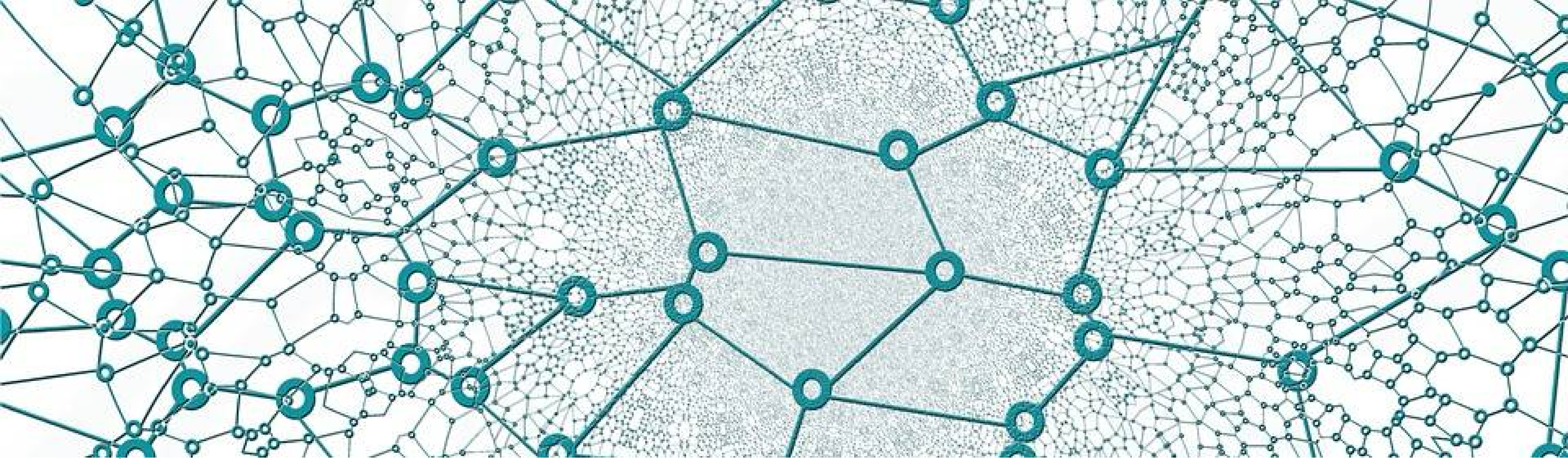

J.P. Morgan Quant Fixed Income Online Conference

September 2018

Fixed Income Strategy:

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J.P. Morgan Securities LLC

Keynote Speaker:

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Head of J.P. Morgan Artificial Intelligence Research
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Agenda

Some questions for you…

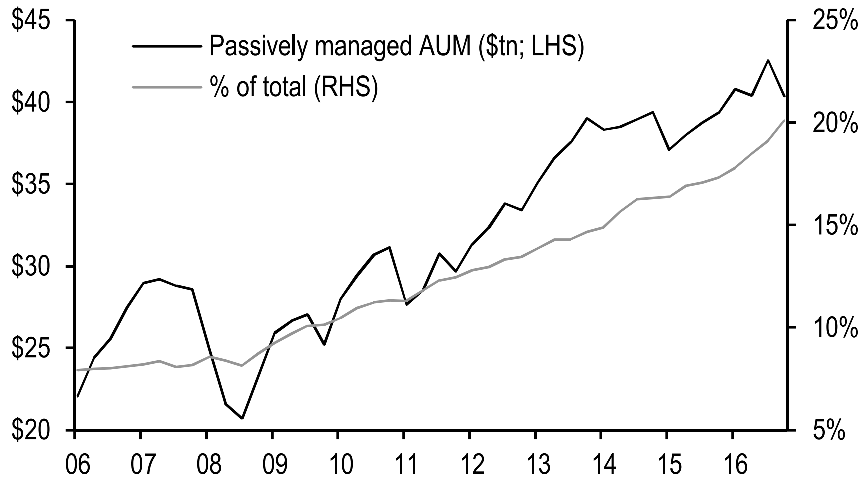
How would you describe your level of experience with machine learning and artificial intelligence?

- Very little
- Some but not a lot
- Quite a bit
- Expert

Passive investment strategies have taken in a disproportionate share of investment flows, especially for equities but also fixed income …

Passive strategies have grown materially as a share of global AUM, and at an accelerating pace …

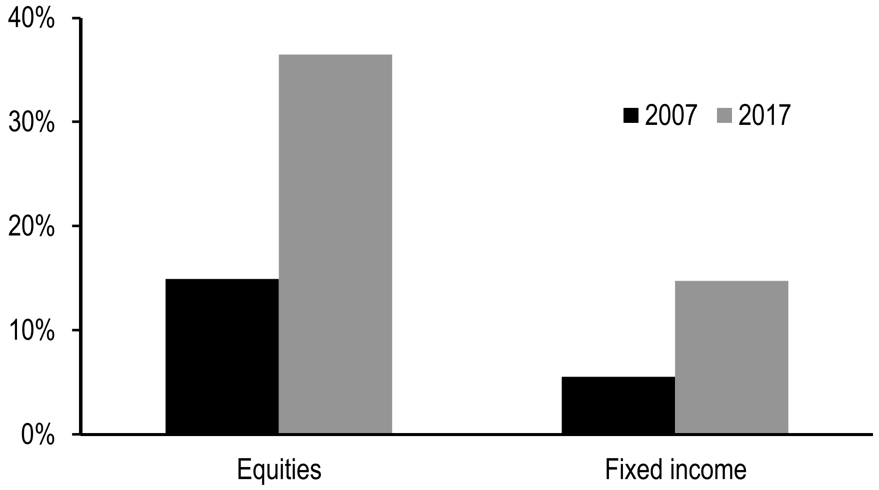
Global assets managed passively, overall AUM (LHS; $tn) and % of total (RHS)



Note: Data from The implications of passive investing for securities markets, V. Sushko & G. Turner, BIS Quarterly Review, March 2018.
Source: J.P. Morgan, BIS

… and though this is more prevalent and pronounced in equities, fixed income has also participated

% of AUM in passive strategies in 2007 versus 2017, all currencies; %



Source: J.P. Morgan, BIS

Note: For further discussion on this effect see also:
M. Kolanovic, *What will the next crisis look like?*, Ten Years After the Global Financial Crisis, 9/10/18

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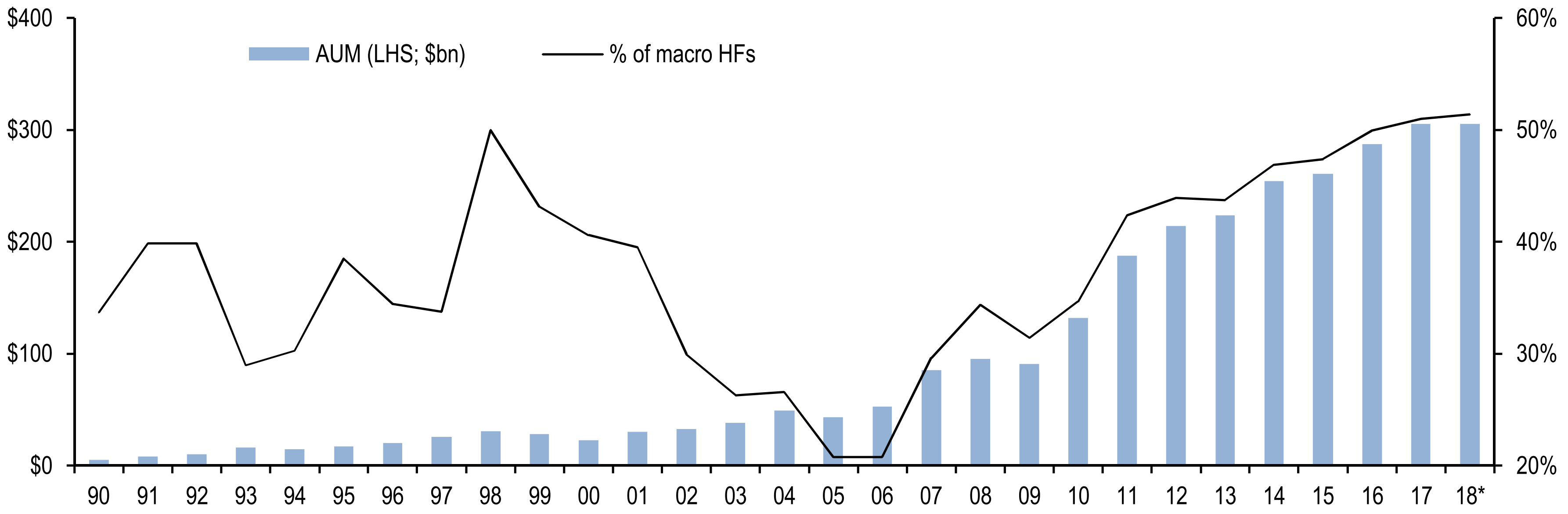
… and even hedge funds have turned to a more systematic approach to investing

Even among macro hedge funds, total AUM in systematic strategies has grown rapidly, and now accounts for more than $300tn and the majority of assets

Total AUM among systematic diversified macro hedge funds (LHS; $bn) and as a fraction of total macro hedge fund AUM (RHS; %)



Source: J.P. Morgan, HFR

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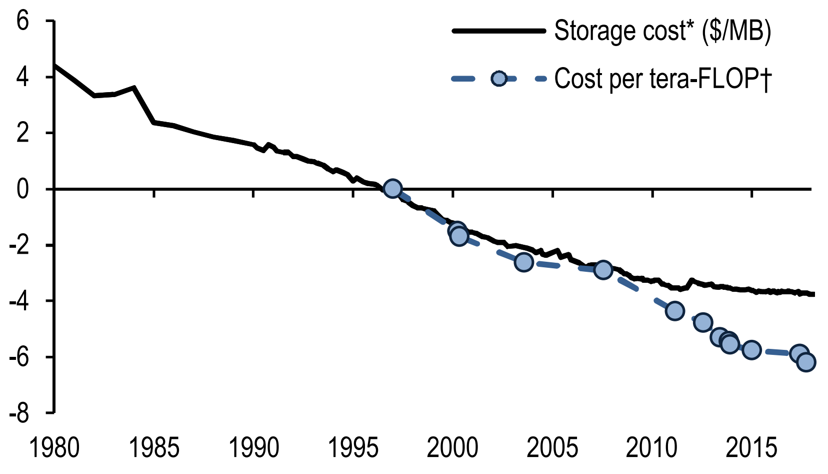
Exponential declines in both computing and storage costs have made it cheaper and faster to make use of the explosion in data, but we are only starting to do so truly at scale

The costs of both computing and storage have been declining exponentially for decades …

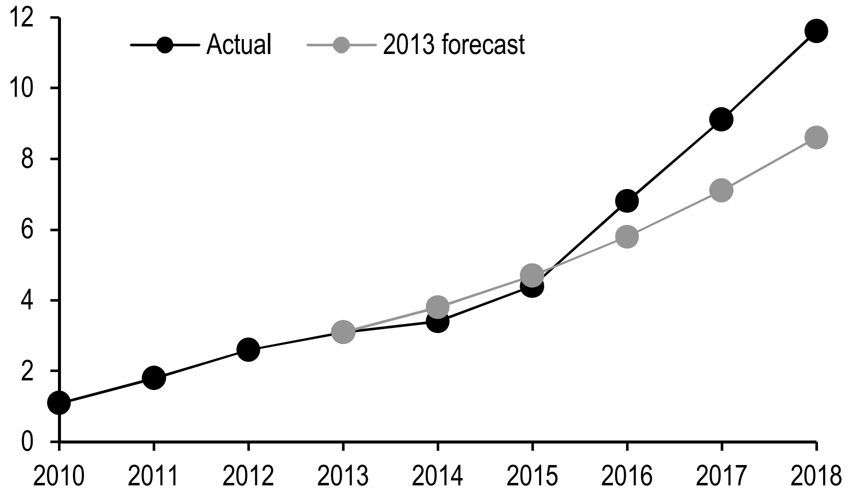
Change in log-10 of storage* ($/MB) and processing† ($/tera-FLOP) costs over time



* Based on estimates from John McCallum and available on his website (along with sources).
† World Bank estimates from the World Development Report 2016: Digital Dividends, published May 2016.
Source: J.P. Morgan, jcmit.net, World Bank

… and the growth in data is not only explosive, but has accelerated relative to even arguably ambitious projections a few years ago

Actual data center throughput by year versus 2013 forecast; ZB per year

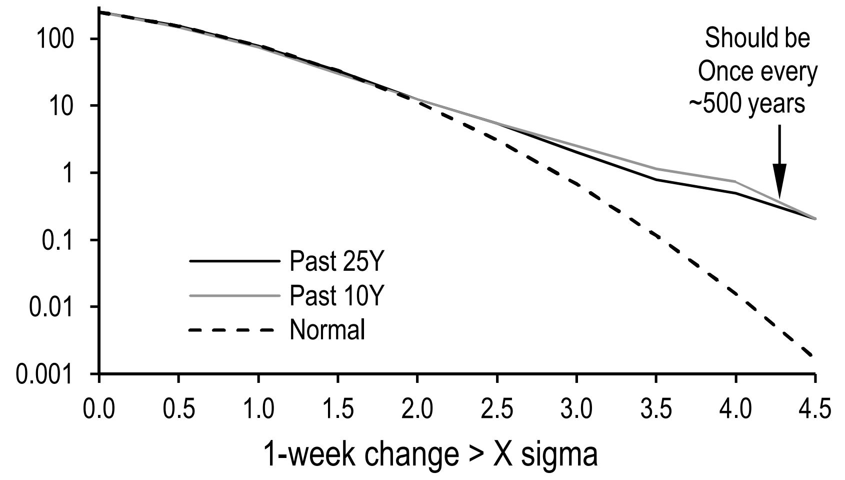


Note: Based on the Cisco Cloud Index, produced annually along with forecasts since 2010.
Source: J.P. Morgan, Cisco

The persnickety case of financial time series: fat tails and relatively few observations

The distribution of returns in fixed income has very fat tails …

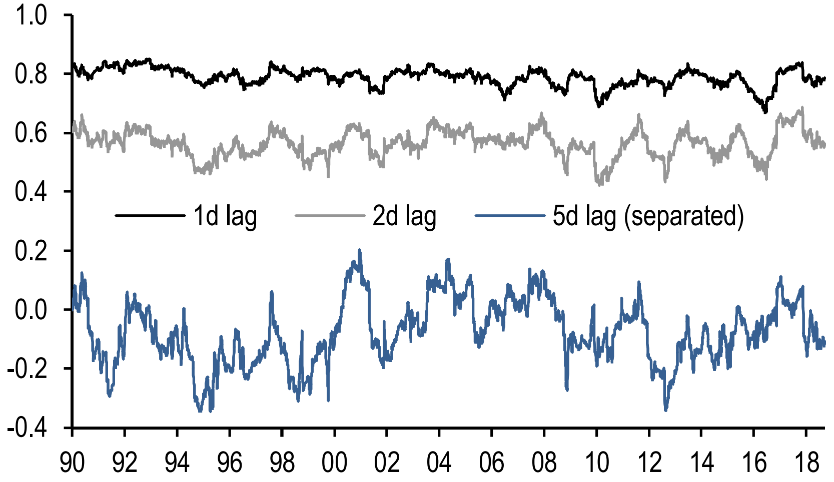
Average annual instances of1-week change versus *ex-ante* 1-year trailing standard deviation of weekly changes for 10-year Treasury yields, actual over the past 25 and 10 years as well as a normal expectation



Source: J.P. Morgan

… and a high degree of autocorrelation among overlapping periods limits the effective number of observations

Correlation coefficient of weekly changes in 10-year Treasury yields with 1-, 2-, and 5-day lagged weekly changes; unitless

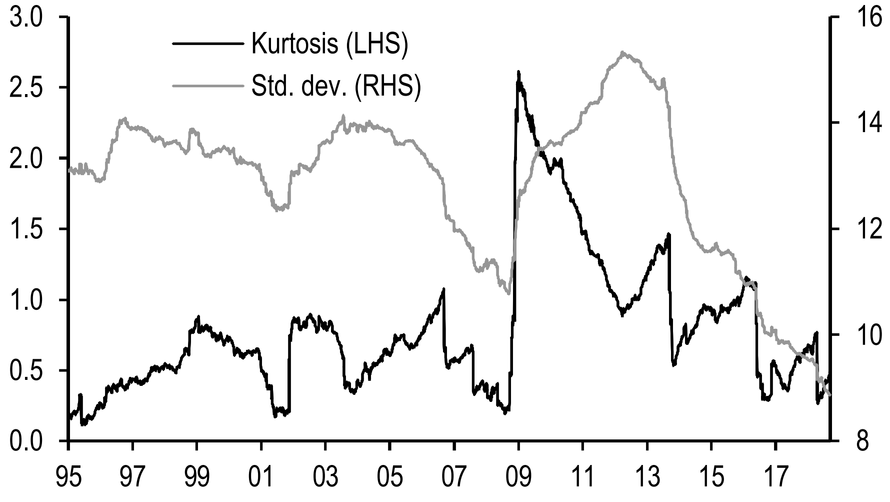


Source: J.P. Morgan

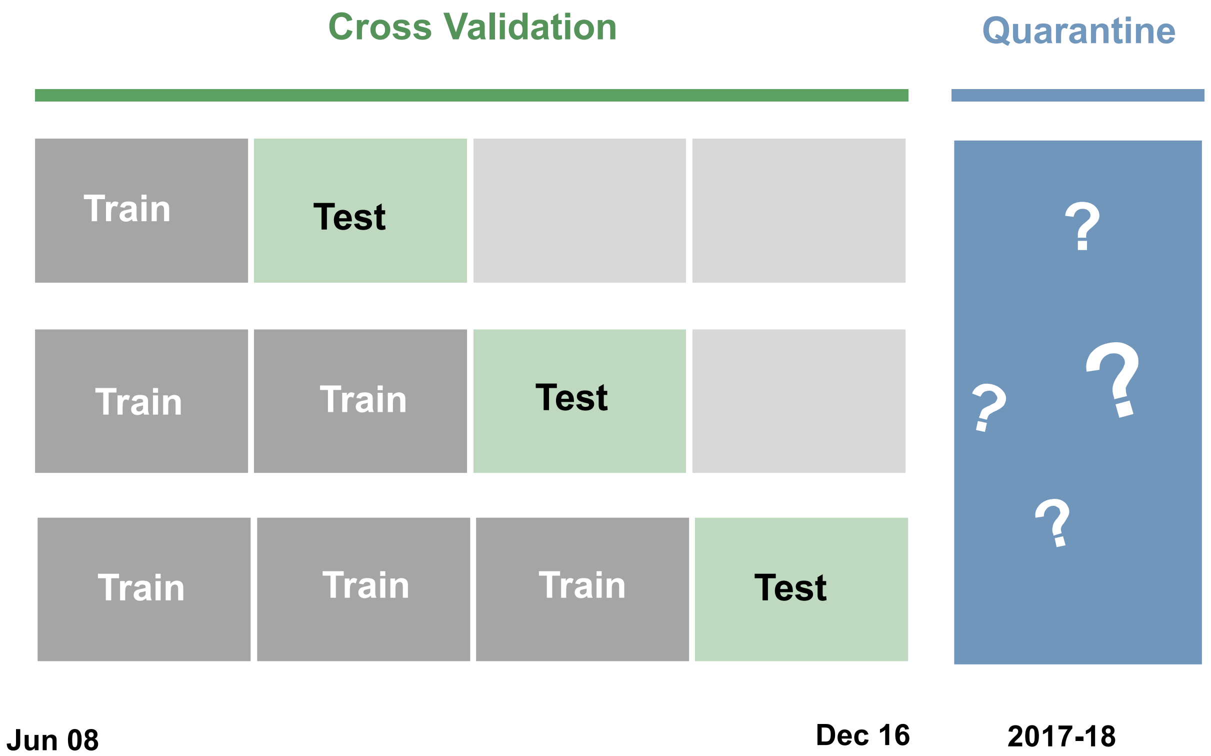
The persnickety case of financial time series: invariance of scale, non-stationary data

Highly non-stationary behavior of financial time series requires a different approach to data segmentation and tests of generality …

Rolling 1-year Kurtosis and standard deviation of daily changes in 10-year Treasury yields



Source: J.P. Morgan



The persnickety case of financial time series: how to deal with an abundance of potential drivers

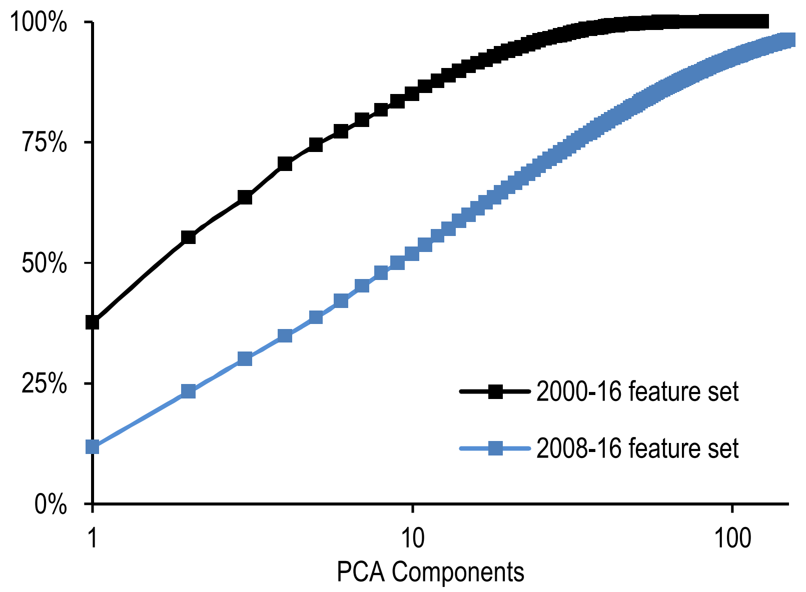
We employ a comprehensive set of input features within and beyond USD interest rate markets

Treasuries	yield, yield error, carry, specialness, matched-maturity swap spreads, OIS swap spreads, market depth, repo rates, term premium
Swaps	Realized volatility, carry
OIS	Implied vol surface, skew
TIPS	Breakevens
MBS	Mortgage basis, hedge adjusted carry, convexity, option-adjusted duration, OAS, positioning
Cross-Asset	HG and HY bond indices, European rates, equity index levels and volatility, FX indices and carry, commodity indices
Econ	Global and regional and domestic economic indices and surprise indices, various date flags
Dates	Flags for FOMC meetings, payrolls and month-ends

Source: J.P. Morgan

PCA allows us to reduce the dimensionality of our input feature set

Cumulative explained variance of PCA components for the 2008-16 and 2000-16 dataset we used to cross-validate our ML predictors



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Some questions for you…

What do you use machine learning for?

