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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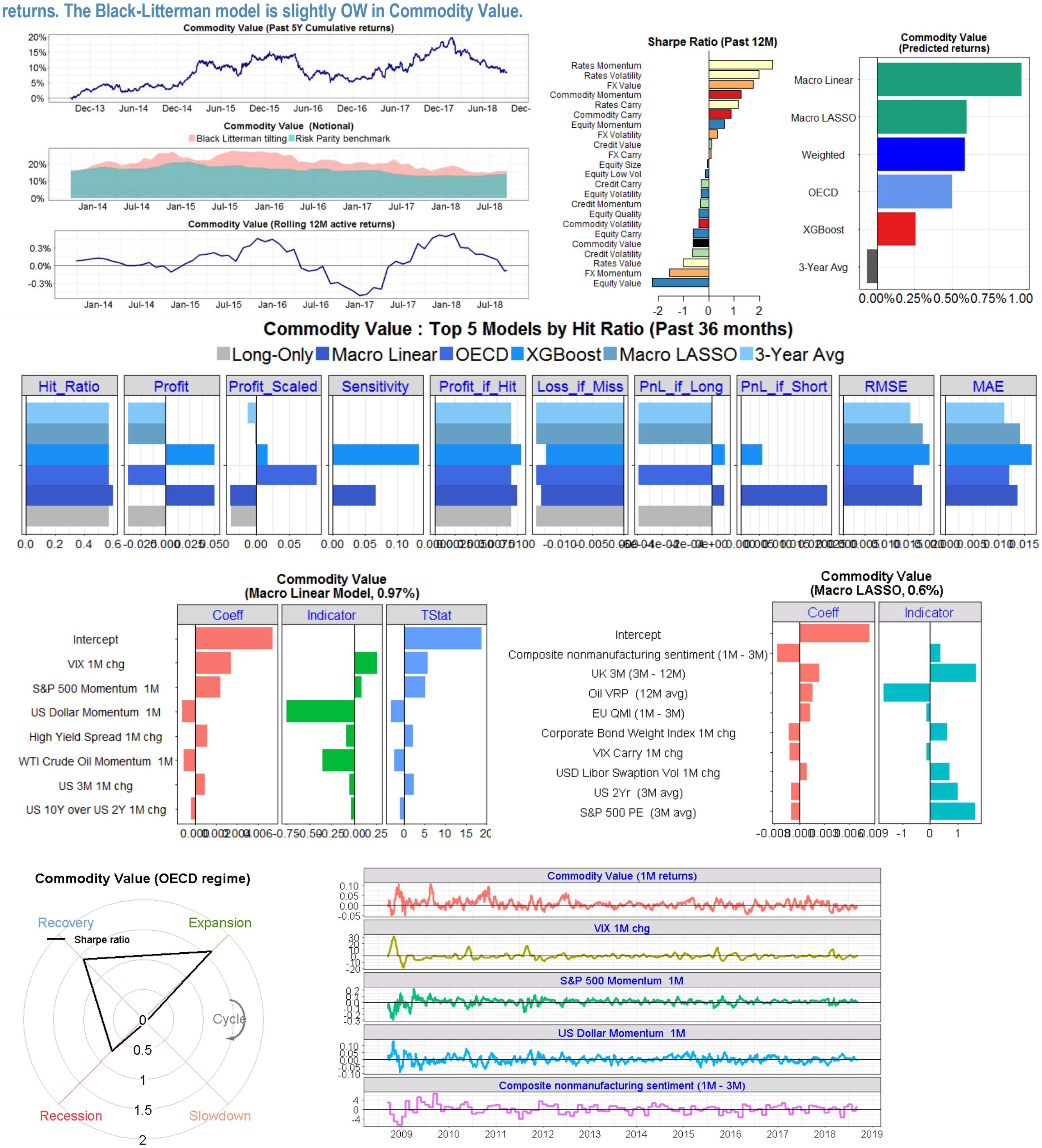
Commodity Value

Figure 45: Commodity Value has been down since 2018, and past 12M Sharpe ratio is negative. However, the Macro Linear model (with highest recent hit rate) predicts a very positive next 1M returns of 97bps (but note that it is dominated by the positive intercept). Increasing VIX and S&P 500 momentum contribute to the high prediction. We see a similarly "intercept-dominating" model in Macro LASSO, although prediction is lower due to an improving sentiment in US non-manufacturing. The current OECD regime (Recession) predicts positive 1M returns. The Black-Litterman model is slightly OW in Commodity Value.



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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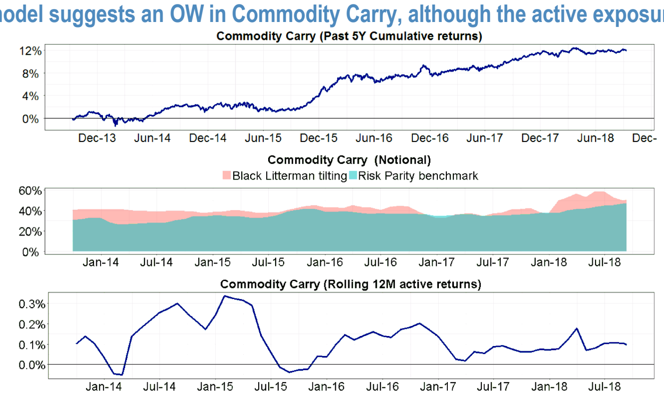
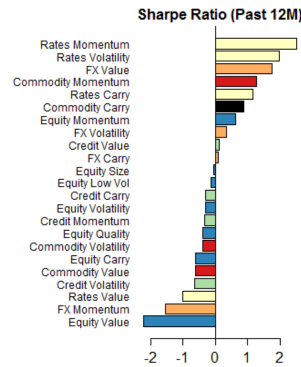
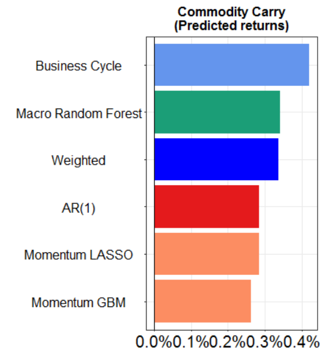
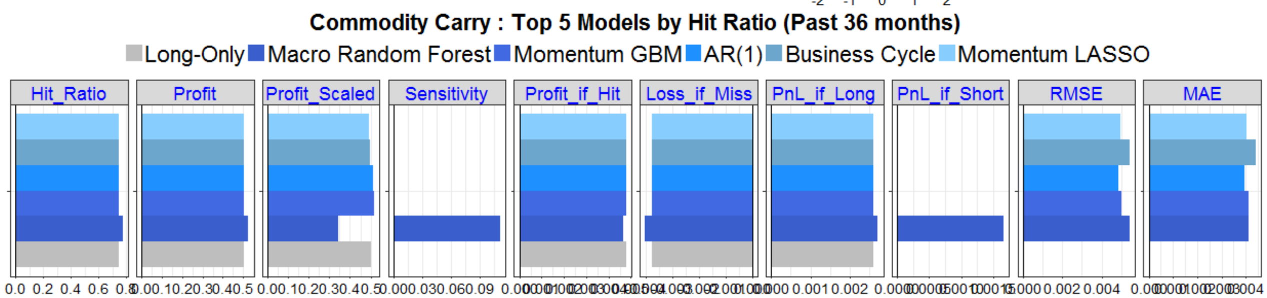
Commodity Carry

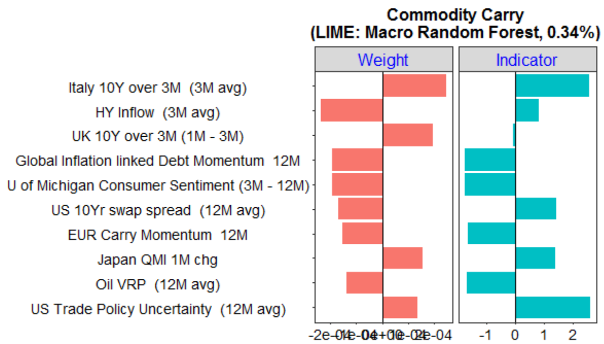
Figure 46: Commodity Carry has performed well in the past year with low volatility, giving a decent Sharpe ratio. A simple long-only model would have performed well, and we find difficulty in outperforming this with other models. We find that the AR(1) model is simply dominated by the positive intercept term, and the Momentum LASSO model reduces to a constant model with a positive intercept. As such, model predictions show a tiny dispersion. Steepening of the yield curves in Italy and UK may be positive for Commodity Carry. The Black-Litterman model suggests an OW in Commodity Carry, although the active exposure has scaled down a bit since early 2018.