- Background/context
- One among many inputs into investment decisions
- Systematic alpha generation over daily to weekly holding periods
- Intraday/high frequency trading

The persnickety case of financial time series: the drivers of rates themselves are both uncertain and evolve over time, not to mention changing sensitivities

J.P. Morgan 10-year Treasury yield fair value model circa late-2010 …

	Projected evolution of drivers					Model statistics	
Drivers	Current	4Q10	1Q11	2Q11	4Q11	Coefficient	T-stat
Fed funds target (6M fwd), %	0.18	0.17	0.20	0.25	0.30	0.589	34.9
OIS curve, %	0.51	0.48	0.54	0.70	0.86	1.079	23.8
Structural deficit, % GDP	3.70	3.70	3.75	3.85	4.00	0.142	4.4
Trade surplus, % GDP	-3.5	-3.2	-3.2	-3.3	-3.4	0.107	6.8
Slack index*	0.75	0.75	0.55	0.38	0	-0.143	-7.2
Intercept						2.150	12.9
Baseline 10Y UST projected yield	2.91	2.85	2.96	3.19	3.46		
Adjustment for Fed purchases/supply		-0.35	-0.30	-0.20	0		
Target 10Y UST yield		2.50	2.65	3.00	3.45		

Economic slack index is defined as average of 5-year z-scores of the unemployment rate, capacity utilization, and jobless claims. OIS curve, or Fed expectations are the 18Mx3m minus 6Mx3M OIS rate after 6/1/06 and the 2nd/6th constant maturity Eurodollar curve in the prior period.

Structural deficit calculated as the rolling 10-year regression intercept from regressing the 1-year forward-looking Federal budget deficit as a percentage of nominal GDP against the ex-ante nominal GDP growth and the ex-ante 1-year Federal budget deficit as a percentage of nominal GDP Fed funds target (6M fwd) is market expectations for the 4-meeting ahead Fed funds target rate.

Source: J.P. Morgan 2010 Outlook

… as compared to more recent periods

Variable	Current value	Coeff.
Intercept		-0.78
5yx5y Inflation swap rate; %	2.29	1.041
1y-ahead Growth Forecast; %	2.3	0.18
3m3m OIS rate; %	1.47	0.173
Fed Rate Fwd Guidance; months	0	-0.027
G7 ex-US Avg 3m3m OIS rate; %	-0.046	0.339
CFTC positions; 3yr z-score	-1.5	-0.14

Regression for 10-year yields (%) from 1/2/07 – 12/30/16. R-squared: 92%, SE: 26bp
Source: CFTC, Federal Reserve, J.P. Morgan

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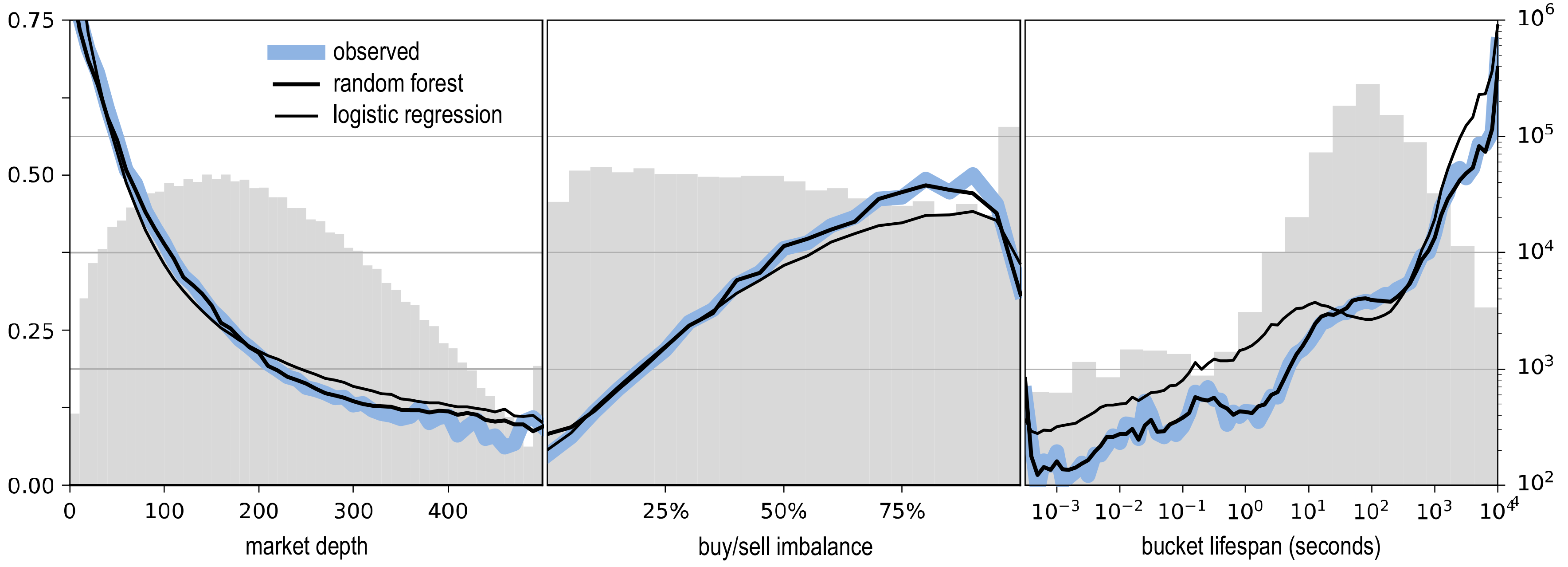
The persnickety case of financial time series: non-linear relationships are common and can be difficult to parametrize

Price impact for a $100mn flow tends to rise sharply when market depth drops below $200mn; higher velocity flows tend to enjoy lower price impact; higher flows imbalances raise impact — to a point, before reversing

Observed and modeled expected price impact by market depth, bid/ask imbalance and volume bucket lifespan (LHS; ticks) with histograms of bucket frequencies overlaid (RHS; counts)



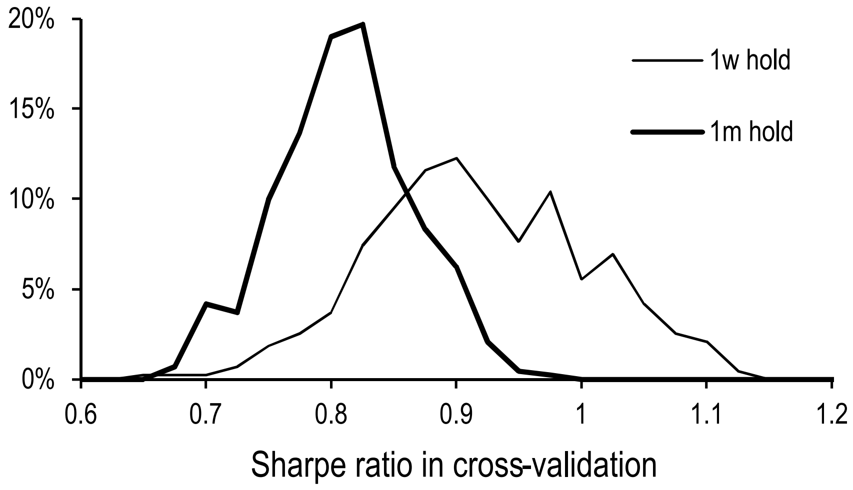
* Models use four features—market depth, buy/sell imbalance, flow lifespan (velocity) and hidden depth—to describe price impact. See section entitled 'Measuring price impact' for a description of how we define this quantity, and section entitled 'A framework for describing drivers of price impact' for a description of our RF and LR classifiers.

Source: J.P. Morgan, BrokerTec

The persnickety case of financial time series: signal quality degrades rather quickly

Projecting financial asset returns over anything close to a medium-term holding period becomes much more difficult …

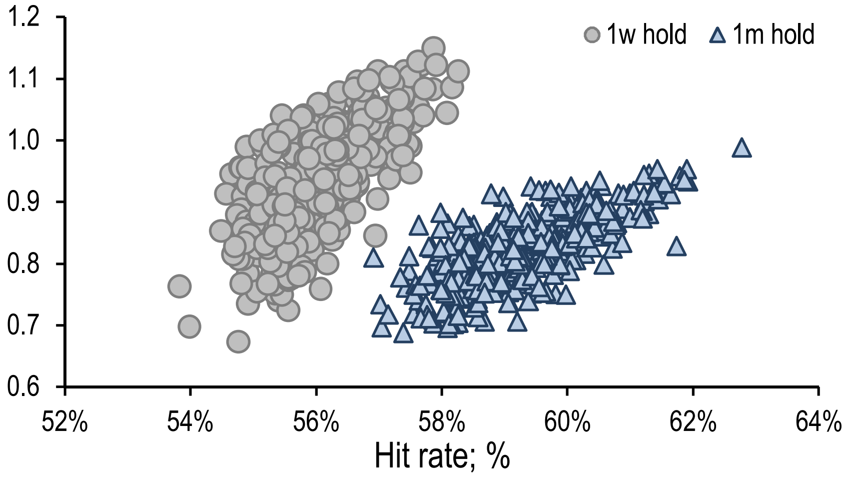
Distribution of Sharpe ratios achieved using a balanced GBM hyper-parameter search for 10-year Treasuries over 1-week and 1-month holdings periods, all over a 2008-16 cross-validation period; %



Source: J.P. Morgan

… and requires a higher degree of precision to achieve the same risk-adjusted returns

Hit rate (%) versus Sharpe ratio (unitless) for the same set of hyper-parameter searches as the left chart



Source: J.P. Morgan

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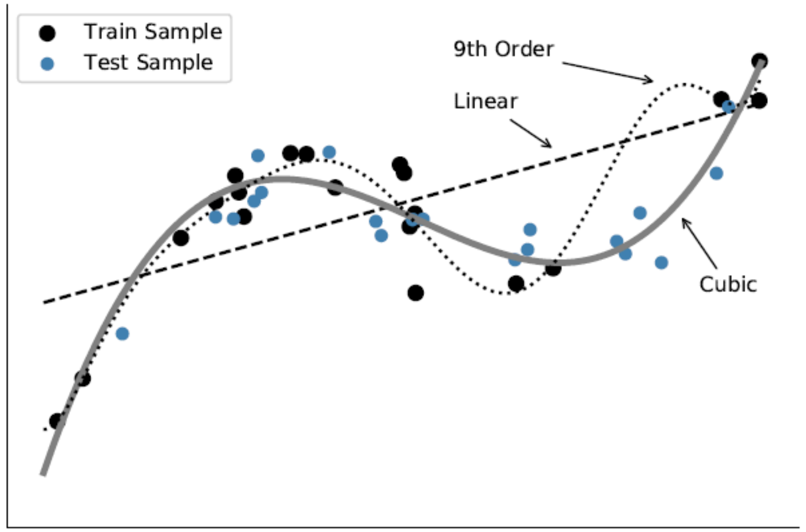
Avoid the temptation to over-fit…it rarely generalizes well

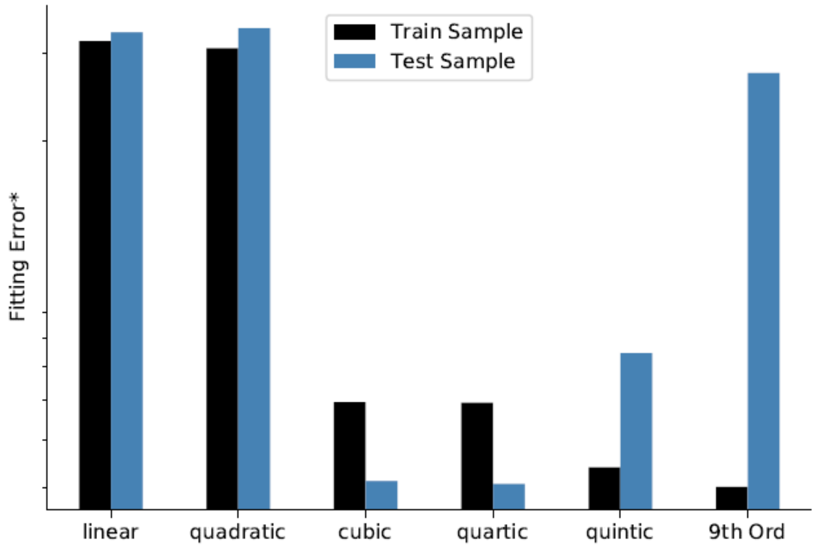
Case in point: fitting data to a polynomial

A hypothetical 1-dimensional dataset split into a "train" and "test"samples; ordinary least squares regression is applied of varying polynomial order, fitted on the train sample

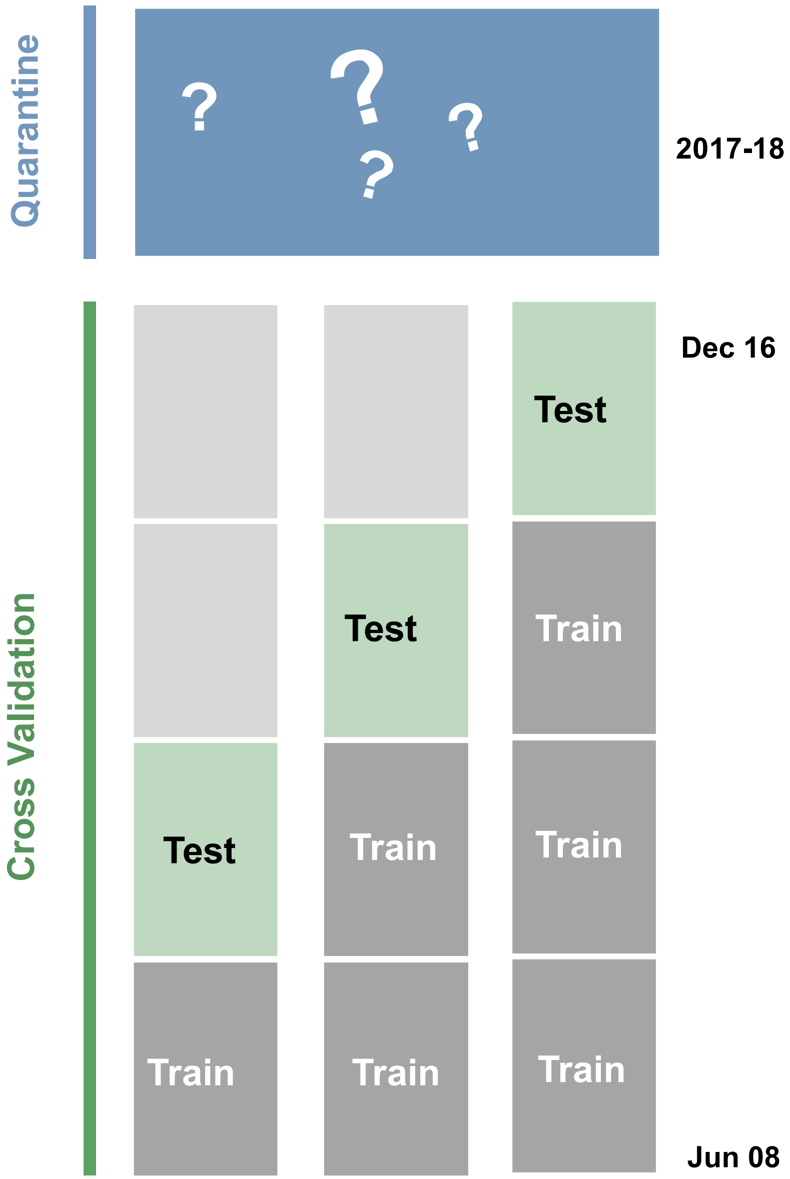


Source: J.P. Morgan

Fitting error* both in- and out-of-sample for the same data set and regression predictors



*Fitting error defined as log of the sum of the squares of the residuals (SSR) between the predicted y-values and the data points, both within the training sample each predictor was fitted on (Train Sample) and outside this sample (Test Sample).
Source: J.P. Morgan



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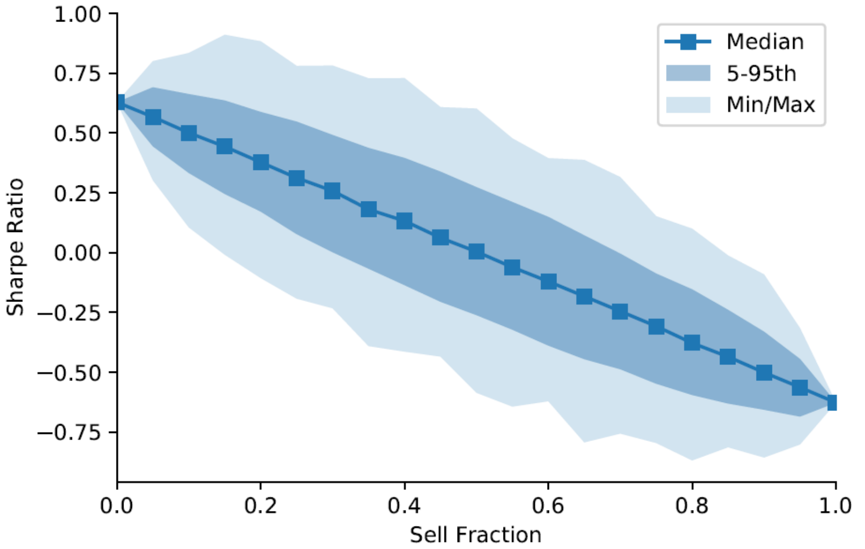
How do we think about statistical significance in this context?

When benchmarking systematic returns, one needs to take into account trending markets and the potential to get lucky …

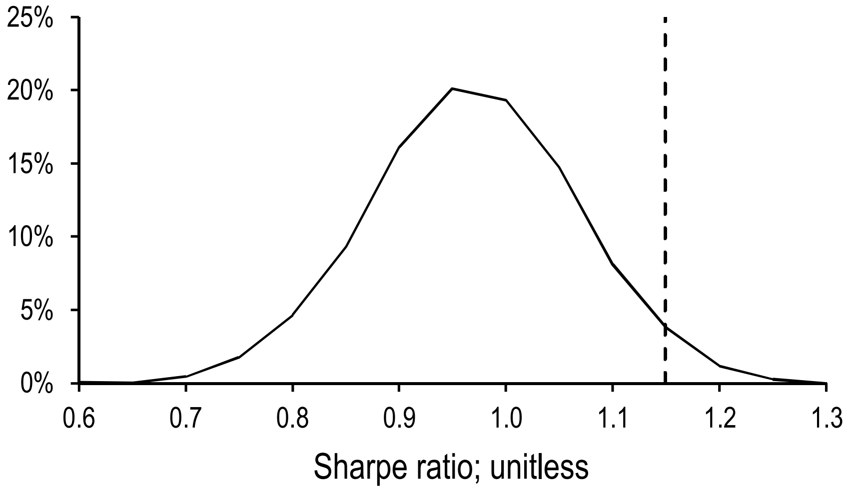
Sharpe ratio percentile thresholds* for daily trades of 10-year Treasuries held for one week from 2010-16; unitless



*Percentiles come from 3000 trials randomly permuting daily buy/sell decisions at a fixed percentage of selling days (sell fraction) and then calculating Sharpe ratio for each trial.
Source: J.P. Morgan

… and even keeping the hit ratio fixed, sizing can be a significant driver of risk-adjusted returns

Frequency of Sharpe ratios keeping direction (and hit rate) fixed but randomly permuting trade sizes over the cross-validation period of our best performing random forest classifier, actual as a dotted line; %



Source: J.P. Morgan

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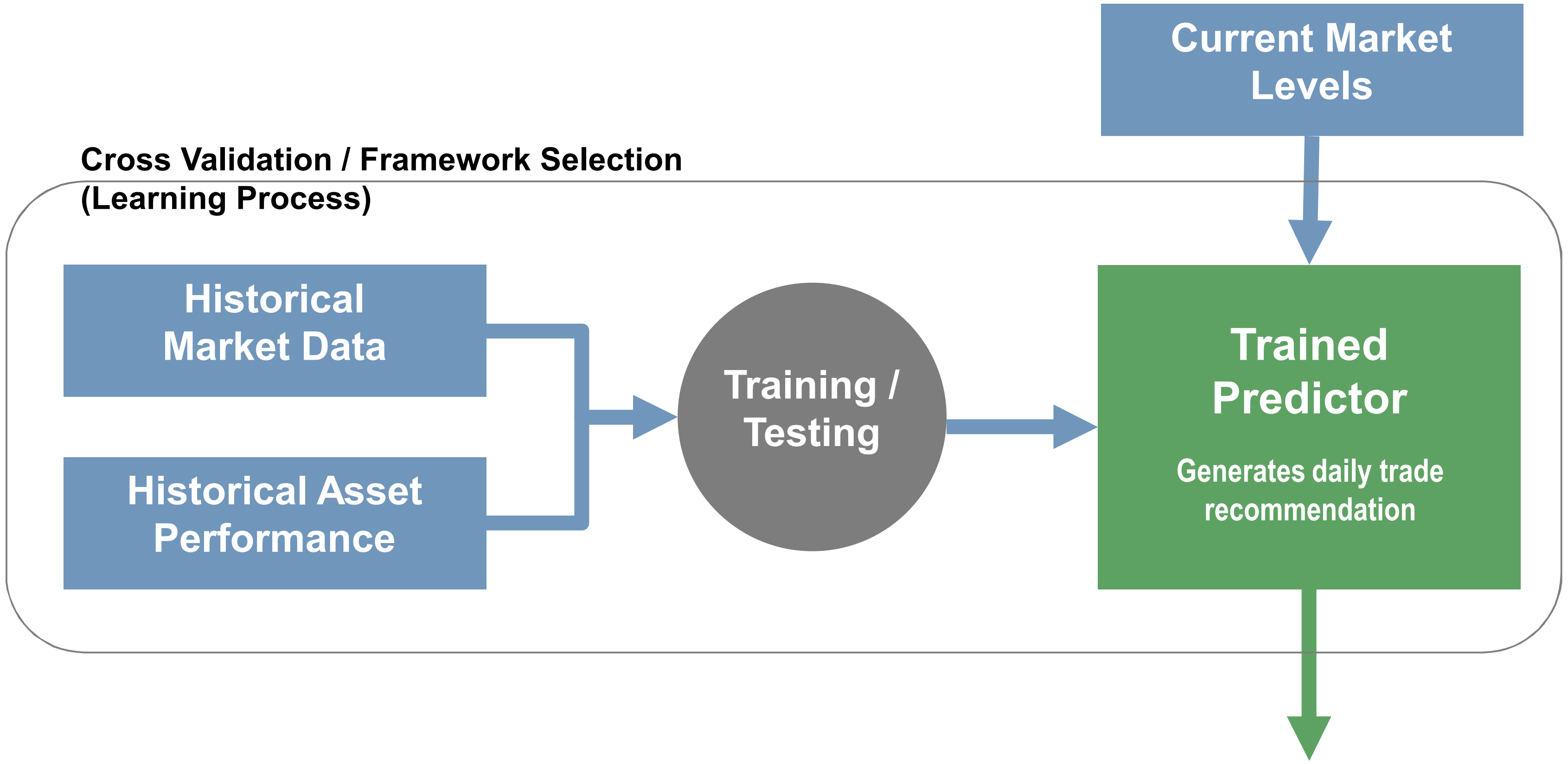
Some questions for you…

To what extent do you currently use machine learning and other quant signals as part of your day to day process?