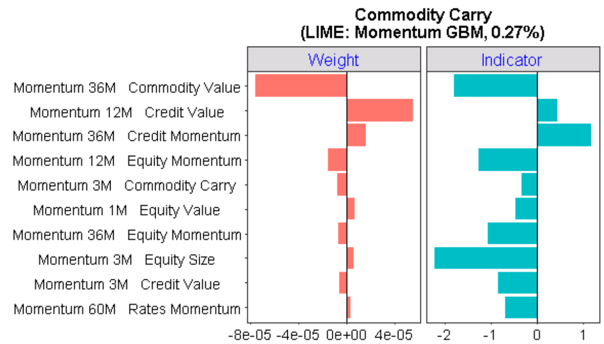


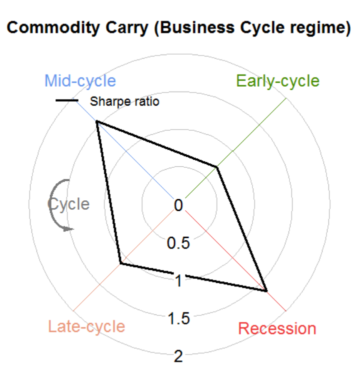


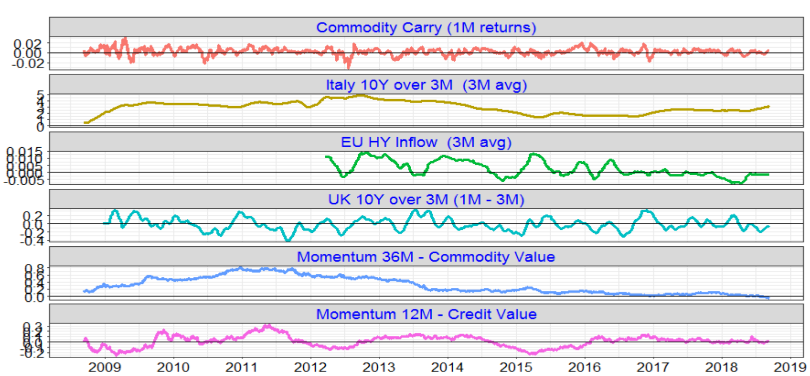








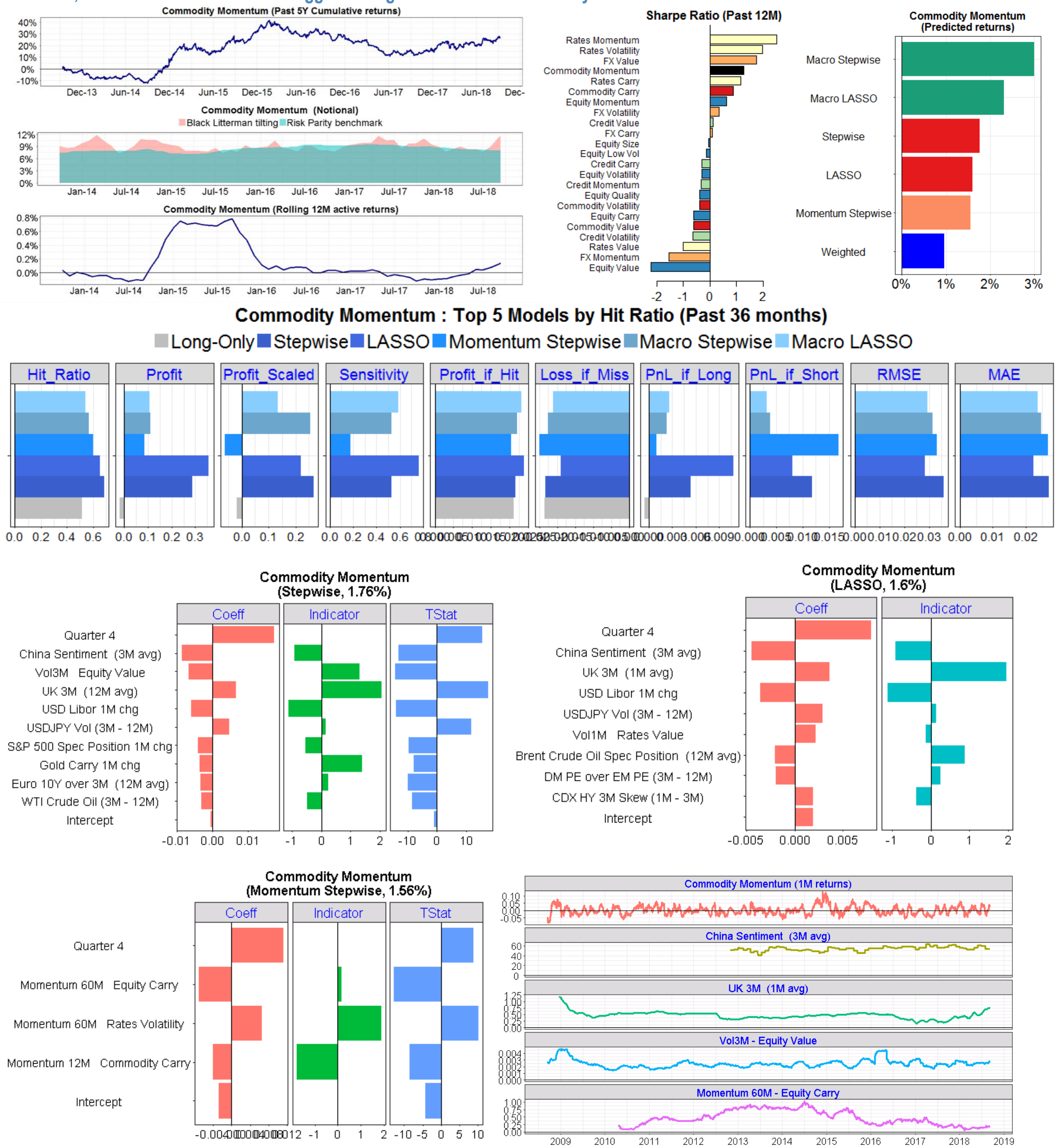




Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

Commodity Momentum

Figure 47: Commodity Momentum has performed well in the past 12 months with a Sharpe ratio around one. Recently, the Stepwise and the LASSO models have delivered the highest hit rates, and all of them have selected Q4 as a significant indicator for better performance (but latest prediction is still made in Q3). Commodity Momentum seems to be negatively correlated to China sentiment, 3M volatility in Equity Value and long term performance in Equity Carry (Vol Carry). Higher 3M rates in the UK may help the performance. With the very positive predictions, our Black-Litterman model suggests a significant OW in Commodity Momentum.



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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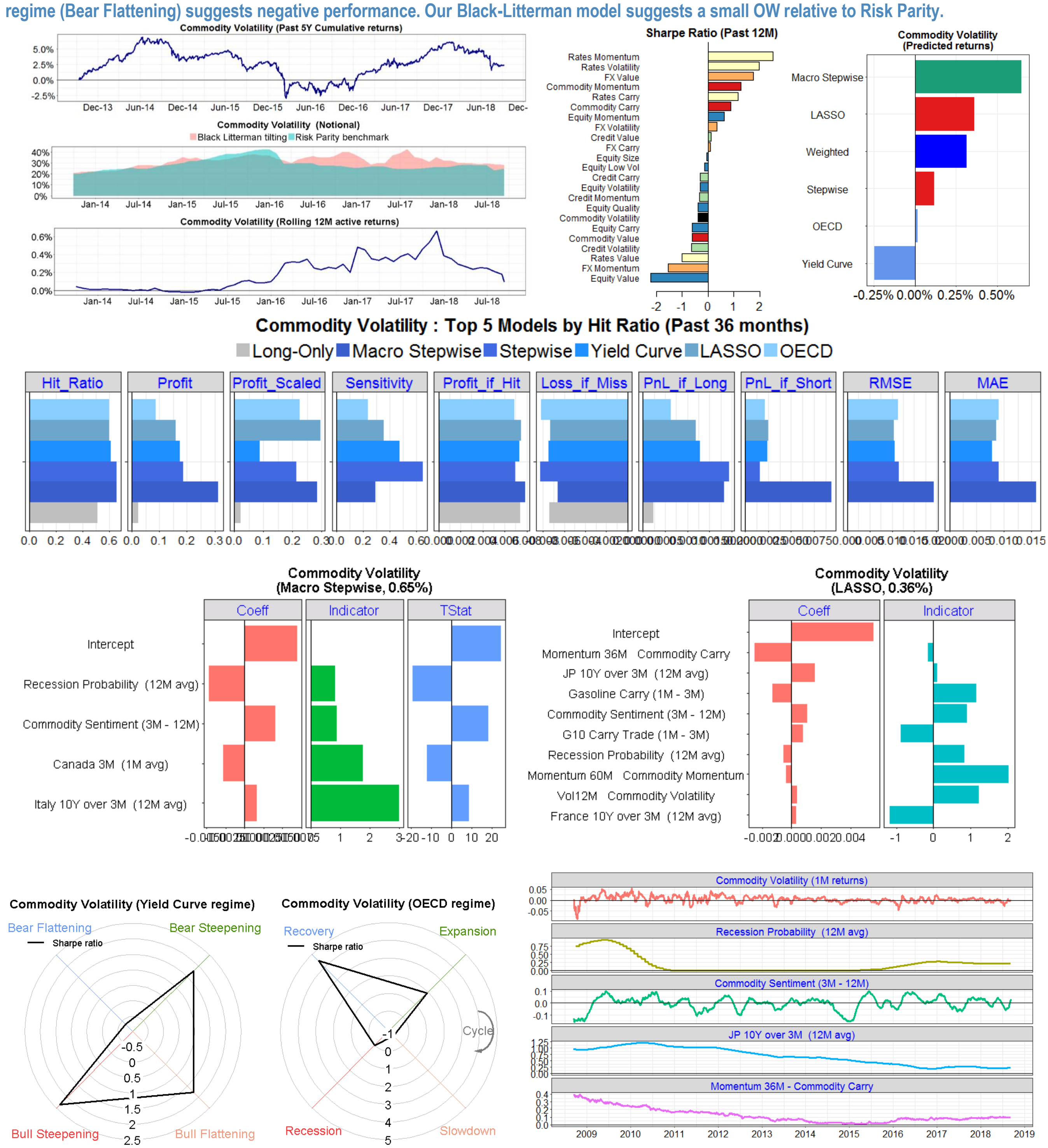
Commodity Volatility

Figure 48: Commodity Volatility had good performance in 2016-2017, but recently Sharpe ratio has been negative. Stepwise selection models tend to give higher hit rates in the past 3 years. Among those, the macro version indicates some risk if recession probability continues to rise. Nevertheless, commodity sentiment seems to be supportive for returns. Most predictions are positive, except that the current yield curve regime (Bear Flattening) suggests negative performance. Our Black-Litterman model suggests a small OW relative to Risk Parity.



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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Appendix

Machine Learning model calibration

In this study, we calibrate our Machine Learning models once a year at the end of December. We consider a rolling window of 10 years of daily data in the estimation. About 70% of data is used for in-sample training, and the remaining 30% of data is reserved for cross validation, where we allow the model to search through a set of hyper-parameters (e.g. depth of the tree, number of boosting iterations, regularization parameters) and select the ones which minimizes the RMSE in the cross validation sample.

We then keep the model fixed for the next 12 months, and every month-end we use the latest observations to predict 1-month ahead risk premia returns. We run the models separately for each risk premia, and we normalize all predictors using rolling 12-month z-scores.