- Never
- Occasionally
- Frequently
- Exclusively

Machine learning applied to trade execution in fixed income markets



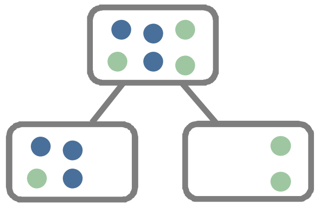
Positioning	Confidence Level	Optimal Size
Buy or Sell	50% - 100%	0.0 – 1.0

Source: J.P. Morgan

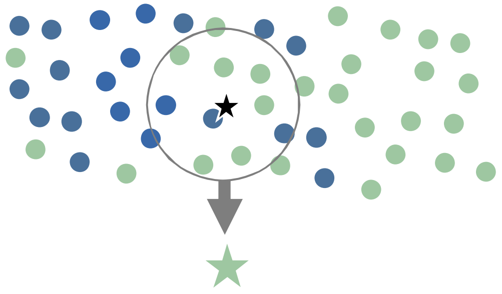
A taxonomy of machine learning techniques we have considered

"Classical" Methods

Decision Trees



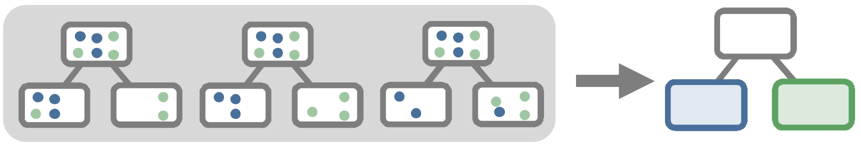
K-Nearest Neighbors (KNN)



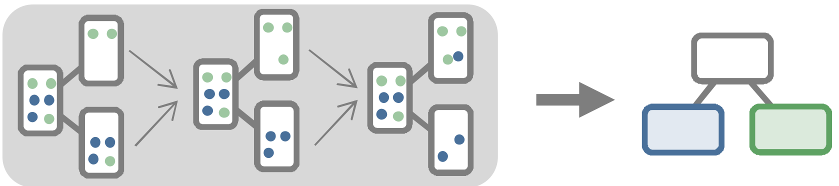
Support Vector Machines (SVM)

Ensemble Methods

Random Forest (RF)

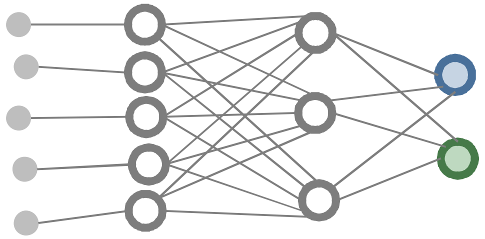


Gradient-boosted machines (GBM)



"Deep learning" methods

Artificial Neural Networks (ANN)



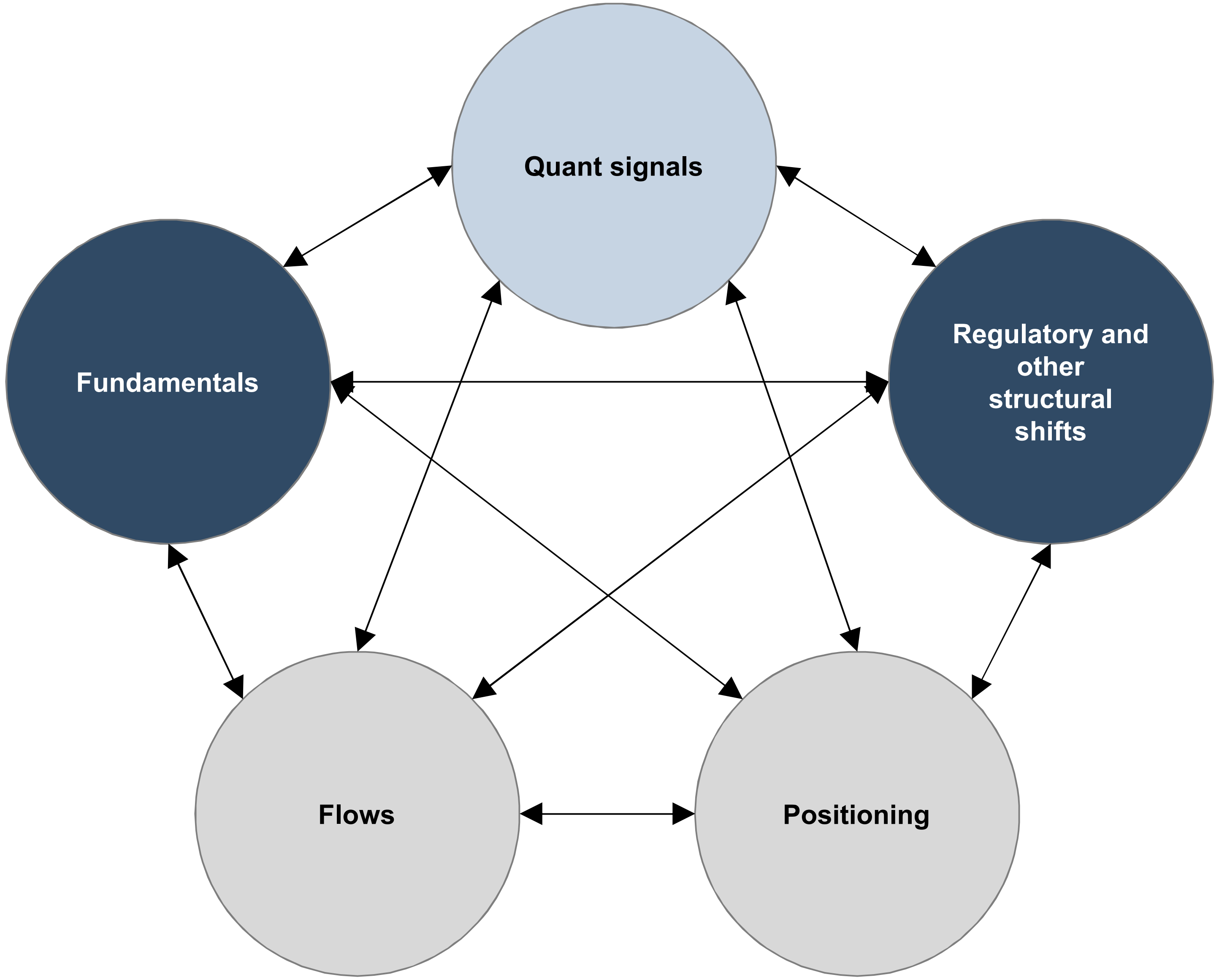
Hard voting

Soft voting

Stacking

Source: J.P. Morgan

Where do these techniques fit into an investment process?



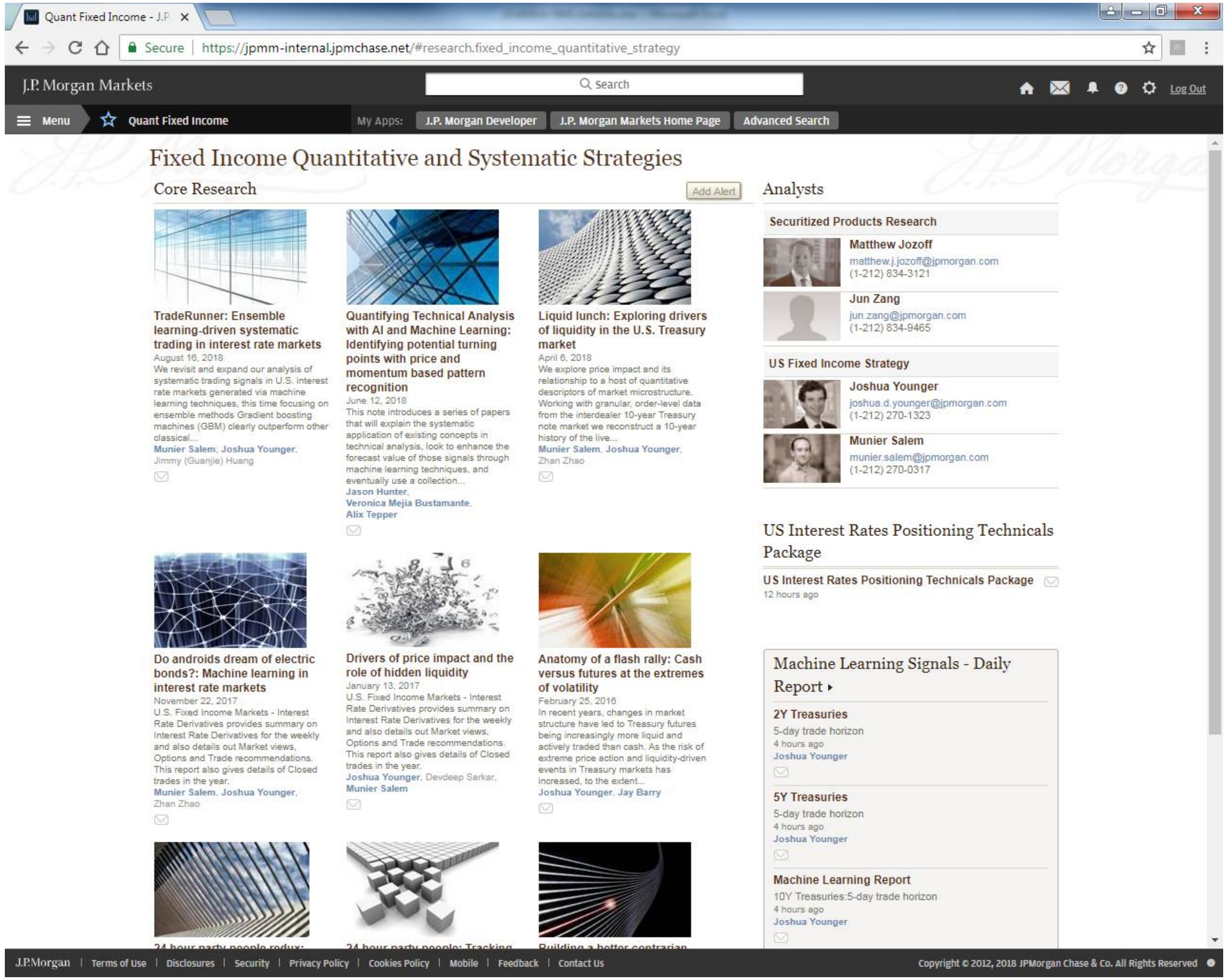
Domain Knowledge

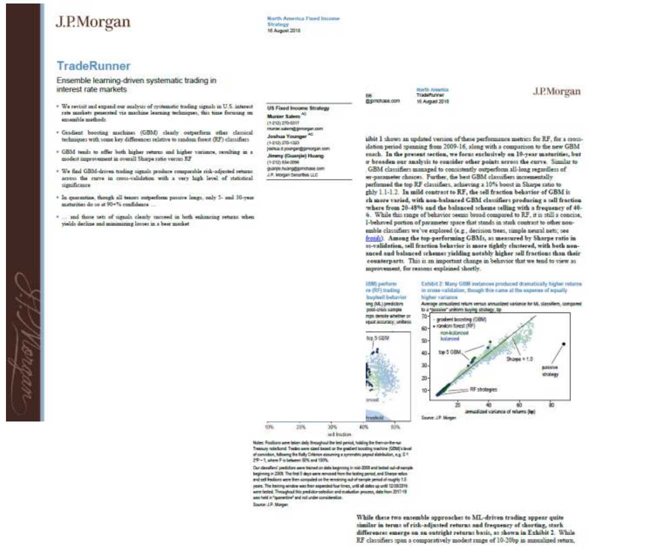
Color, anecdote & indirect inference

Systematic

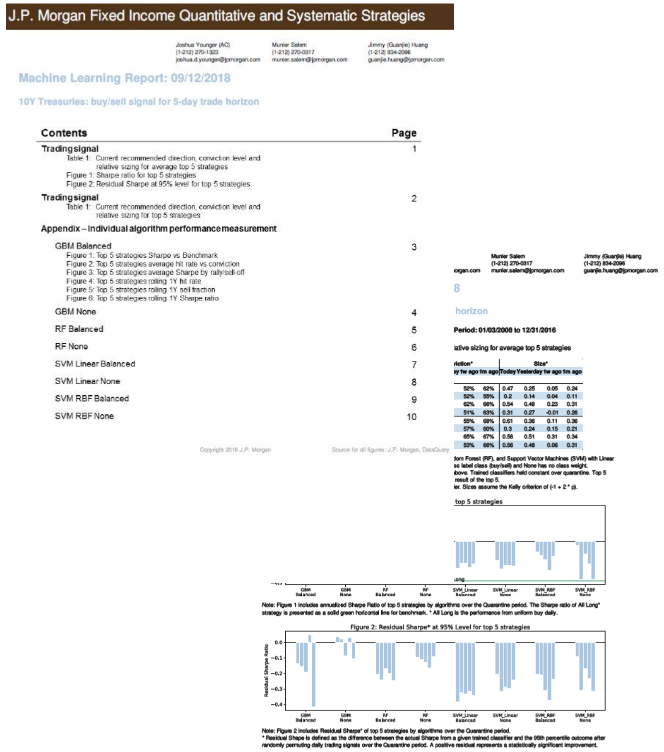
Source: J.P. Morgan

Where to find research related to these and other projects





Published research



Daily analytics

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Our initial plans: three related threads of research applying machine learning techniques to markets

- Projection
  - Doing some of the groundwork on methods/frameworks
  - Frameworks for thinking about statistical significance and how well results generalize
  - Daily analytics and medium-frequency (~daily to weekly) trading signals
- Description
  - What “matters” and when
  - Factor importance and attribution
- Design
  - Making use of high-frequency market data (i.e., BrokerTec) to analyze market structure
  - How to best think about (and seek) liquidity
  - What happens under stress

Agenda

Outline

- AI at J.P. Morgan

- AI and Autonomous Agents

- Gradient-Based Exploration for New Policies

(joint work with R. Silva & F. Melo, CMU)

J.P. Morgan AI Research Areas

Many dimensions of relevance to financial services:

Area	Relevance
DATA, including Cryptography	• Data: scale, sparse, noisy, inconsistently defined • Regulatory, client concerns about data protection
Learning from Experience	• Multiple agents, instruction, sparse rewards • Variability and dynamics in regime, market, client
Explainability & Interpretability	• Fiduciary role dictates transparency for clients • Usability of models in business processes
Values - Ethics, Fairness	• Regulatory standards for creating suitable products • Required to be non-discriminatory, non-biased

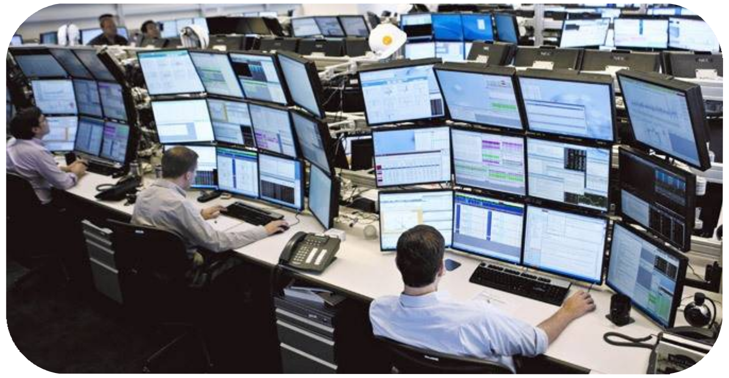
AI in Financial Services

Uncertainty

- Market direction
- Credit quality

Human-machine interaction

- Call centers
- Trade processing



Complex environments

- Collaborative & adversarial players
- Dynamic markets

Data, Models – Decision Making, Learning – Acting

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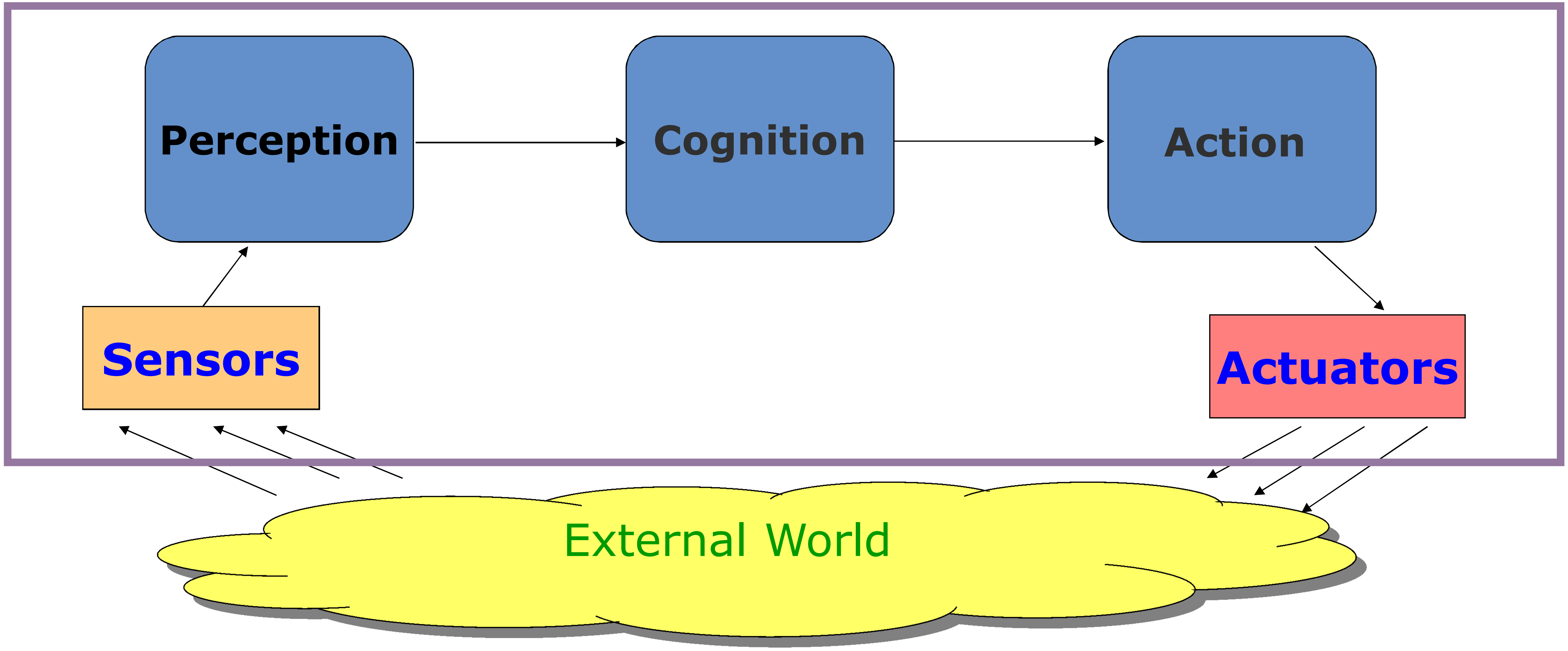
AI and Autonomous Agents



Perception: Processing, understanding of sensory data **Cognition:** Knowledge, language, planning, learning, interaction
Action: Motion, manipulation, speech, gesture, execution