Figure 49: Walk-forward cross validation for model estimation. Once a model is calibrated, it is fixed for a year. Predictions are obtained every month with the latest observations

Training Data	Cross Validation	Forecasts
About 7 years of daily data (Rolling window)	About 3 yearsr of daily data (For tuning hyper-parameters)	Monthly Predictions

Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

Optimality of Risk Parity Portfolio

Consider the Maximum Sharpe Ratio (MSR) portfolio, i.e. the Tangency portfolio which satisfies

$$\max_{\boldsymbol{\omega}} \frac{\boldsymbol{\omega}'\boldsymbol{\mu}}{\sqrt{\boldsymbol{\omega}'\boldsymbol{\Sigma}\boldsymbol{\omega}}}$$

By taking derivatives, we can show that the solution is $\boldsymbol{\omega} = \gamma^{-\mathbf{1}}\boldsymbol{\Sigma}^{-\mathbf{1}}\boldsymbol{\mu}$

for some constant γ, which can be taken as $\gamma = \mathbf{1}'\boldsymbol{\Sigma}^{-\mathbf{1}}\boldsymbol{\mu}$ if we constraint the weights to sum to unity. If $\boldsymbol{\Sigma} = \mathrm{diag}(\sigma_1^2, \dots, \sigma_n^2)$ is a diagonal matrix, we have

$$\omega_j = \frac{\mu_j}{\sigma_j^2}$$

If asset's Sharpe ratios are constant ($\mu_i/\sigma_i = \mu_j/\sigma_j$ for all *i, j*), then the weights are inversely proportional to volatilities, which boils down to the risk parity portfolio.

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Black Litterman mechanism

In the traditional Black-Litterman framework, the implied returns are "reverse-engineered" from a Mean-Variance Optimal (MVO) portfolio as

$$\mu = \delta \Sigma \omega$$

where μ is the vector of implied returns, δ is a risk-aversion parameter, Σ is the covariance matrix and ω is the vector of the holdings in the MVO portfolio, usually taken as the market cap-weighted portfolio.

In our approach, since we start from the risk parity portfolio, we obtain the implied returns in another way. We use the property that risk parity portfolios are optimal (i.e. have maximum Sharpe ratio) when pairwise correlations are constant and asset Sharpe ratios are the same (Maillard, Roncalli and Teiletche (2010), Roncalli (2014)). Implied returns of the risk parity portfolio are then given by

$$\mu_j^{implied} = E[Sharpe] \times \sigma_j \quad \forall \, risk \;\; premia \; j$$

These implied returns (i.e. priors) are assumed to follow the Gaussian distribution

$$X \sim N(\mu, \Sigma)$$

Our view $V = (v_1 \quad \cdots \quad v_N)'$ is a vector consisting of our expected returns, and can be expressed as

$$V = PX + \varepsilon$$

where P is a "view matrix", and $\varepsilon \sim N(0, \Omega)$ are the errors such that $Cov(\varepsilon) = \Omega$ quantifies the uncertainty of our views. Since we have exactly one view per risk premia, $P = I$ is an identity matrix here (but in general our views can be any linear combination of risk premia returns). The prior and the views follow the joint Gaussian distribution:

$$\begin{pmatrix} X \\ V \end{pmatrix} \sim N\left(\begin{pmatrix} \mu \\ P\mu \end{pmatrix}, \begin{pmatrix} \Sigma & \Sigma P' \\ P\Sigma & P\Sigma P' + \Omega \end{pmatrix} \right)$$

The posterior distribution is given by $X|V = v \; \sim N(\mu_{BL}, \Sigma_{BL})$ where

$$\mu_{BL} = \mu + \Sigma P'(P\Sigma P' + \Omega)^{-1}(v - P\mu)$$

$$\Sigma_{BL} = \Sigma - \Sigma P'(P\Sigma P' + \Omega)^{-1} P\Sigma$$

These posterior returns and covariance could then be used for portfolio construction.