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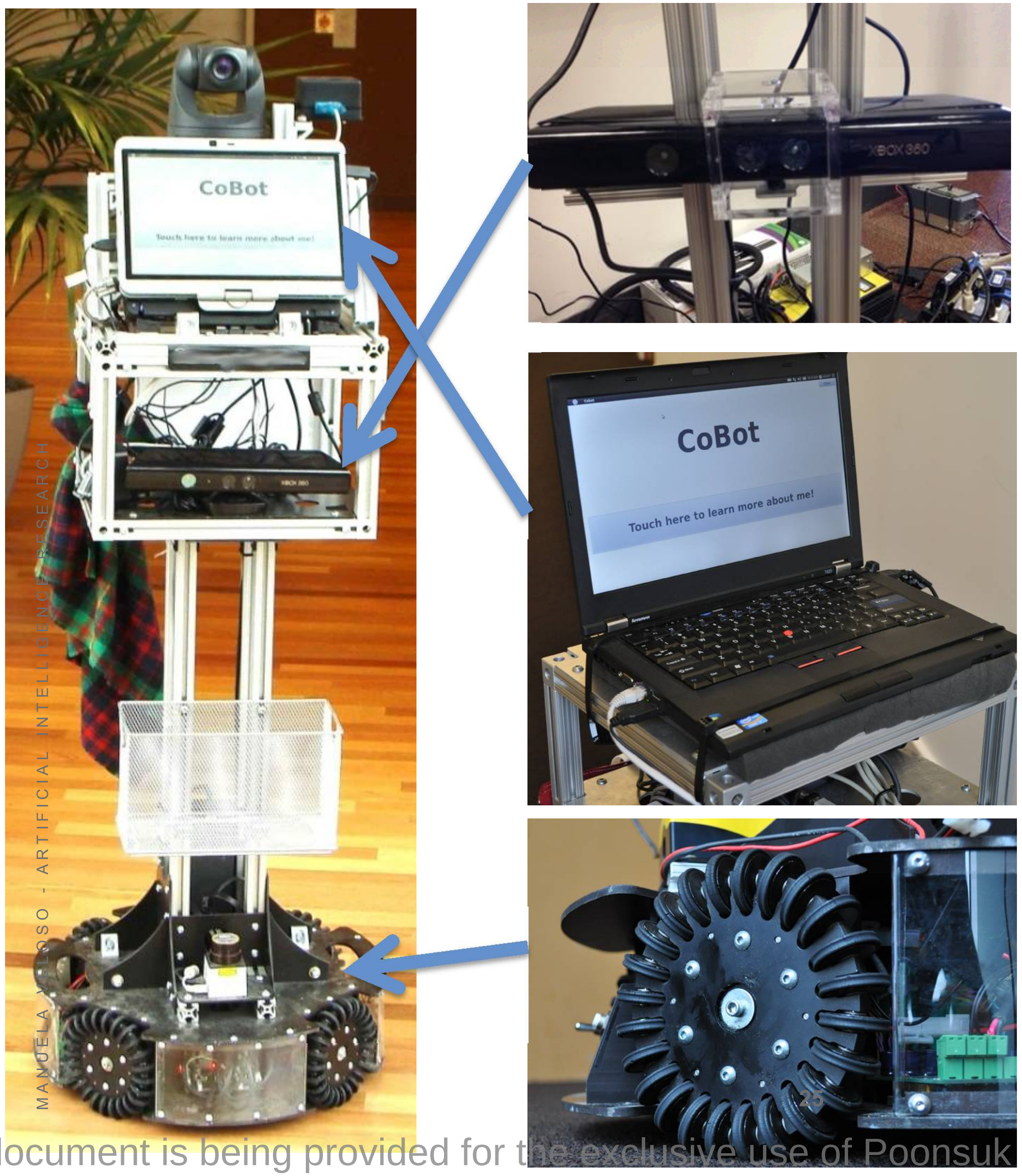
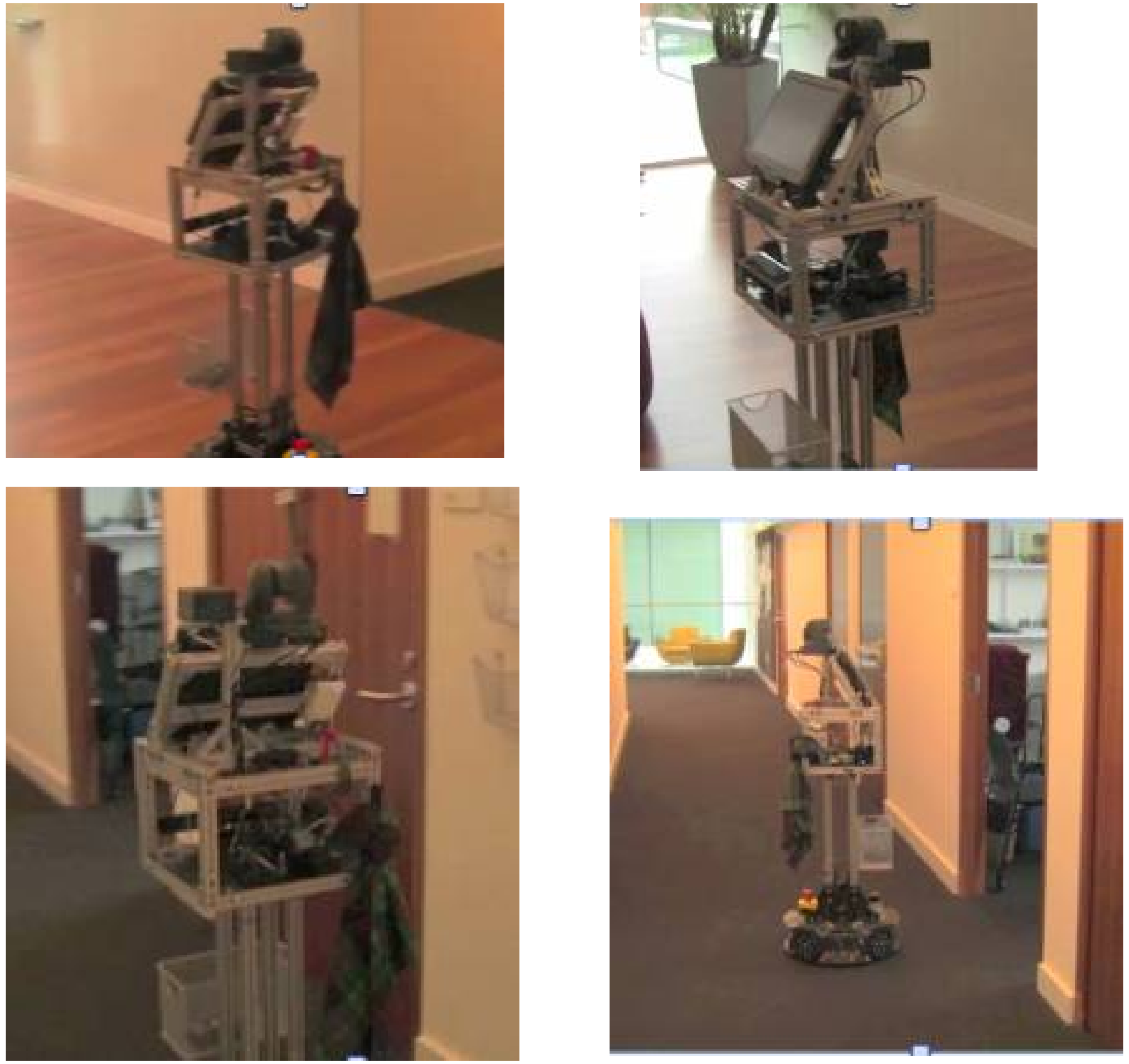
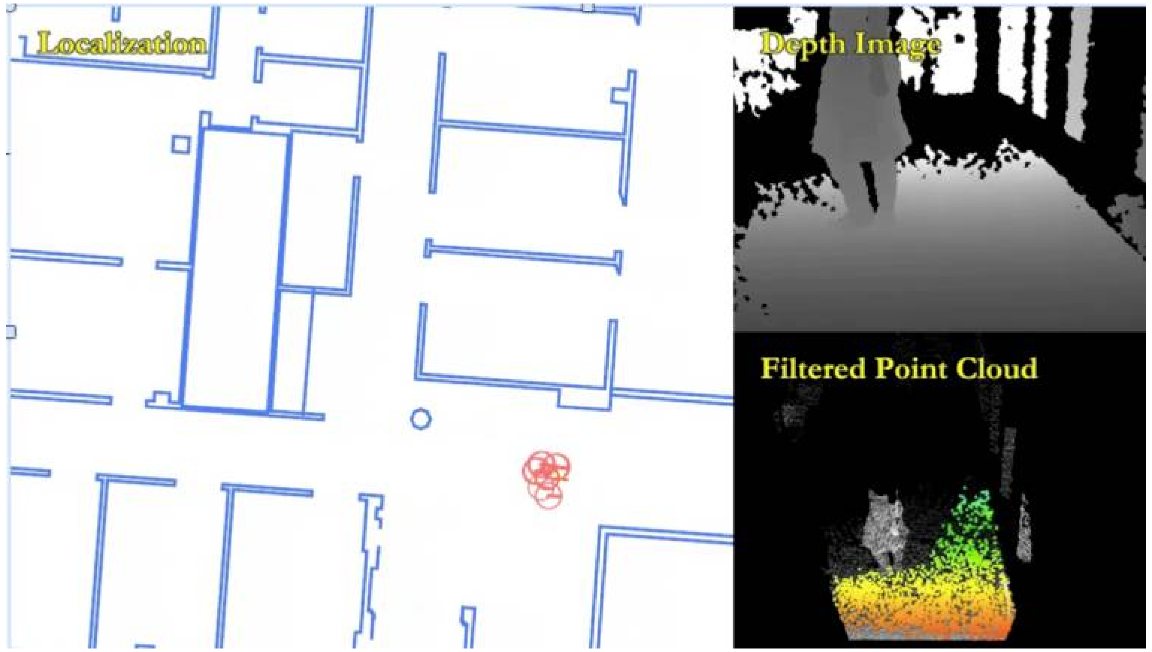
Autonomous *Mobile* Robots: CoBot

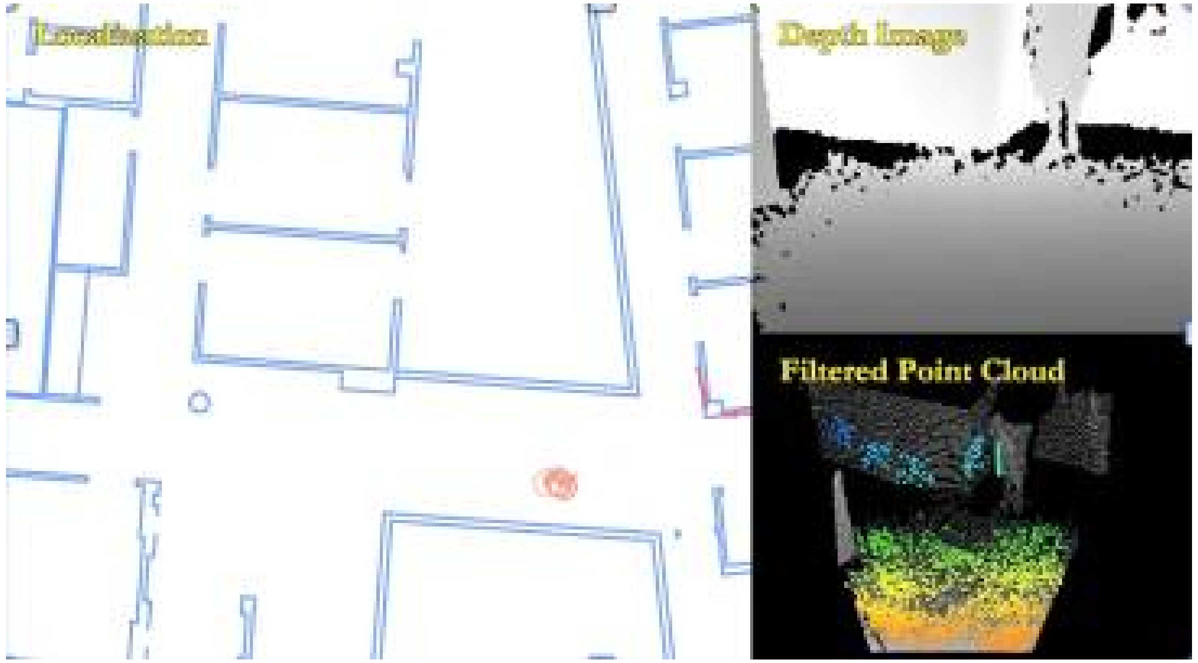




Thanks to J.Biswas, B. Coltin, S. Rosenthal, CMU
www.cs.cmu.edu/~coral/cobot

Uncertainty: Acting and Sensing



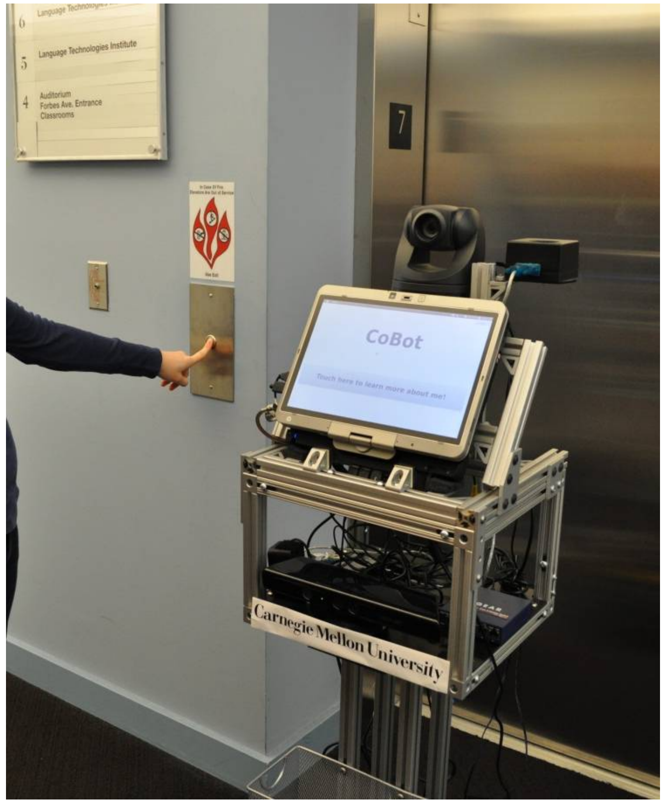


Domain Knowledge: Map
State: Position with uncertainty
Sensing: Data from depth vision
Action: Planned motion towards goal

As data is gathered, uncertainty about position decreases, and actions are selected and executed with accuracy towards the goal.

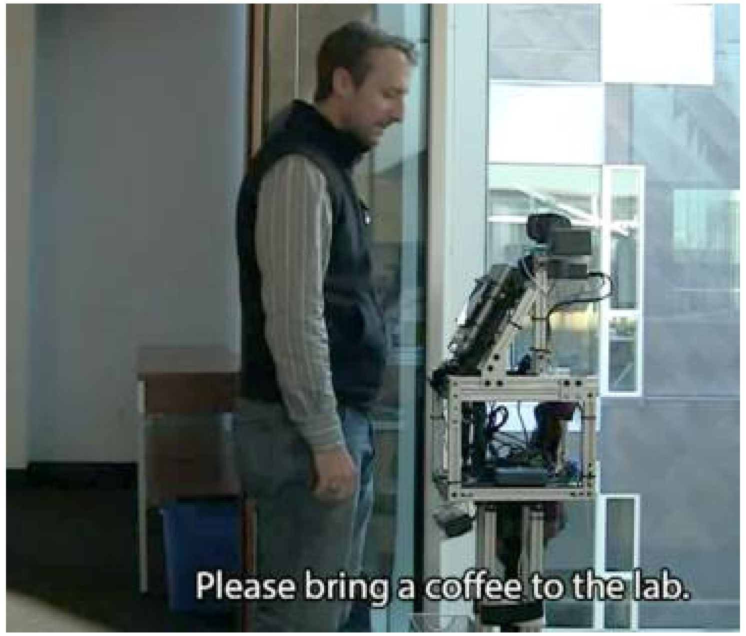
Symbiotic Autonomy: Ask for Help and Learn

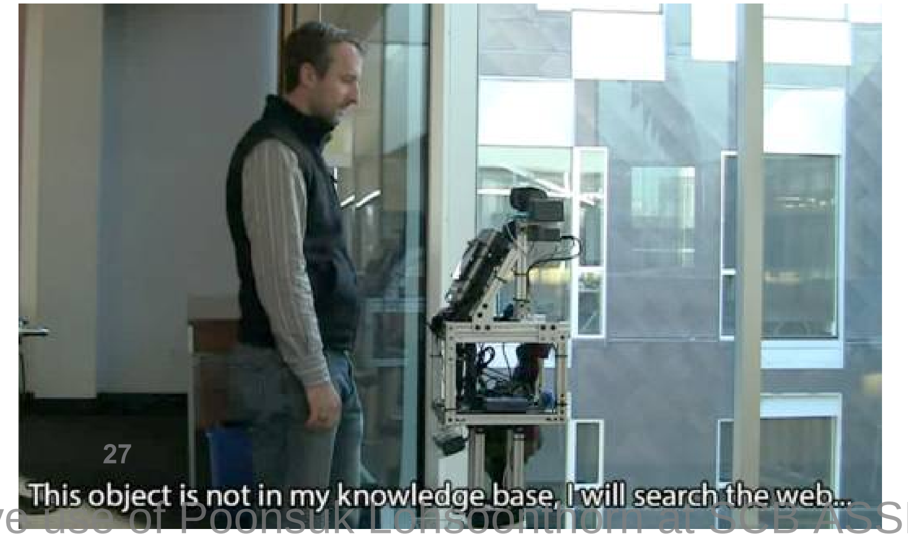
Physical Limitations



“Can you please press the elevator button?”

Cognitive Limitations: Search the web





Learn from experience

```
objectGroundsTo(coffee,7602);2.32258066988
objectGroundsTo(coffee ?,7602);0.108887748439
objectGroundsTo(coffee pot,7602);0.13809493047
objectGroundsTo(lunch,7412);0.09169896245
objectGroundsTo(munch,7412);0.0687742218375
objectGroundsTo(lunch?,7412);0.045849481225
objectGroundsTo(bunch,7412);0.0229247406125
objectGroundsTo(launch,7412);0.0229247406125
```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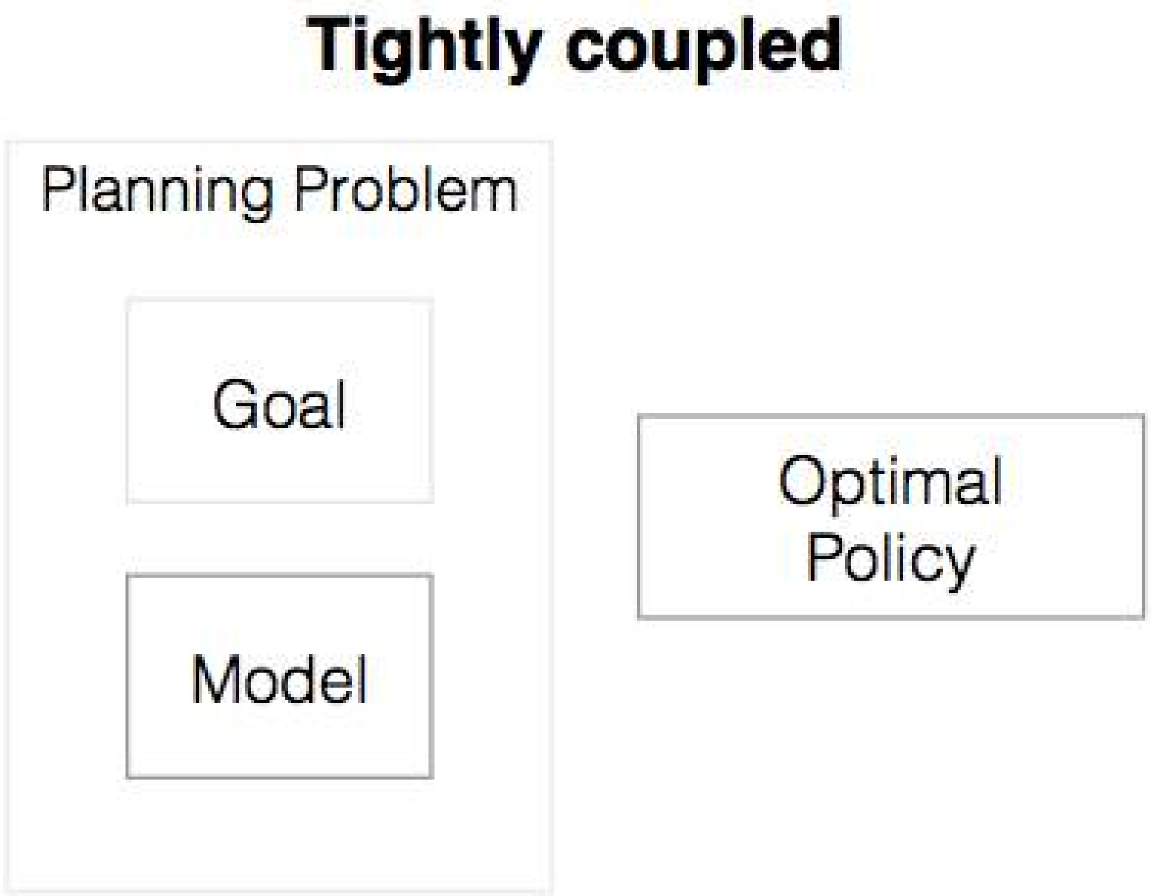
Outline

- AI at J.P. Morgan

- AI and Autonomous Agents
  - Perception-Cognition-Action
  - Symbiotic Autonomy

- Gradient-Based Exploration for New Policies *(joint work with R. Silva & F. Melo, CMU)*

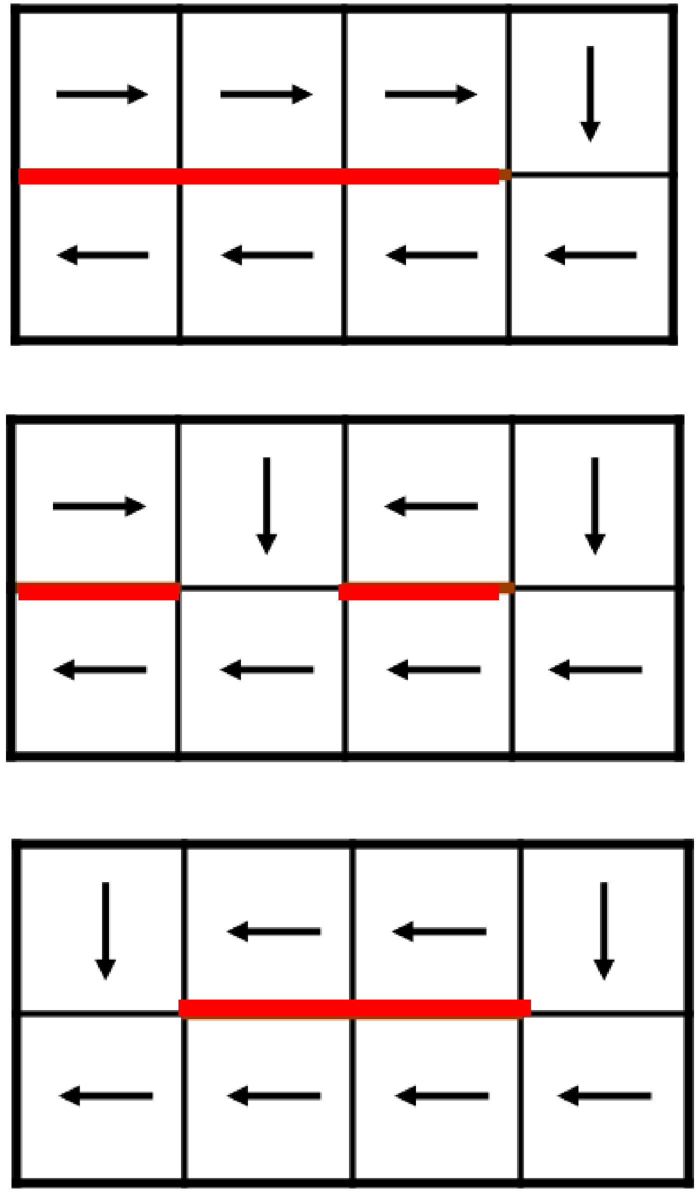
Model-Based Planning: Model Drives Optimization



Model assumes a fixed state, set of actions, a given reward.

What if the state/world were different?! Ask for help.

Optimal Policy is State-Dependent



Formalize the problem of planning while taking into account that it is possible to change the world, in order to achieve better solutions.