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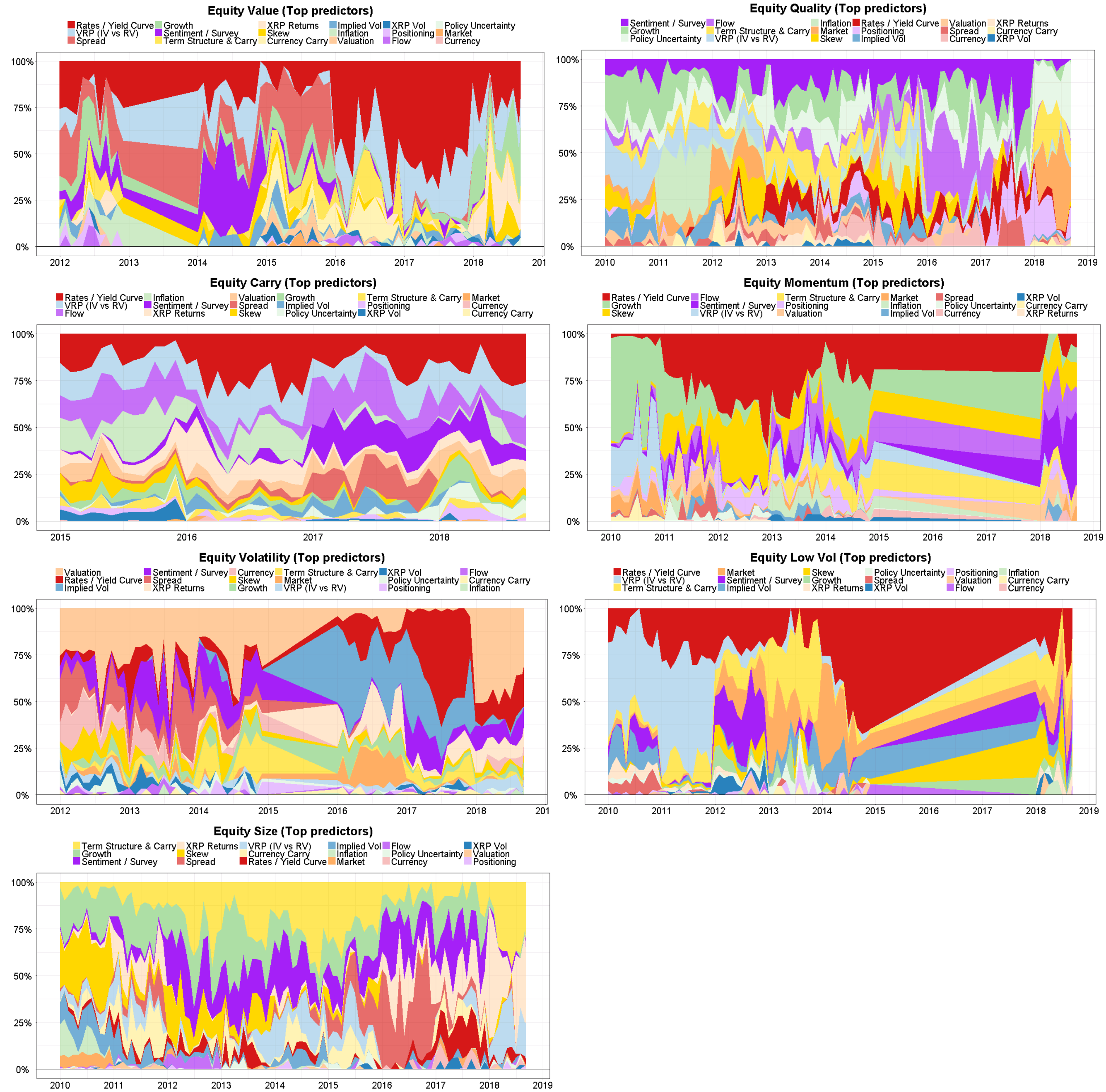
Top features selected by the Machine Learning models

Figure 50 to Figure 54 show the importance of different categories of predictors in predicting risk premia returns. We measure importance by collecting the features with the largest absolute weights in the top Machine Learning models.

Equity Risk Premia

Figure 50: Equity Risk Premia: Top categories of predictors selected in the top models (ranked by rolling 3-year hit ratio)



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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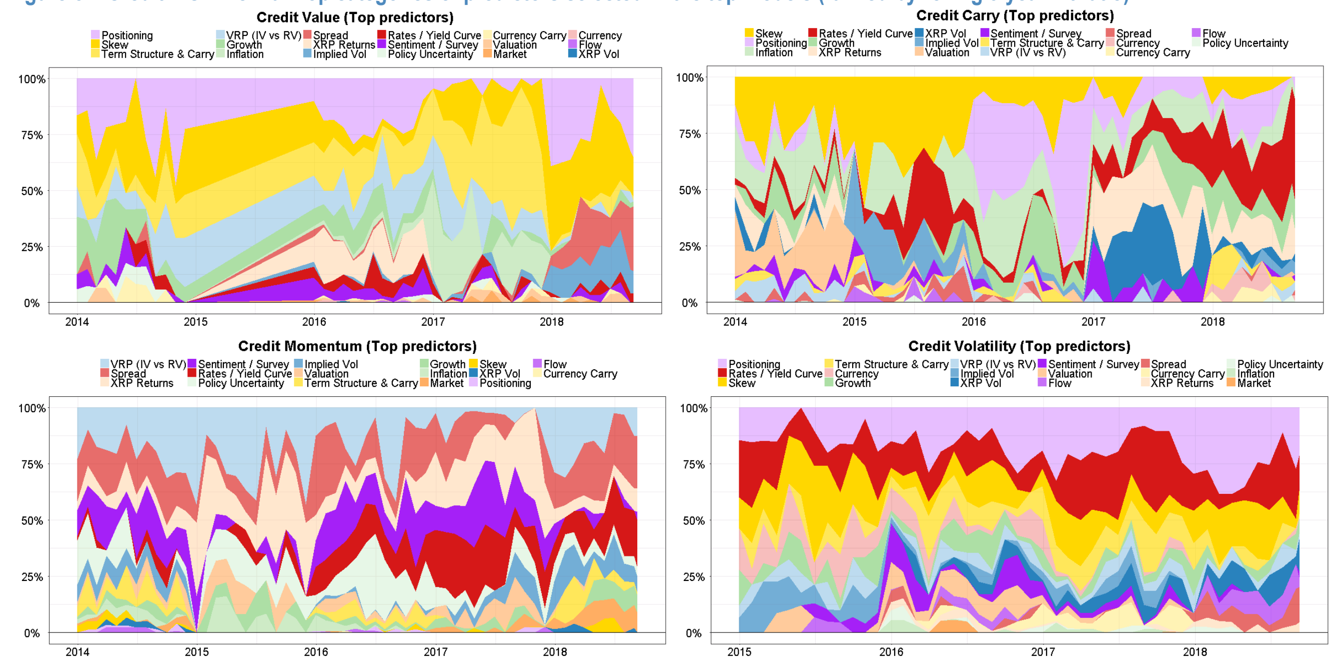
Credit Risk Premia