Focus: Markov Decision Problems

- Set of states $\mathcal{X}$
- Set of actions $\mathcal{A}$
- State probability transition function $P(y \mid x, a)$
- Immediate reward function $r(x, a)$
- Discount factor γ

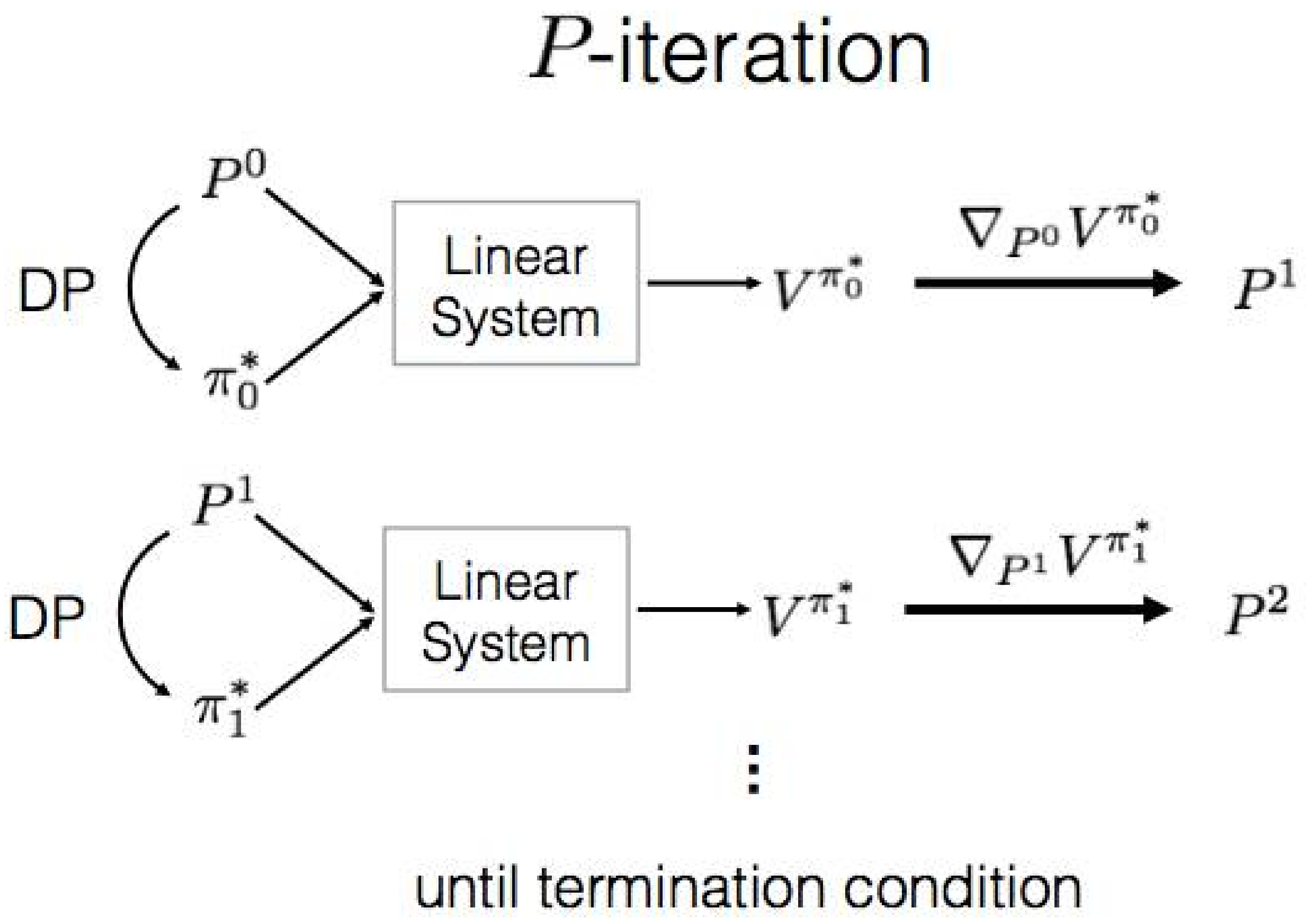
Finding an Optimal Policy: Solving an MDP

$$\max_{P} \quad V^{\pi^*}$$
$$\text{s.t.} \quad \pi^* = \text{argmax}_{\pi} \{V^{\pi}(P)\}$$
$$P_a \in \mathcal{P}_a \subseteq S^{|\mathcal{X}| \times |\mathcal{X}|} \quad \forall a \in \mathcal{A}$$

In Markov Decision Problems:

Changing the world corresponds to changing P

Search for Different Possible State Considering Cost of Change



J.P.Morgan

P-Iteration Experimental Results

Scenario	N	$J(\theta_0)$	K	$F(\theta)$
Corridor	2	−1.40	1	**−1.23**
	5	−3.49	1	**−2.32**
	10	−5.61	1	**−3.86**
			2	**−3.86**
			3	**−3.86**
			4	**−3.87**
			5	−3.90
	20	−7.54	1	**−5.85**
			3	**−5.85**
			5	−5.87
			7	−5.89
			10	−5.92
	50	−9.00	1	**−8.12**
			5	−8.13
			10	−8.15
			15	−8.17
			25	−8.23
Maze	2	−1.40	1	**−1.23**
	6	−7.28	5	**−3.98**
	7	−7.97	6	**−4.51**
	11	−9.17	10	−6.16
	15	−9.56	14	−7.24
Taxi	—	80.13	1	**82.66**
			2	**83.43**
			3	**86.57**
			4	**87.04**
			5	**89.88**

P-Iteration is able to find a state that produces a better policy even considering the cost of asking for the change.

What if the World Were Different: Gradient-Based Exploration for New Optimal Policies,
Rui Silva, Francisco Melo, and Manuela Veloso
In *Proceedings of General Conference on Artificial Intelligence*, Luxembourg, September 2018,
Best Paper Award.

Conclusion

- AI at J.P. Morgan: *An Exciting Pursuit*

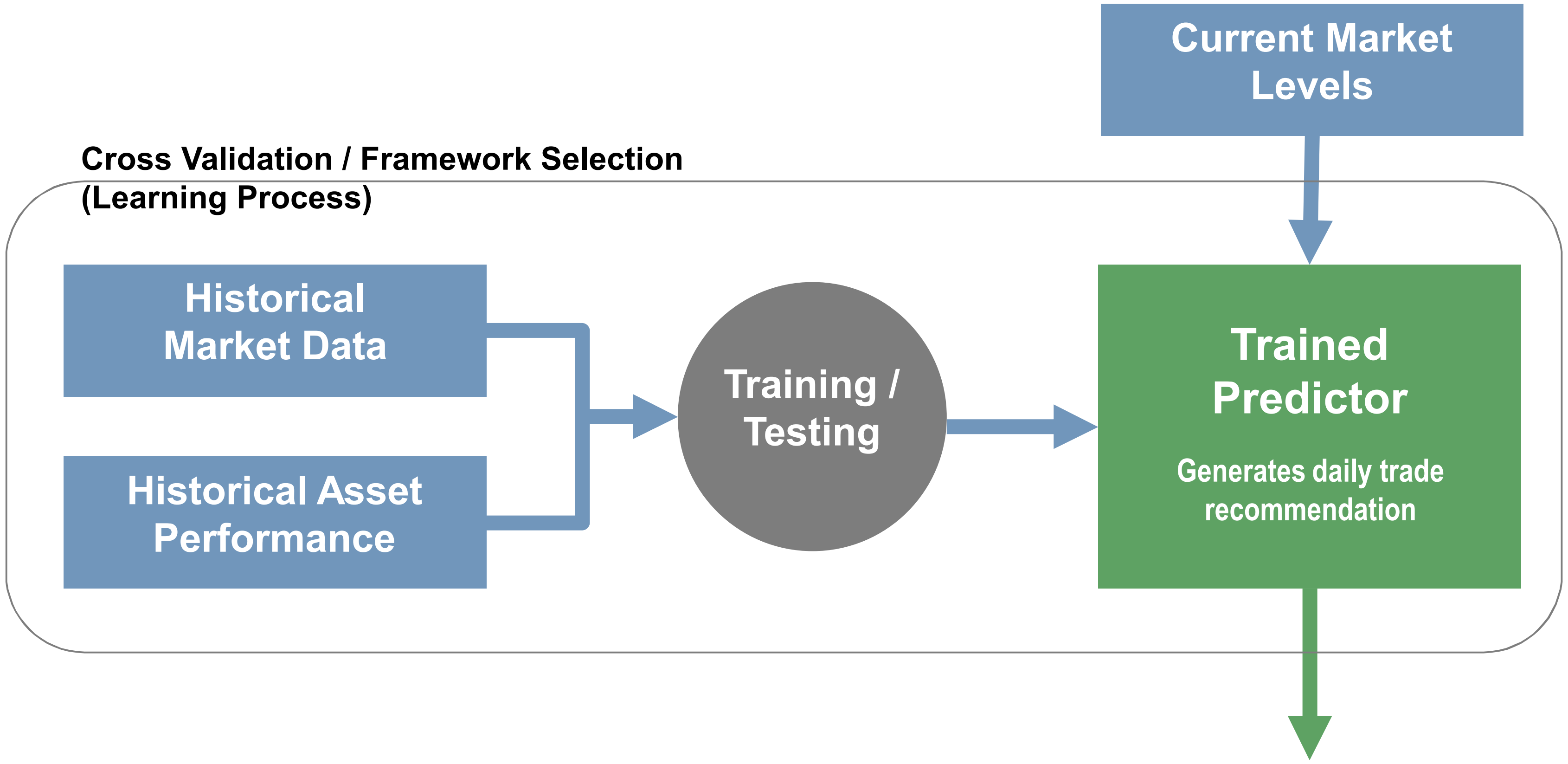
- AI and Autonomous Agents: *A Complex Enterprise*

- Gradient-Based Exploration for New Policies:
A New Planning Paradigm
(joint work with R. Silva & F. Melo, CMU)

Agenda

Page

Machine learning applied to trade execution in fixed income markets



Positioning	Confidence Level	Optimal Size
Buy or Sell	50% - 100%	0.0 – 1.0

Source: J.P. Morgan

Our predictors receive a broad array of market indicators – over 1,000 data points per day

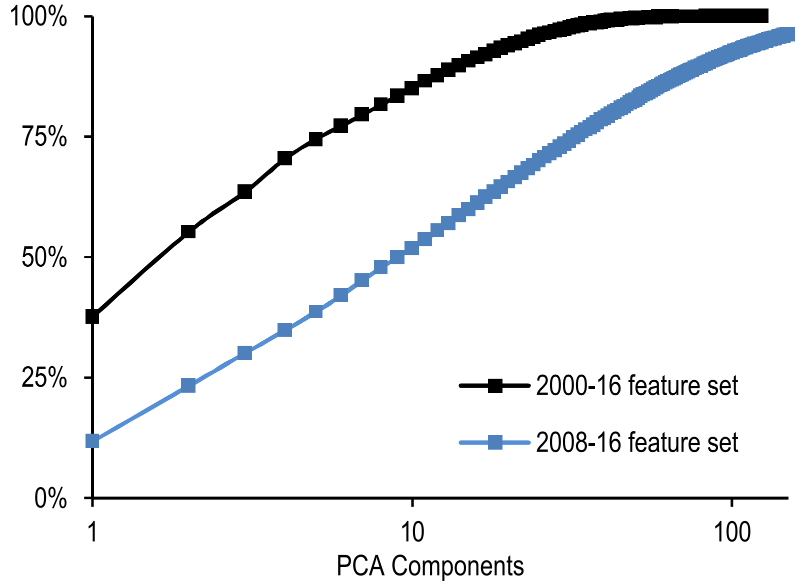
We employ a comprehensive set of input features within and beyond USD interest rate markets

Treasuries	yield, yield error, carry, specialness, matched-maturity swap spreads, OIS swap spreads, market depth, repo rates, term premium
Swaps	Realized volatility, carry
OIS	Implied vol surface, skew
TIPS	Breakevens
MBS	Mortgage basis, hedge adjusted carry, convexity, option-adjusted duration, OAS, positioning
Cross-Asset	HG and HY bond indices, European rates, equity index levels and volatility, FX indices and carry, commodity indices
Econ	Global and regional and domestic economic indices and surprise indices, various date flags
Dates	Flags for FOMC meetings, payrolls and month-ends

Source: J.P. Morgan

PCA allows us to reduce the dimensionality of our input feature set

Cumulative explained variance of PCA components for the 2008-16 and 2000-16 dataset we used to cross-validate our ML predictors



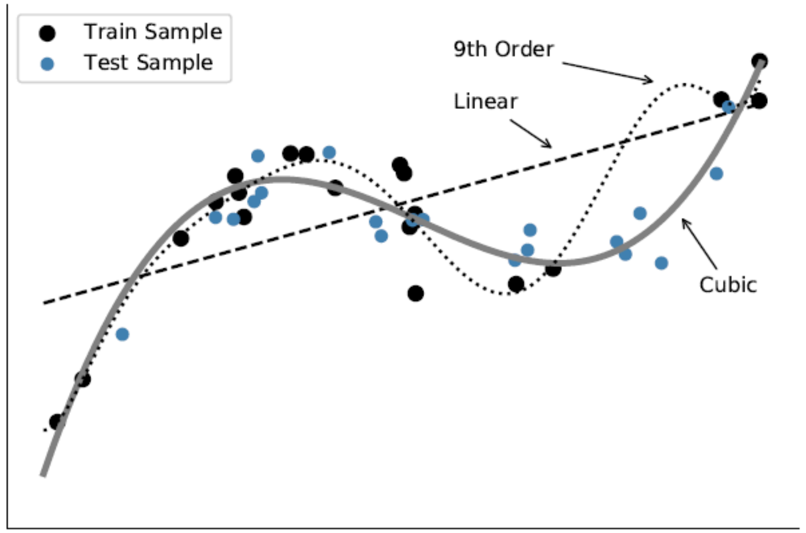
Source: J.P. Morgan

J.P.Morgan

Cross-validation can help select optimal choices among an ML technique's hyperparameters …

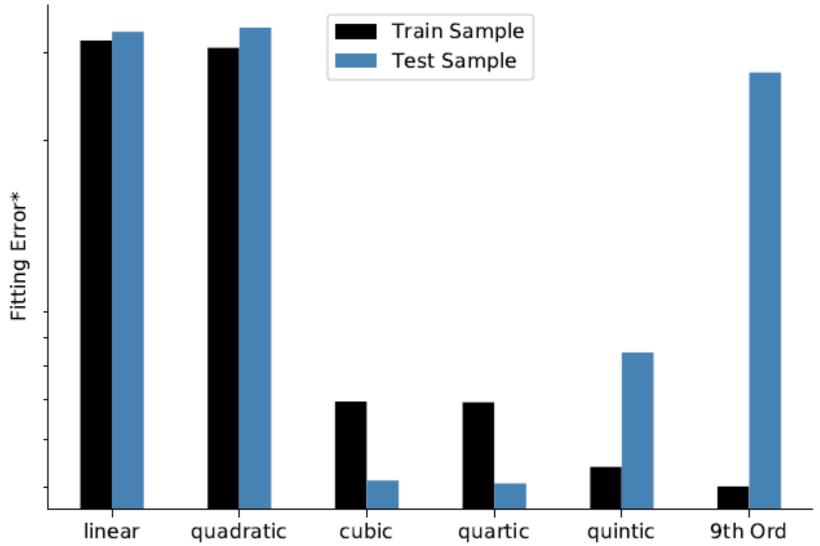
… for example, in the case of ordinary least squares regression: polynomial order

A hypothetical 1-dimensional dataset split into a "train" and "test"samples; ordinary least squares regression is applied of varying polynomial order, fitted on the train sample



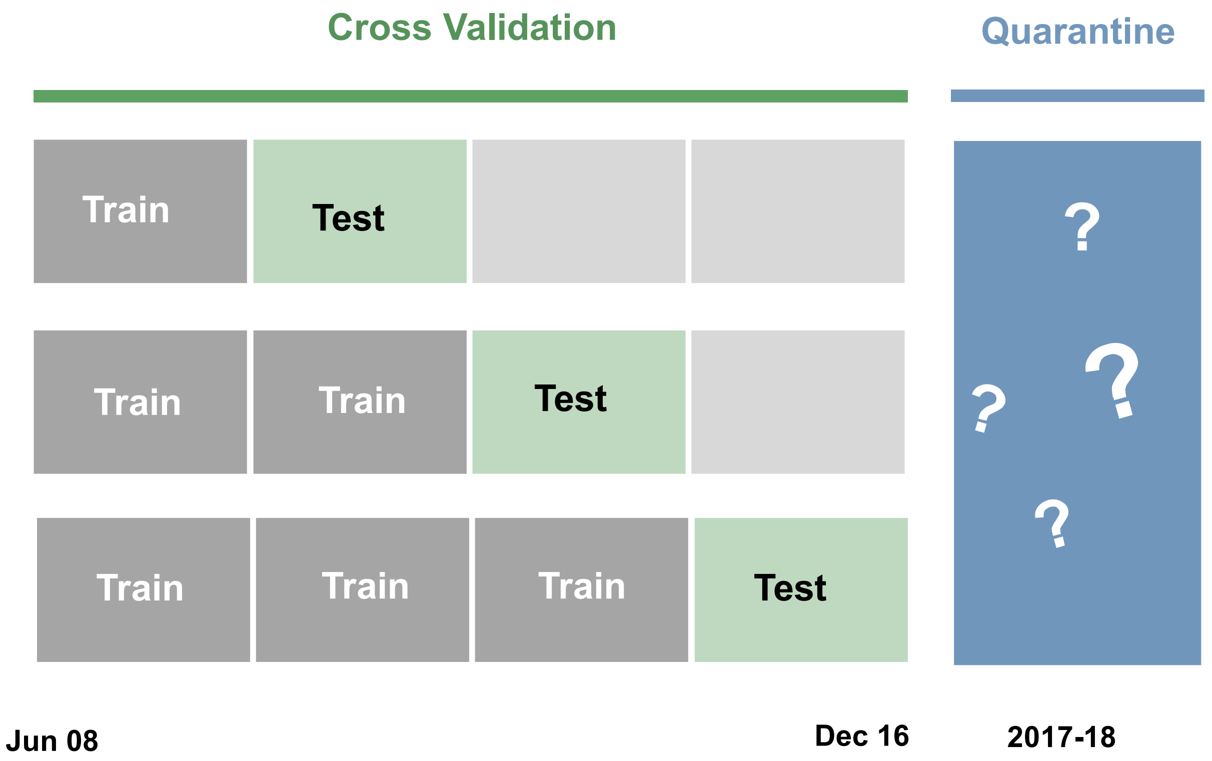
Source: J.P. Morgan

Fitting error* both in- and out-of-sample for the same data set and regression predictors



*Fitting error defined as log of the sum of the squares of the residuals (SSR) between the predicted y-values and the data points, both within the training sample each predictor was fitted on (Train Sample) and outside this sample (Test Sample).
Source: J.P. Morgan

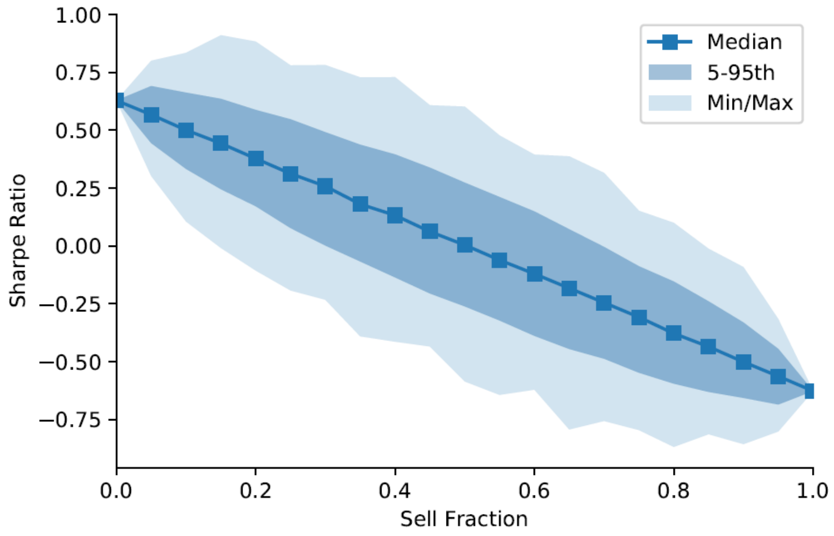
… but pitfalls remain, particularly given our sparse data, and fat-tailed distribution of returns.



Source: J.P. Morgan

Doing much better than an all-long strategy by random chance requires a lot of luck, especially when forced to go short some fraction of the time

Sharpe ratio percentile thresholds* for daily trades of 10-year Treasuries held for one week from 2010-16; unitless

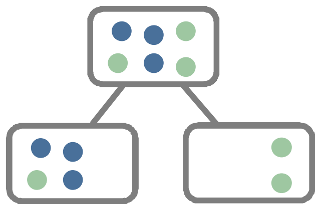


*Percentiles come from 3000 trials randomly permuting daily buy/sell decisions at a fixed percentage of selling days (sell fraction) and then calculating Sharpe ratio for each trial.
Source: J.P. Morgan

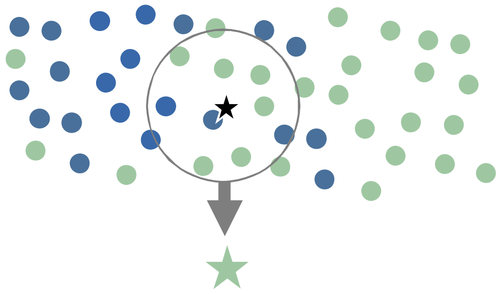
We explored a variety of learning techniques …

“Classical” Methods

Decision Trees



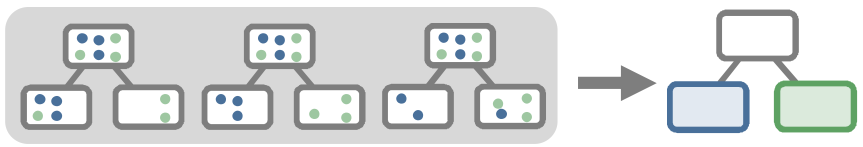
K-Nearest Neighbors (KNN)



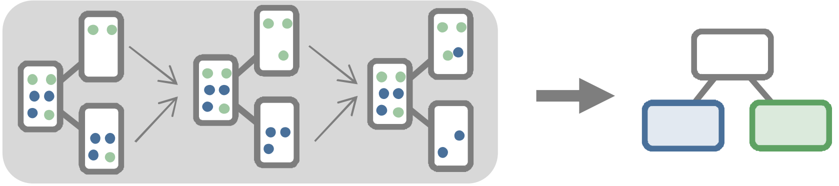
Support Vector Machines (SVM)

Ensemble Methods

Random Forest (RF)

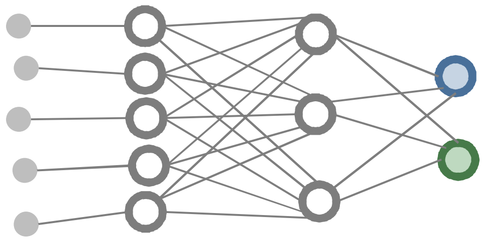


Gradient-boosted machines (GBM)



“Deep learning” methods

Artificial Neural Networks (ANN)



Hard voting

Soft voting

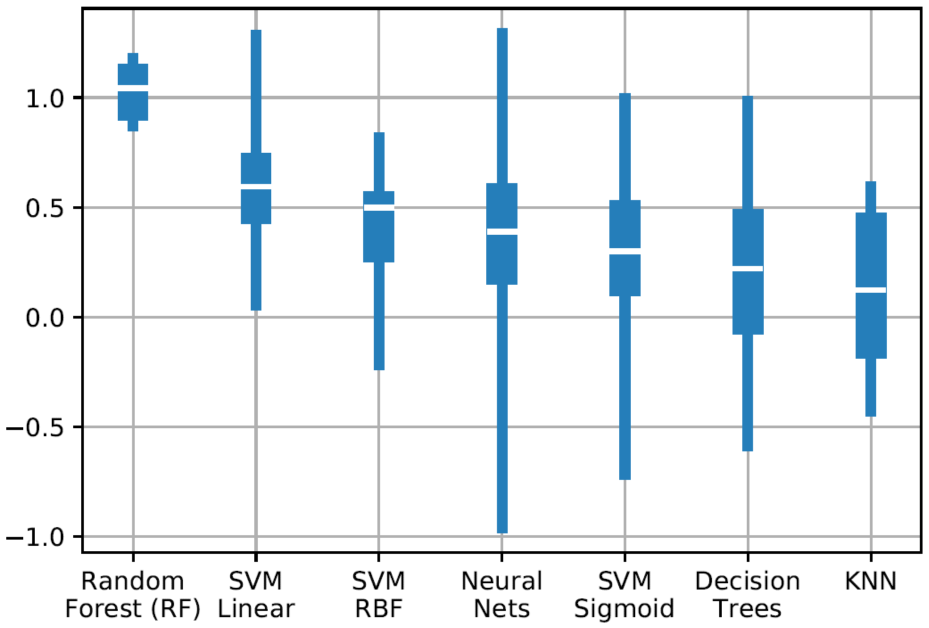
Stacking

Source: J.P. Morgan

Cross-validation provided a great laboratory for exploring various techniques and calibrating their hyperparameters …

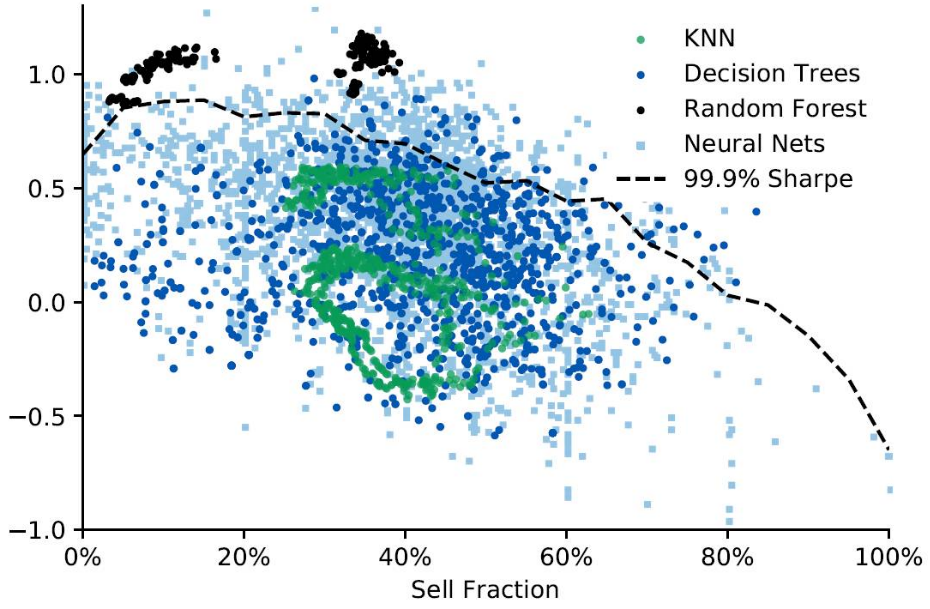
Trading 10-year Treasuries, we found several ML techniques could produce predictors with out-of-sample Sharpe ratios meaningfully above an all-long strategy

Distribution of Sharpe ratio broken out by ML technique; each predictor was trained to take daily positions in 10-year Treasuries* over the test sample†; the thin lines show the min/max range, thick lines the inner-quartile range, and white strip is the median outcome; unitless



Looking at risk-adjusted returns across a range of experiments, classical techniques were sensitive to choices of hyperparameters, RF outperformed, and ANNs were erratic

Sharpe ratio versus fraction of days short for various ML predictors tested on 10-year Treasuries* held daily for 5 days over our post-crisis sample space†; unitless



* Positions were taken daily throughout the test period (see next note), holding the then-on-the-run 10-year note. Trades were sized based on the predictor's level of conviction, following the Kelly Criterion assuming a symmetric payout distribution, e.g. S = 2*P – 1, where P is between 50% and 100%.

† Predictors were trained on data beginning in mid-2008 and tested out-of-sample beginning in early 2010. The first 5 days were removed from the testing period, and Sharpe ratios and sell fractions were then computed on the remaining out-of-sample period of roughly 1.5 years. The training window was then expanded four times, until all dates up until 12/30/2016 were tested. Throughout this predictor-selection and evaluation process, data from 2017 was held in "quarantine" and not under consideration.

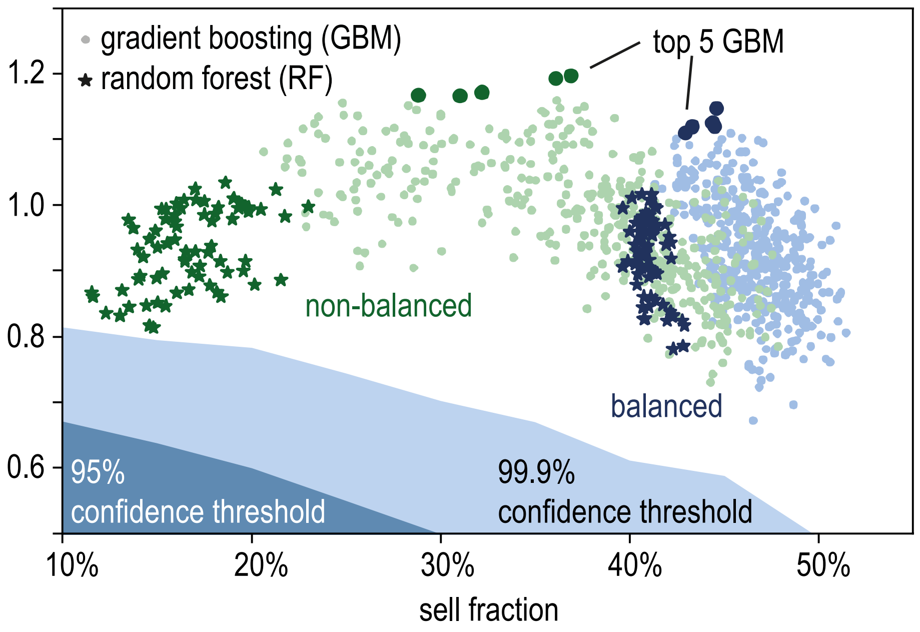
Source: J.P. Morgan

J.P.Morgan

Cross-validation provided a great laboratory for exploring various techniques and calibrating their hyperparameters …

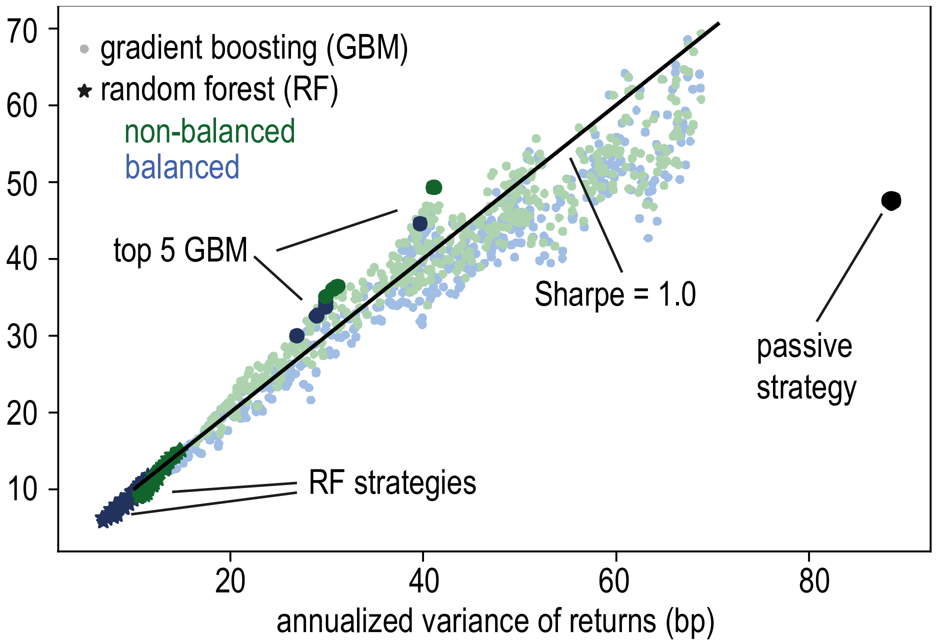
We find gradient boosting machines (GBM) perform incrementally better than random forest classifiers (RF) trading duration; GBM spanned a broader range of buy/sell behavior

Sharpe ratio versus fraction of days short for machine learning (ML) predictors tested on 10-year Treasuries held daily for 5 days over our post-crisis sample space; the ‘balanced’ (blue) and 'non-balanced' (green) clumps denote whether or not the algorithm sought to predict rallies and selloffs with equal accuracy; unitless



Many GBM instances produced dramatically higher returns in cross-validation, though this came at the expense of equally higher variance

Average annualized return versus annualized variance for ML classifiers, compared to a “passive" uniform buying strategy; bp



* Positions were taken daily throughout the test period (see next note), holding the then-on-the-run 10-year note. Trades were sized based on the predictor’s level of conviction, following the Kelly Criterion assuming a symmetric payout distribution, e.g. S = 2*P – 1, where P is between 50% and 100%.

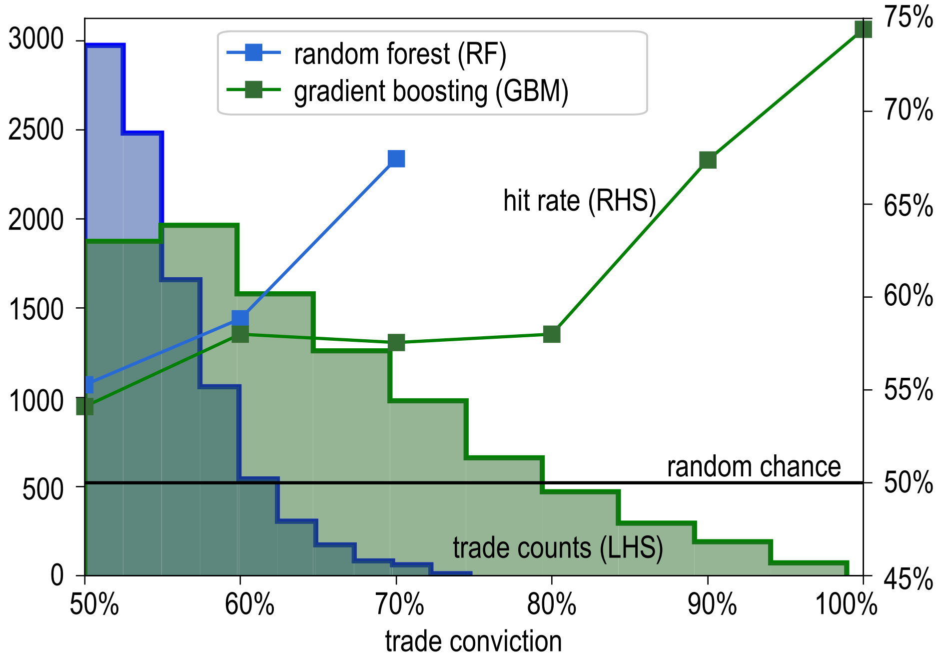
† Predictors were trained on data beginning in mid-2008 and tested out-of-sample beginning in early 2010. The first 5 days were removed from the testing period, and Sharpe ratios and sell fractions were then computed on the remaining out-of-sample period of roughly 1.5 years. The training window was then expanded four times, until all dates up until 12/30/2016 were tested. Throughout this predictor-selection and evaluation process, data from 2017 was held in “quarantine” and not under consideration.

Source: J.P. Morgan

Ensemble methods delivered learners that performed well in aggregate, but also in the details …

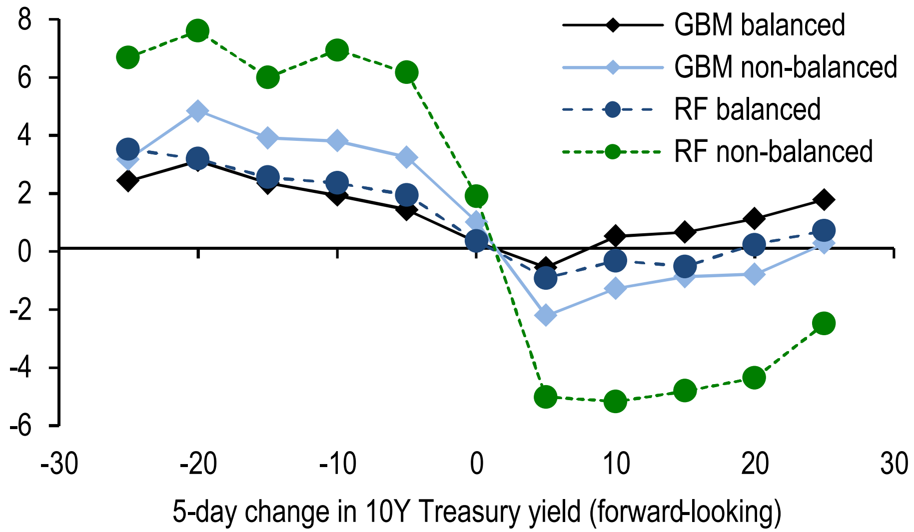
GBM learners traded with higher confidence than RF, while enjoying a similar realized hit-rate in cross-validation …

Distribution of days on which the ML predictors* had X% confidence ('conviction') in their decision to go long or short (LHS, count) for the balanced weighting strategy†, also shown is realized hit-rate vs conviction (RHS; %)



Ensemble learners had stronger outperformance in a rally than underperformance in a selloff, with the asymmetry greatest with "balanced" class-weighting

Annualized Sharpe ratio across ML classifiers broken out by subsequently realized Treasury yield performance within cross-validation; unitless



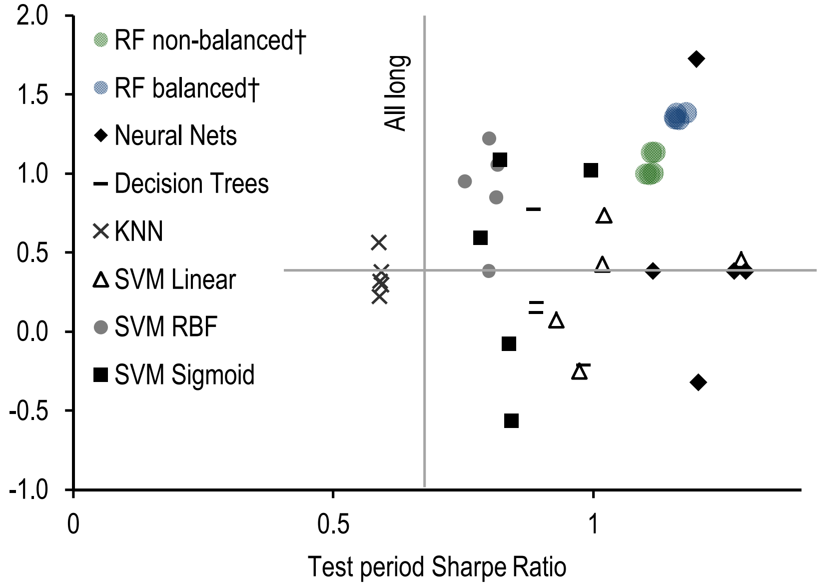
* RF and GBM classifiers cross-validated on 10-year Treasury performance (daily trades, 1-week holding) from 2008-16; trades sized with the Kelly Criterion, see notes of Exhibit 1 for more details.
† Balanced and non-balanced denote whether or not the algorithm sought to predict rallies and selloffs with equal accuracy—balanced predictors cared more about spotting selloffs.

Source: J.P. Morgan

Performance in quarantine was consistent with results from cross-validation, with random forest continuing to outperform …

RF predictors handily—and consistently—outperformed all-long Treasury strategies on our quarantined 2017 dataset, consistent with their behavior in cross-validation

Sharpe ratio on 'quarantined' 2017 data versus on test-set data for various ML predictors trained* to trade 10-year Treasury notes daily for 5-day hold periods (unitless)



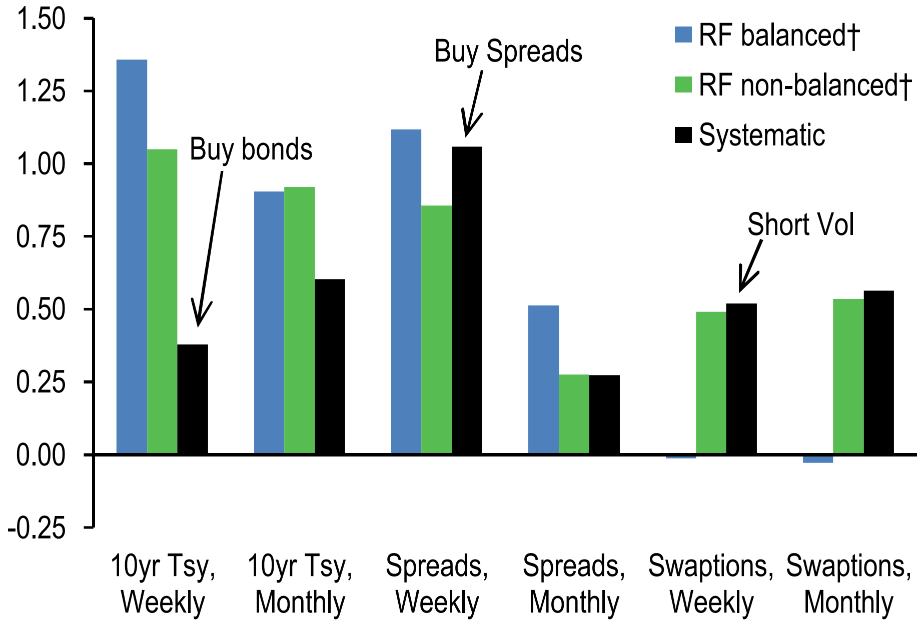
* All predictors cross-validated on 10-year Treasury performance (daily trades, 1-week holding) from mid-2008-16; trades sized with the Kelly Criterion, see notes of Exhibit 7 for more details. For each predictor we pre-selected the 5 top candidates from each technique before setting it loose on the 'quarantined' 2017 data. Absolutely no information from 2017 was used while training and vetting these predictors.

† Balanced and non-balanced denote whether or not the algorithm sought to predict rallies and selloffs with equal accuracy—balanced predictors cared more about spotting selloffs.

Source: J.P. Morgan

Our predictors fared best on duration over the 'quarantined' 2017 period, performing comparably to simple, systematic strategies on swap spreads and swaption straddles

Performance* of RF predictors** on 'quarantined' 2017 data compared to systematic strategies for 10-year Treasuries, matched-maturity swap spreads, and 1Mx10Y swaptions (unitless)



* For Treasuries and swap spreads, "performance" refers to annualized Sharpe Ratio, for 1Mx10Y swaptions, we instead use the average of non-parametric Sharpe, Sterling and drawdown ratios. Nonparametric Sharpe ratio: median versus inter-quartile range; Sterling ratio: median returns versus median losses; and drawdown ratio: returns versus 5th percentile as expected returns versus downside risk.

*Residual Sharpe: for each predictor, we take its daily trade decisions (trade size and direction) and randomly permute (shuffle) them across all days in the quarantine period, re-computing Sharpe for this randomized set. We repeat the exercise thousands of times, taking the 50th, 95th and 99th percentile outcomes. These Sharpes are then subtracted from the predictor's Sharpe. If this residual Sharpe is positive, we deem it statistically significant to that percentile level. In the context of our quarantine set, this is somewhat analogous to a one-sample hypothesis test.

† Balanced and non-balanced denote whether or not the algorithm sought to predict rallies and selloffs with equal accuracy—balanced predictors cared more about spotting selloffs

** All predictors cross-validated on daily trades from mid-2008-16; trades sized with the Kelly Criterion, see notes of Exhibit 7 for more details. For each predictor we pre-selected the 5 top candidates from each technique before setting it loose on the 'quarantined' 2017 data. Absolutely no information from 2017 was used while training and vetting these predictors.