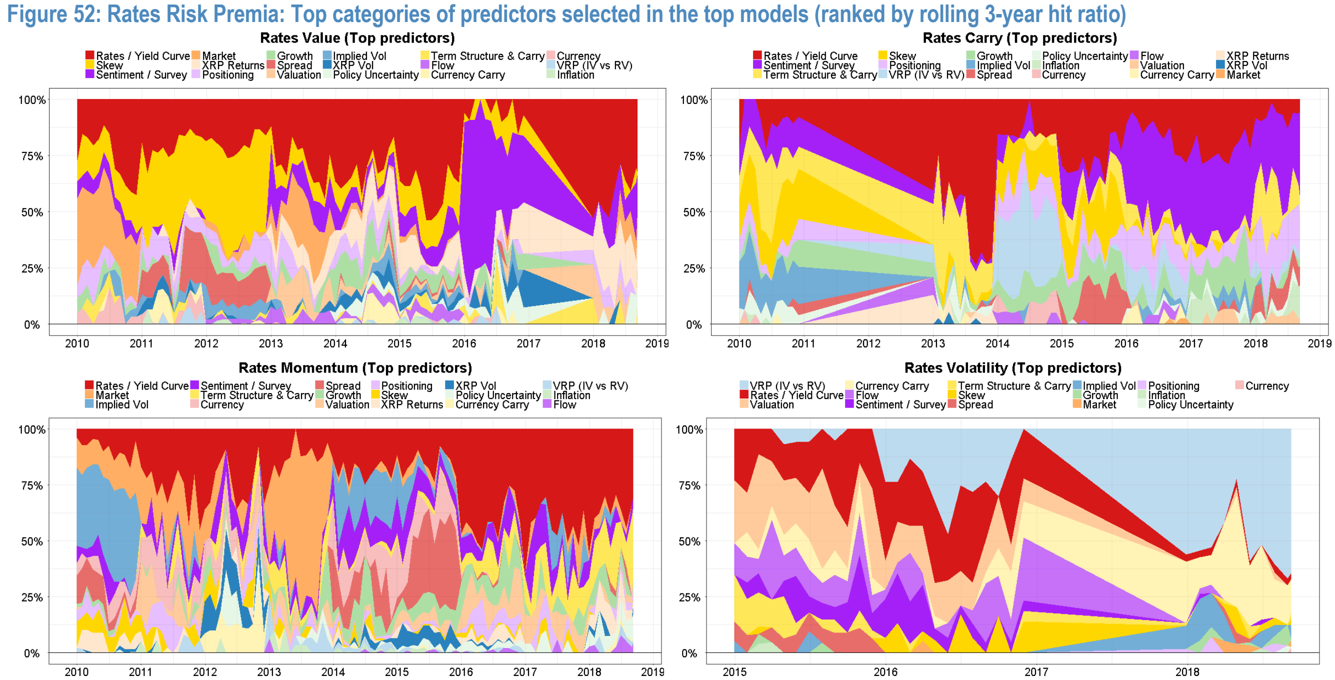
Figure 51: Credit Risk Premia: Top categories of predictors selected in the top models (ranked by rolling 3-year hit ratio)



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

Rates Risk Premia

Figure 52: Rates Risk Premia: Top categories of predictors selected in the top models (ranked by rolling 3-year hit ratio)



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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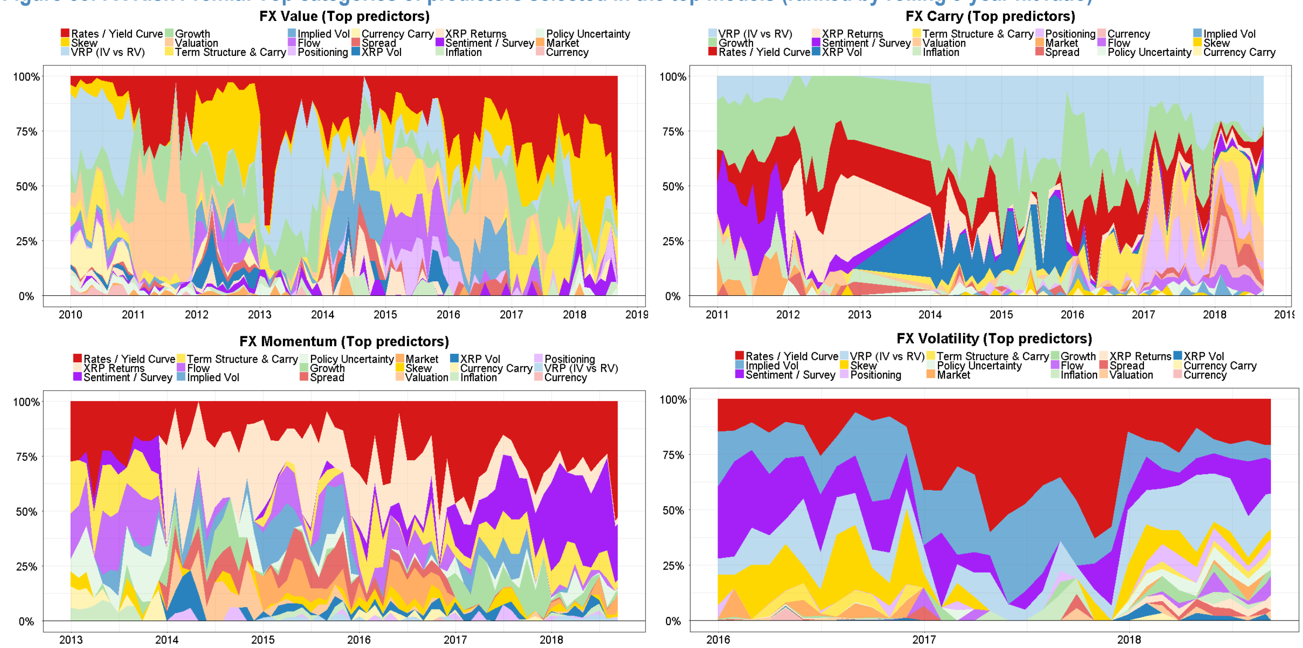
FX Risk Premia

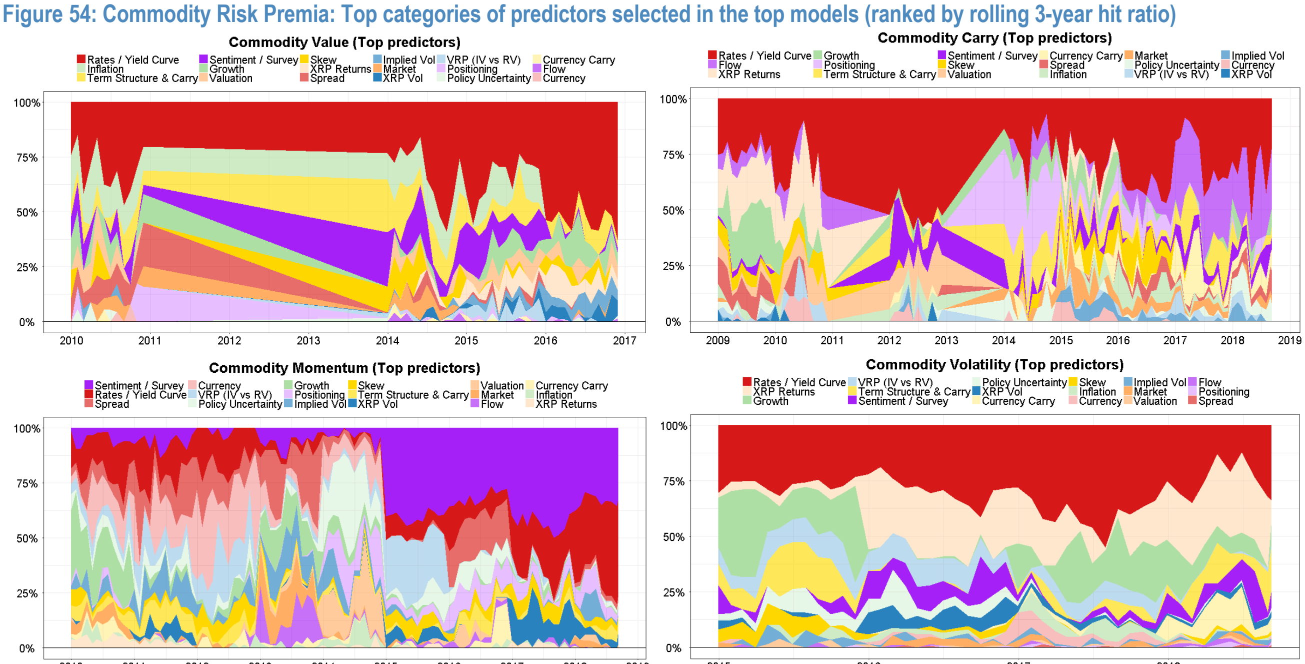
Figure 53: FX Risk Premia: Top categories of predictors selected in the top models (ranked by rolling 3-year hit ratio)



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

Commodity Risk Premia

Figure 54: Commodity Risk Premia: Top categories of predictors selected in the top models (ranked by rolling 3-year hit ratio)



Source: J.P. Morgan Quantitative and Derivatives Strategy; Bloomberg; RavenPack; EPFR

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