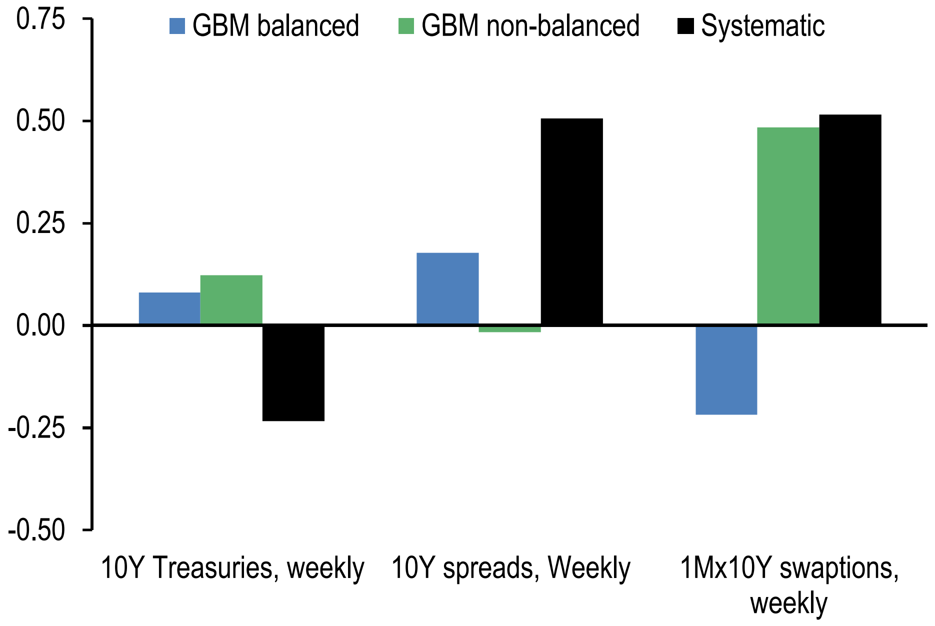
Source: J.P. Morgan

J.P.Morgan

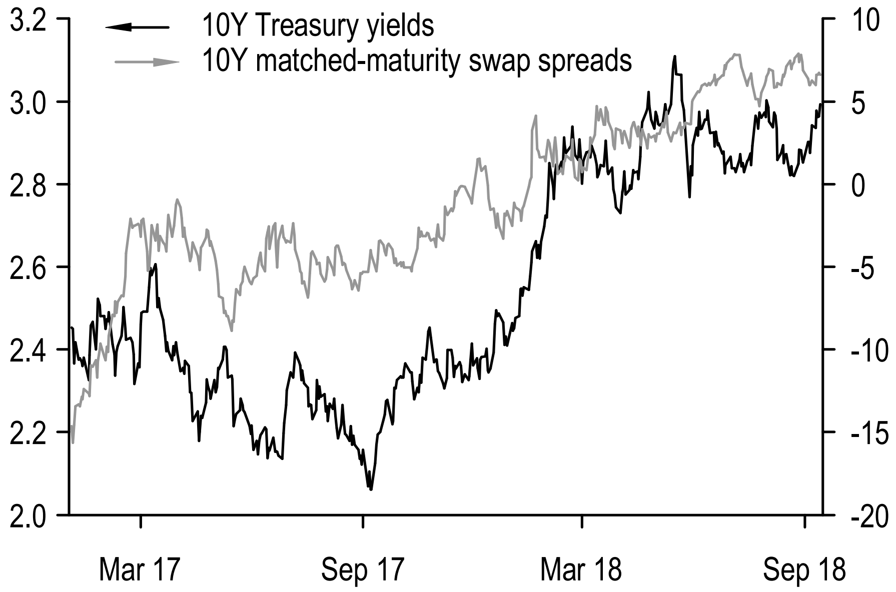
… and while this approach continued to generate positive returns on average through the sell-off of late last year, headline Sharpes deteriorated significantly

The margin of outperformance has narrowed for bonds through 2018, we've underperformed the benchmark in spreads, and vol is once more a draw …

Performance* of RF predictors** on 'quarantined' 2017-2018 data compared to systematic strategies for 10-year Treasuries, matched-maturity swap spreads, and 1Mx10Y swaptions (unitless)



10Y hot-run Treasury note yield (LHS; %) and 10Y matched-maturity swap spread to 10Y Treasuries (RHS; bp)



* For Treasuries and swap spreads, "performance" refers to annualized Sharpe Ratio, for 1Mx10Y swaptions, we instead use the average of non-parametric Sharpe, Sterling and drawdown ratios. Nonparametric Sharpe ratio: median versus inter-quartile range; Sterling ratio: median returns versus median losses; and drawdown ratio: returns versus 5th percentile as expected returns versus downside risk.

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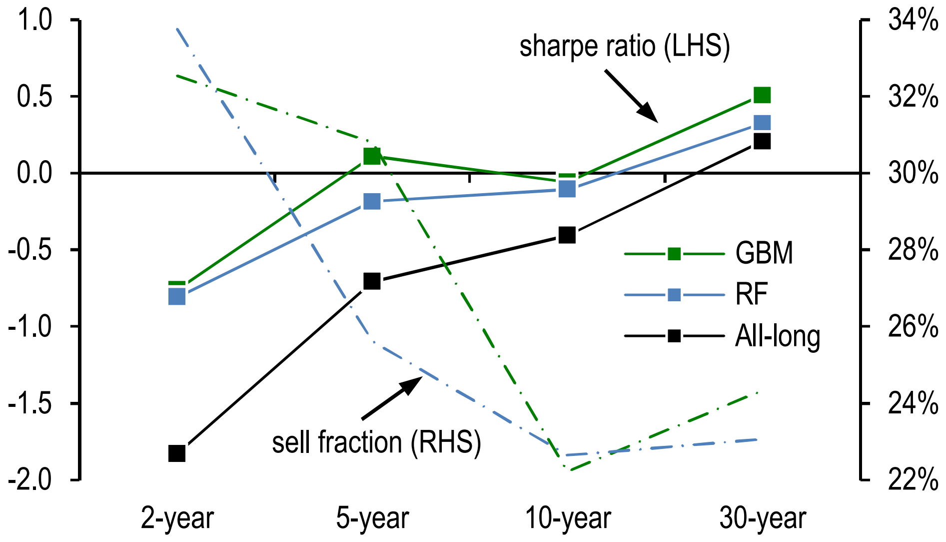
** All predictors cross-validated on daily trades from mid-2008-16; trades sized with the Kelly Criterion, see notes of Exhibit 7 for more details. For each predictor we pre-selected the 5 top candidates from each technique before setting it loose on the 'quarantined' 2017 data. Absolutely no information from 2017 was used while training and vetting these predictors.

Source: J.P. Morgan

Our learners generalized fairly well across the curve, though again recent performance has been lackluster, failing to *significantly* outperform

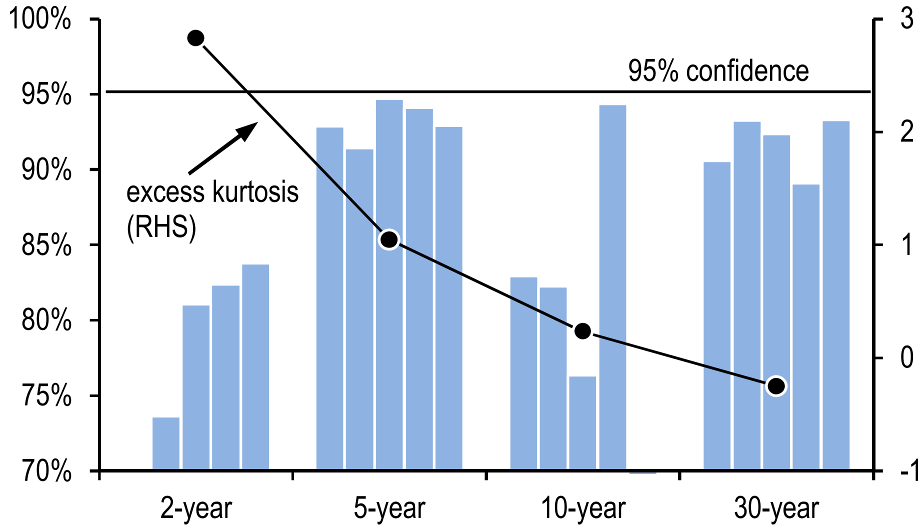
Nearly two years into 'quarantine', amidst a sustained selloff across the curve, our ensemble classifiers have managed to tread water in most tenors, outperforming most in the front-end …

Sharpe ratio and sell fraction of GBM and RF learners as measured in the "quarantined" 2017-18 period; unitless



… and our Monte Carlo framework suggests the out-performance of all-long is unlikely to have occurred by random chance, though we fail to reject the null hypothesis at the 95% level

Statistical confidence that our candidate GBM learners outperformed the passive benchmark on the quarantined 2017-18 dataset; unitless



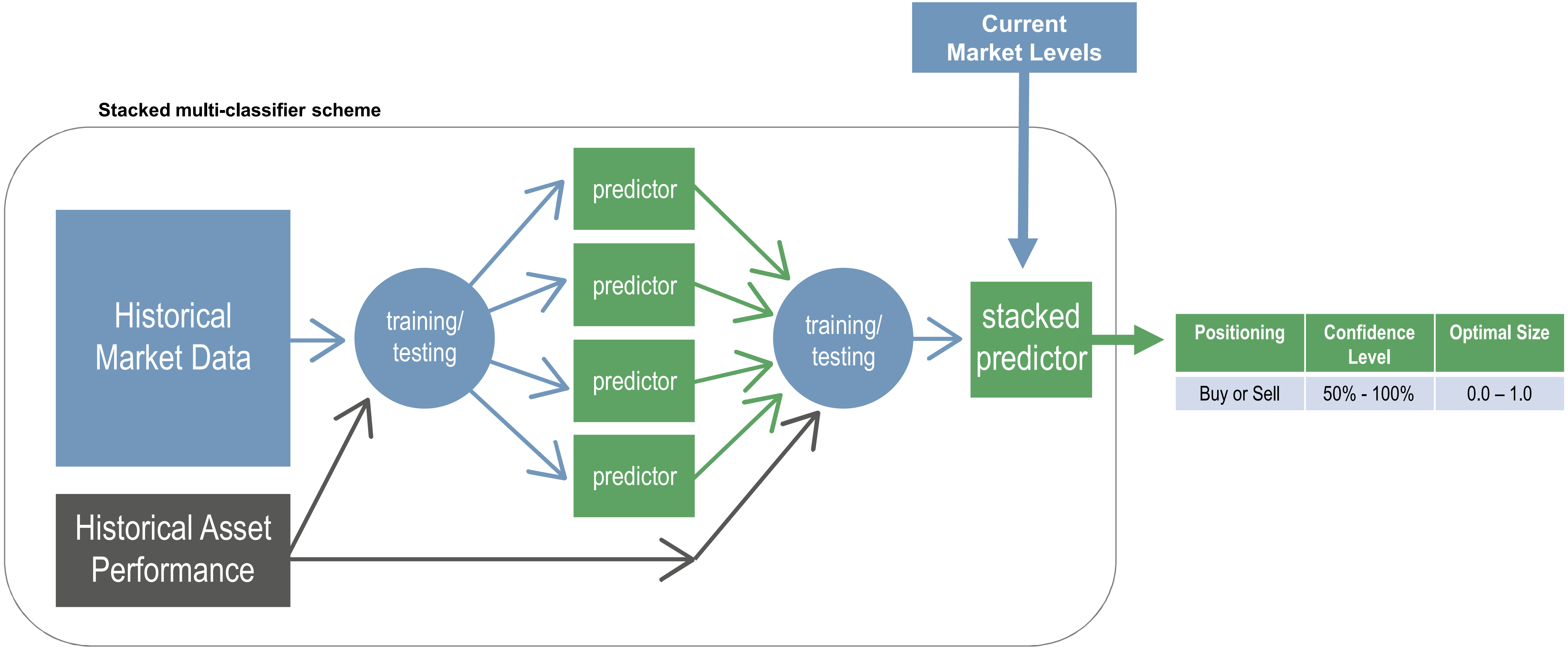
All predictors cross-validated on daily trades from mid-2008-16; trades sized with the Kelly Criterion, see notes of Exhibit 1 for more details. For each predictor we pre-selected the 5 top candidates from each technique before setting it loose on the 'quarantined' 2017-18 data. Absolutely no information from 2017-18 was used while training and vetting these predictors.

Source: J.P. Morgan

MUNIER SALEM - U.S. INTEREST RATE DERIVATIVES & QUANT FIXED INCOME STRATEGY

Teamwork makes the dream work—combining multiple classifiers via “stacking”

Stacked multi-classifier scheme



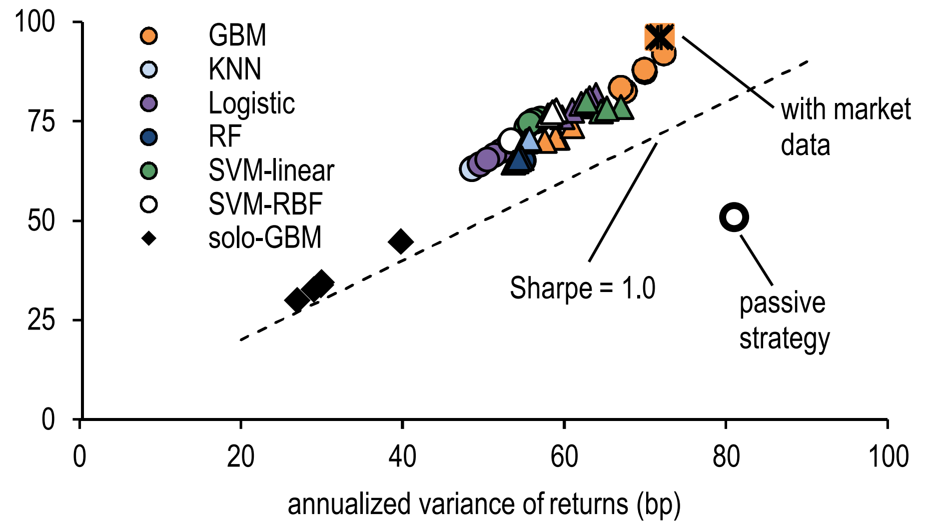
Source: J.P. Morgan

J.P.Morgan

We find stacking meaningfully improves performance in cross-validation …

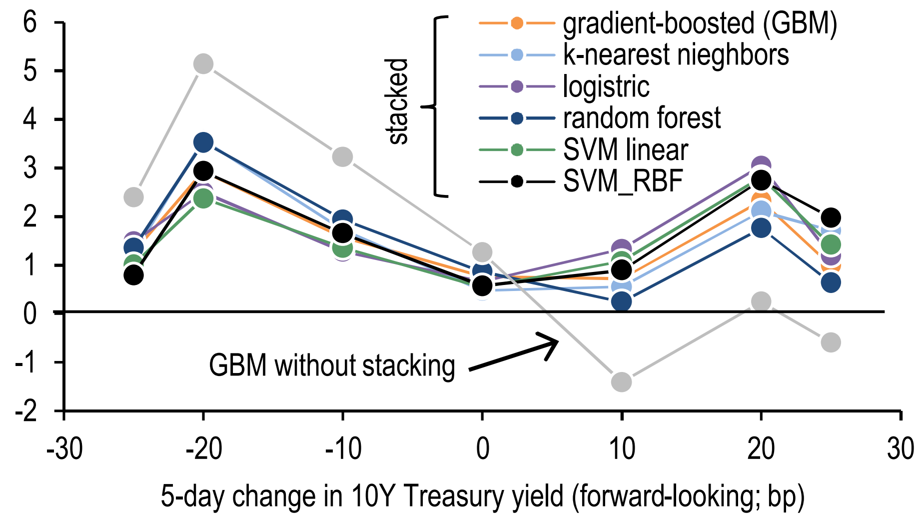
Stacking boosted risk-adjusted returns 15-20% and nearly doubled average returns—regardless of the implementation details

Average annualized return versus annualized variance for stacked ML classifiers, compared to a non-stacked ("solo") GBM predictor and a "passive" uniform buying strategy; bp



All stacking techniques managed to produce predictors that enjoyed positive risk-adjusted returns across rally and selloff environments, on average in cross-validation—a first in our work

Annualized Sharpe ratio across stacking classifiers broken out by subsequently realized Treasury yield performance within cross-validation; unitless



Notes: "Stacking" classifiers refers to training an ML predictor to make trading decisions based on the trading decisions of other, constituent classifiers trained on market data. The above chart shows such stacked classifiers that utilize gradient-boosted machines (GBM), k-nearest neighbors (KNN), logistic regression (LG), random forest (RF) and support vector machine (SVM) learners to consolidate signals from various constituent classifiers that are themselves GBM, RF and SVM learners that utilize both balanced and non-balanced class weighting.

Positions were taken daily throughout the test period, holding the then-on-the-run Treasury note/bond. Trades were sized based on the classifiers' level of conviction, following the Kelly Criterion assuming a symmetric payout distribution, e.g. S = 2*P – 1, where P is between 50% and 100%

"With market data" refers to stacked classifiers that were trained on a feature set that included both solo classifiers and the original market data, with only the market data reduced to 50 dimensions via a global PCA in cross-validation

Our classifiers' predictors were trained on data beginning in mid-2008 and tested out-of-sample beginning in 2009. The first 5 days were removed from the testing period, and Sharpe ratios and sell fractions were then computed on the remaining out-of-sample period of roughly 1.5 years. The training window was then expanded four times, until all dates up until 12/30/2016 were tested. Throughout this predictor-selection and evaluation process, data from 2017-18 was held in "quarantine" and not under consideration.

In our implementation of stacking as presented below, stacked classifiers were trained using in-sample predictions from their constituent classifiers before being cross-validated utilizing out-of-sample predictions from those same constituent classifiers. An alternative approach we explored instead involved training the stacking classifier on out-of-sample predictions. Both approaches yielded similar behavior both in cross-validation and quarantine.

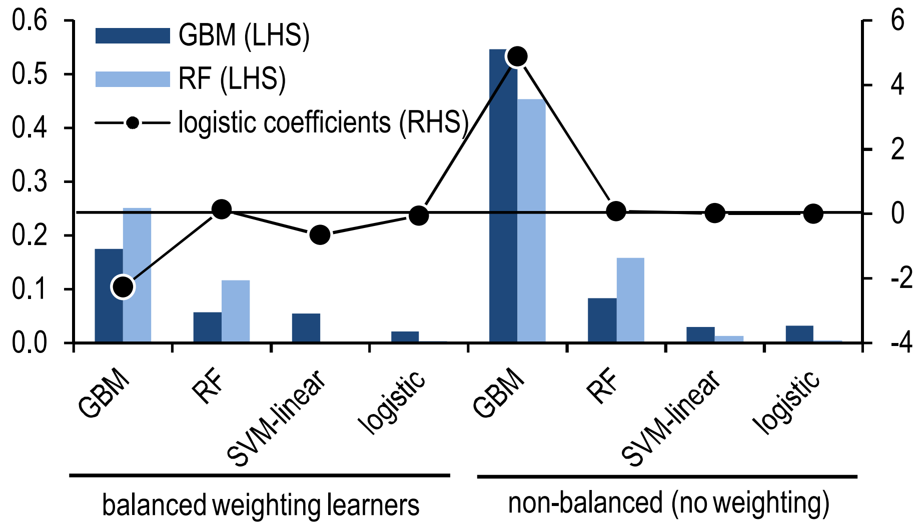
Source: J.P. Morgan

J.P.Morgan

We find stacking meaningfully improves performance in cross-validation …

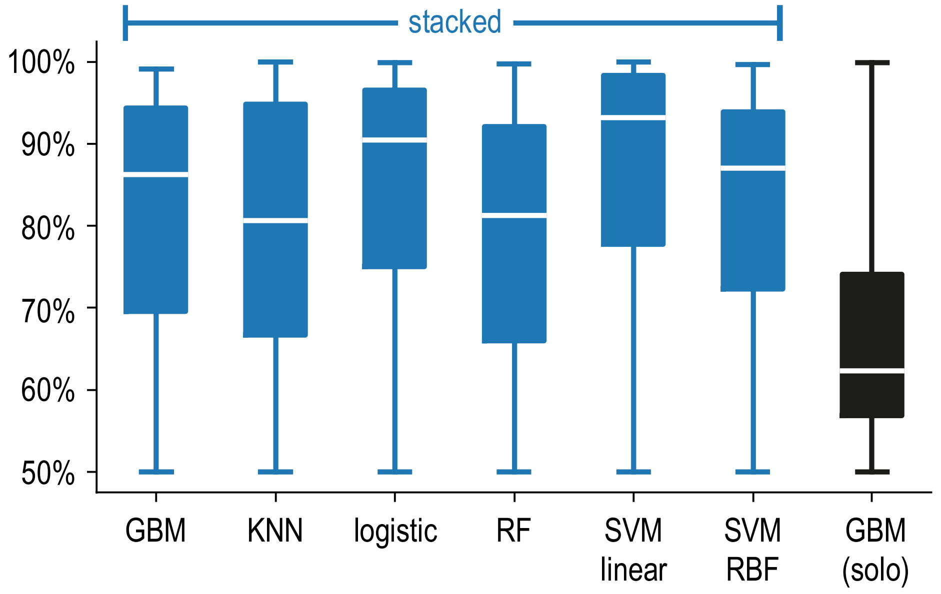
Our stacking classifiers relied most on buy/sell signals from GBM learners, most closely mirroring non-balanced GBM, and using balanced methods as a contrarian signal

Feature importance* extracted from the top 5 GBM and RF stacking classifiers (LHS; unitless); and 'beta' coefficients† from the top 5 logistic classifiers (RHS; unitless)



Stacked classifiers traded with strong conviction at much higher frequency than solo schemes

Distribution of days on which the stacked predictors had X% confidence ('conviction') in their decision to go long or short (blue) compared to our best non-stacked GBM predictors (black); predictors traded in larger size on days when they had more conviction; %



* "Feature importance" here measures the role each input variable plays, on average, in lowering the impurity of samples within the nodes of a random forest's or gradient-boosted machine's constituent decision trees.

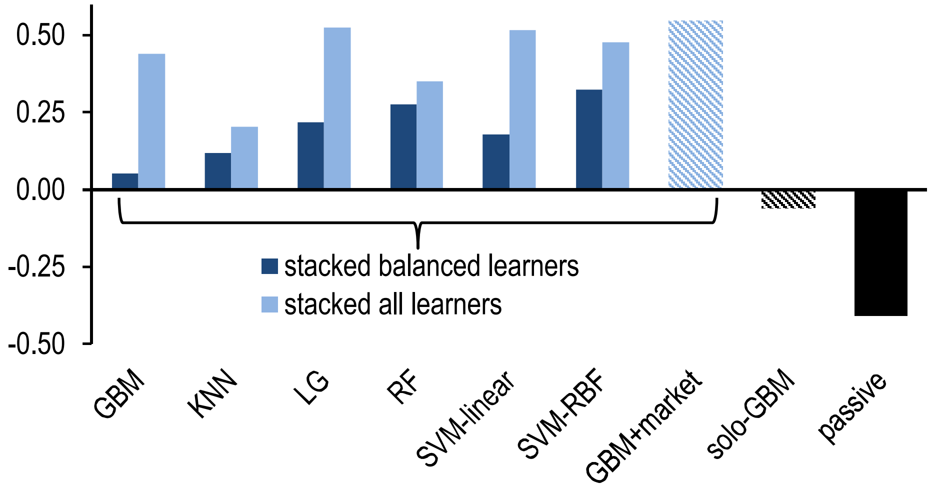
† "Beta coefficients" come from a logistic regression approach, and can be interpreted in analogy to beta coefficients of a linear regression (positive connotes a direct relationship, negative an inverse relationship).

Source: J.P. Morgan

… and delivers positive, significantly improved returns on quarantined 2017-18 data

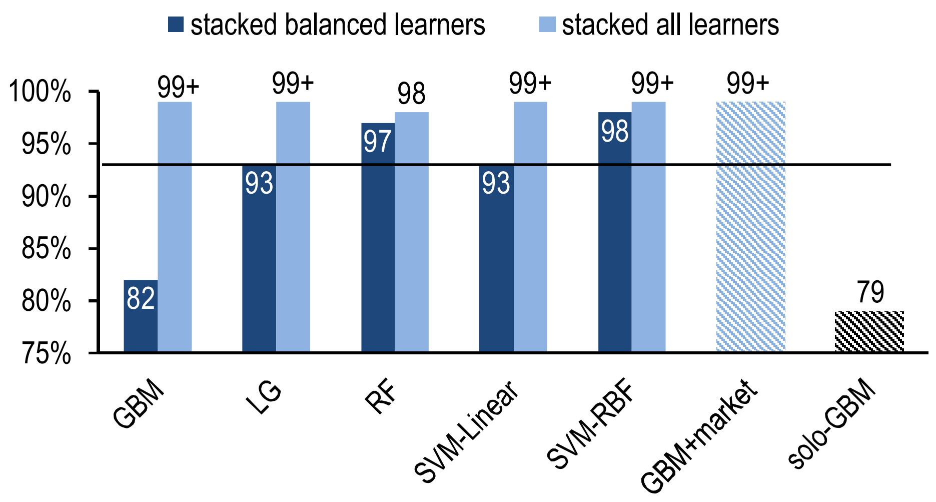
Our stacked predictors managed to produce positive risk-adjusted returns on 'quarantined' 2017-18 data …

Annualized Sharpe ratio of stacked predictors as measured on data from 2017-18 excluded from the cross-validation exercise, compared to both top-performing, non-stacked (solo) GBMs and to a passive, uniform buying strategy; unitless



… and when we stacked all classifiers (balanced and non-balanced), this resulted in outperformance of all long consistently above a 99% confidence threshold …

Statistical confidence that our stacked and non-stacked learners outperformed the passive benchmark on the quarantined 2017-18 dataset; unitless



All predictors cross-validated on daily trades from mid-2008-16; trades sized with the Kelly Criterion. For each predictor we pre-selected the 5 top candidates from each technique before setting it loose on the 'quarantined' 2017-18 data. No information from 2017-18 was used while training and vetting these predictors.

Source: J.P. Morgan

J.P.Morgan

What have we learned thus far?

- Classical machine learning techniques can produce trading signals with positive and statistically significant risk-adjusted returns, both in cross-validation and in quarantine
- Ensemble methods in particular are key in reducing the variance of returns
- This initial approach struggled to navigate the current environment, producing less attractive and less statistically significant risk-adjusted returns on recent data
- Stacking appears to significantly improve performance by using machine learning to select the best among an initial set of trained classifiers for a given environment …
- … resulting in higher average returns, lower variance, and greater statistical significance–both in cross validation and in quarantine

Agenda

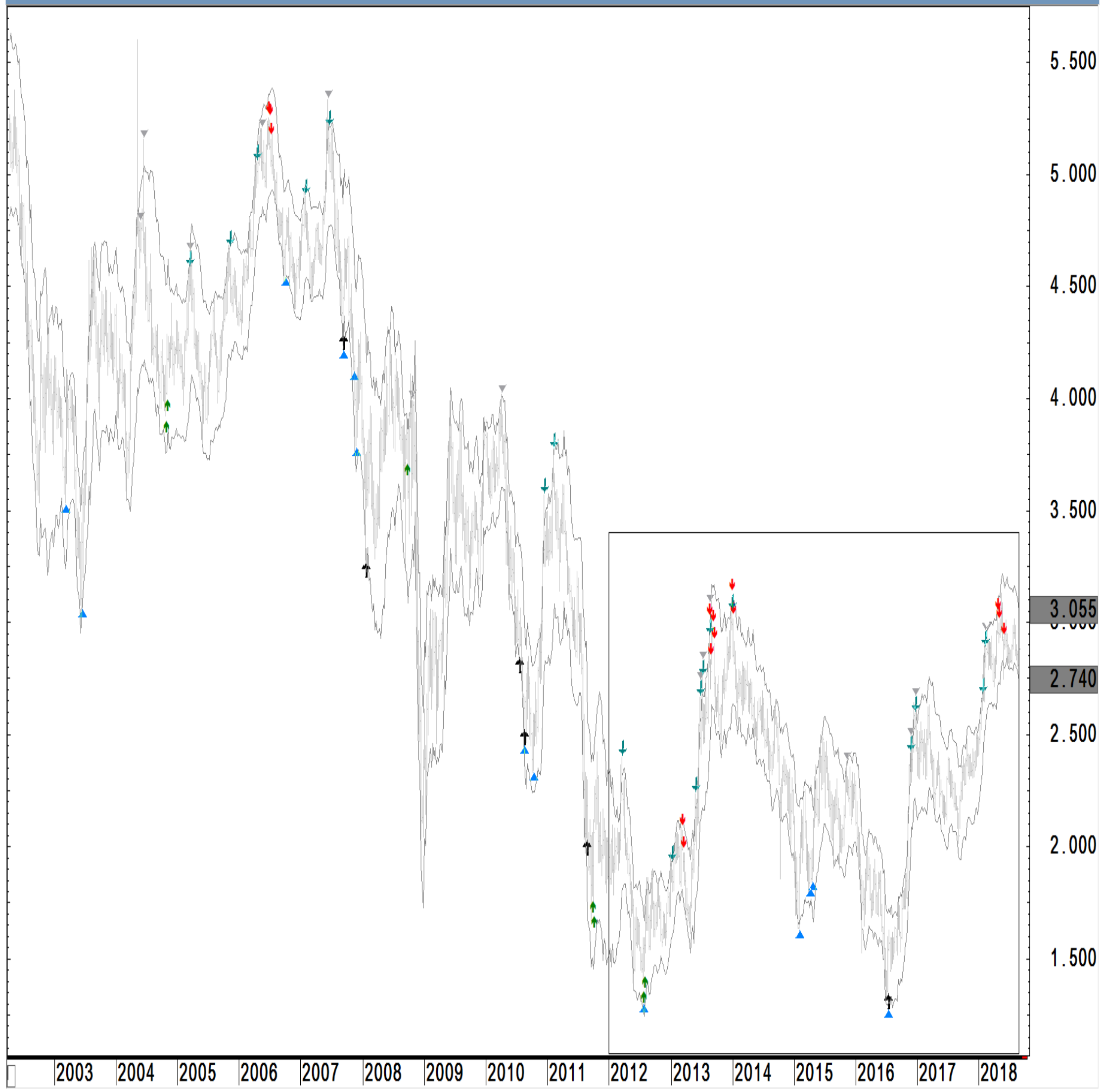
Theory and Framework

- In our view, the use of price and position data to forecast potential turning points and emerging trends in financial markets keys off of two dynamics:
  - First, that market participant sensitivity to unrealized P/L brings the price movement itself into the decision making process once a position is established. Assuming aggregated positions are built near similar entry points at times, a large portion of market participants may see their motivations to act align as a function of price movement.
  - Second, even though market participants absorb new information at the same time it is not done in a homogenous way, as each digests that information within the context of their individual outlook. Just as economic data surprise indices tend to show some level of autocorrelation as aggregated estimates lag, catch up to, and at times overshoot the longevity of data trends, we theorize that a similar process unfolds with market positioning.
- One of our main aims is to construct algorithms that systematically identify price and position patterns that suggest mature price trends, crowded positions, and markets that are vulnerable to mean reversion or an outright trend reversal. Ultimately, the signals are meant to help identify potential inflection points in the market, which have the potential to mark asymmetric risk/reward trade setups, or provide a tactical entry/exit points for a more medium-term fundamental view.

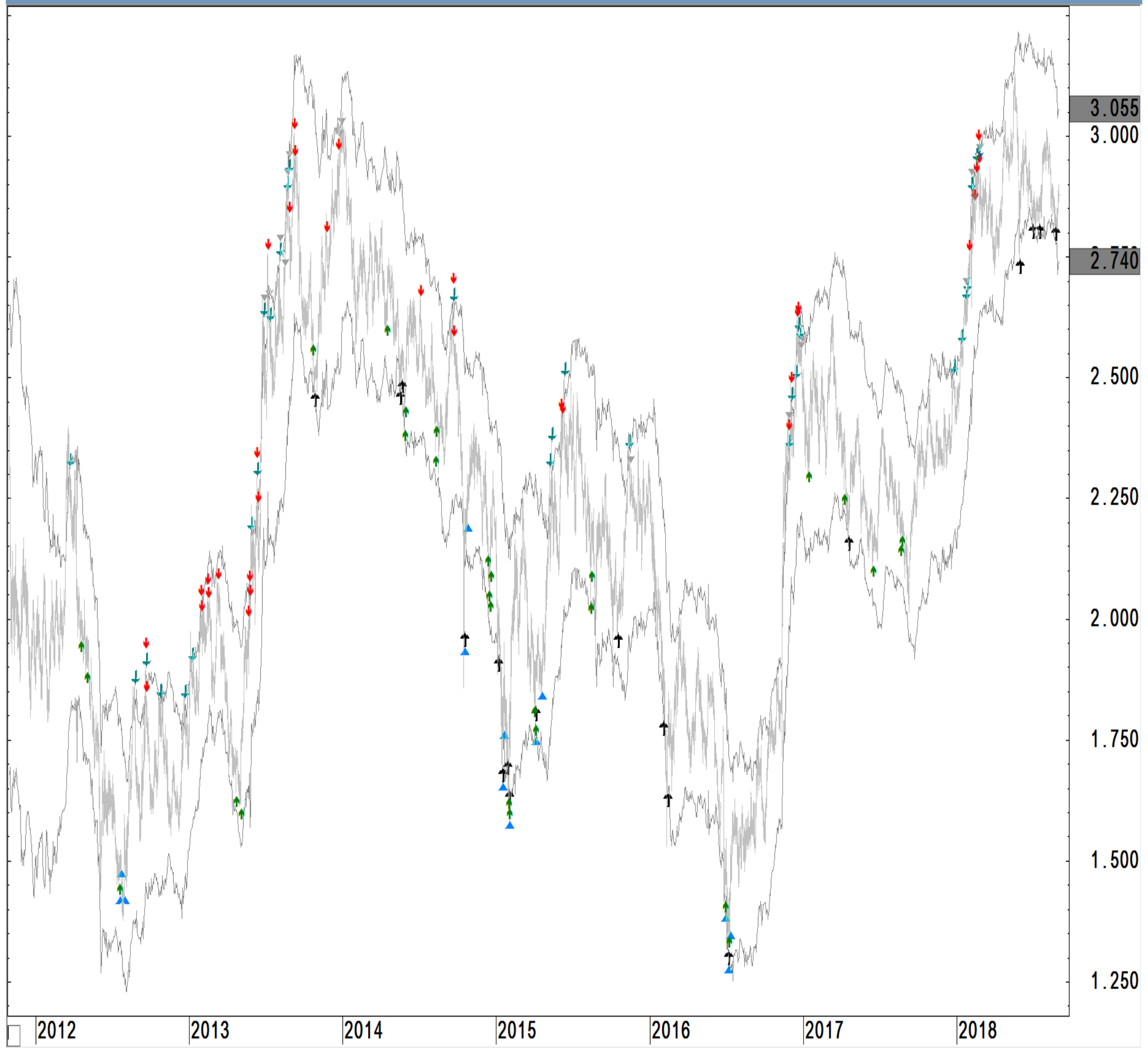
J.P.Morgan

The 10-year note yield with the full array of momentum and position driven signals on the weekly and daily time frames

10-year note yield, weekly bars; %



10-year note yield, daily bars; %



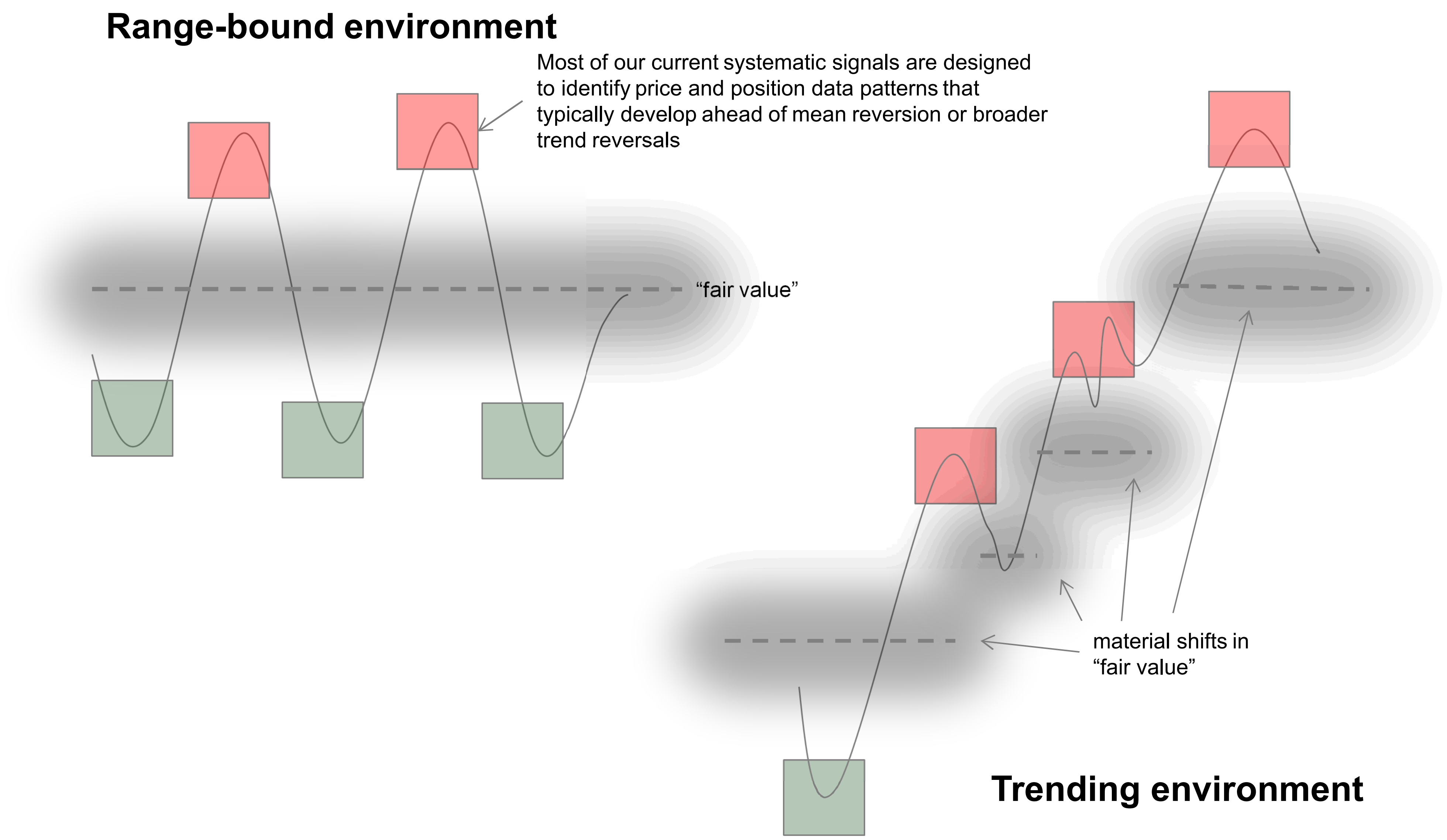
Source: J.P. Morgan, CME, CFTC, CQG

J.P.Morgan

Mean-reverting or Trending environment: a classification problem

- In our experience, markets tend to have either mean-reverting or trending characteristics at a particular scale.
- Since the majority of our price and position driven signal algorithms look to identify potential inflection points, signal failures are far more common in aggressively trending markets, where mean reversion is either limited or nonexistent.
- Early in our system development, we looked for quantifiable market based characteristics to help isolate and filter out bad signal outcomes. To date, we have not found a simple one variable factor that consistently filters bad signals
- In the interim, we have utilized cross-market, macro, lower-frequency and more qualitative technical signaling to help predict mean-reverting from trending environments…
- …However, we are now exploring if Machine Learning techniques can offer a feasible price and position based signal filter

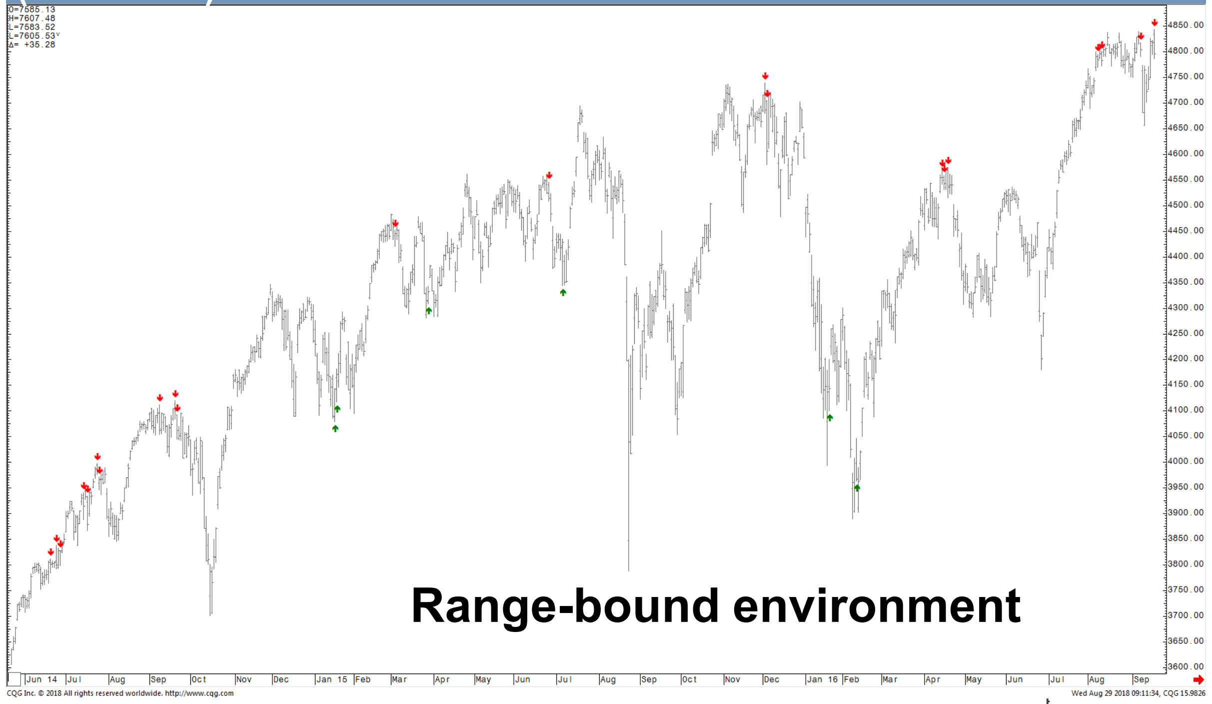
Mean-reverting or Trending environment: a classification problem



Source: J.P. Morgan

Mean-reverting or Trending environment: a classification problem

NASDAQ 100 Index, daily bars w/ Momentum Divergence signals (2014-2016)

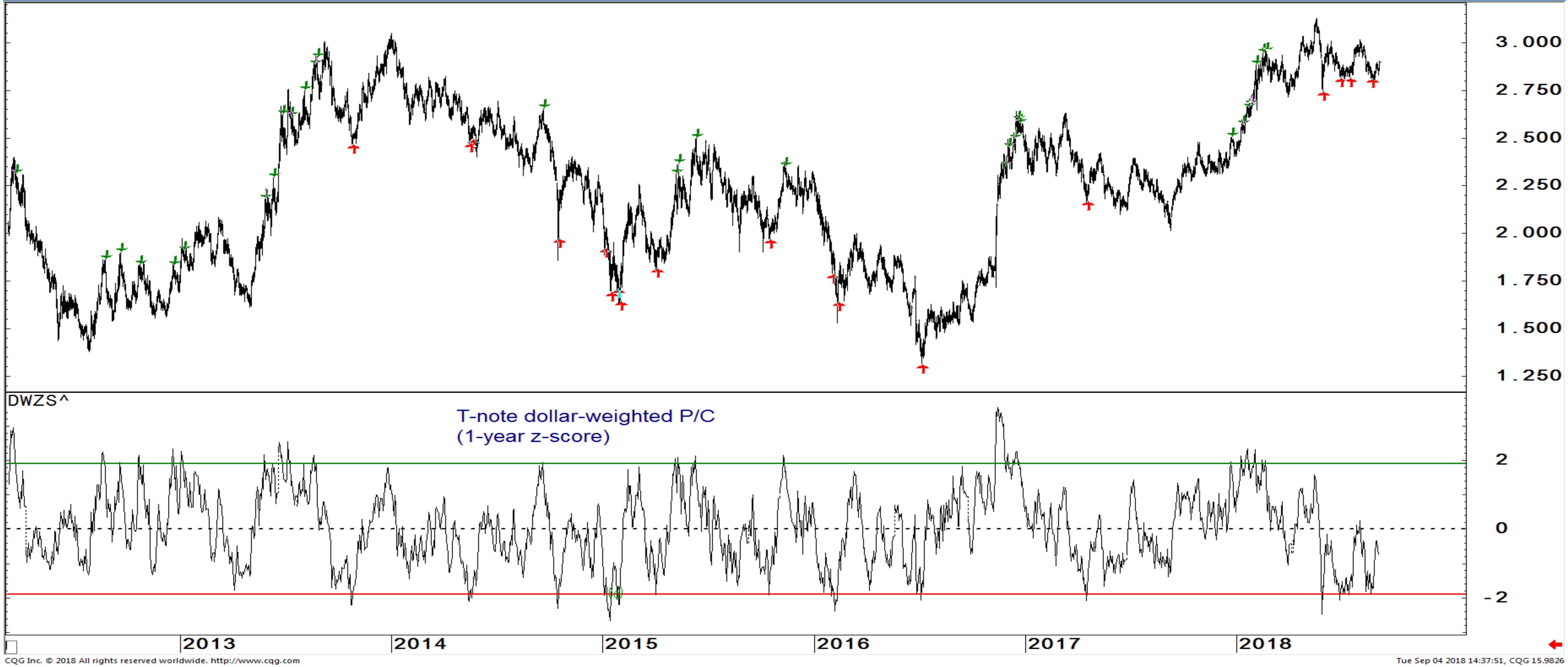


NASDAQ 100 Index, daily bars w/ Momentum Divergence signals (2016-2017)

Source: J.P. Morgan, CQG

Signal: TY dollar-weighted Put/Call ratio 1-year z-score and systematic strategy

10-year note yield, daily bars; %

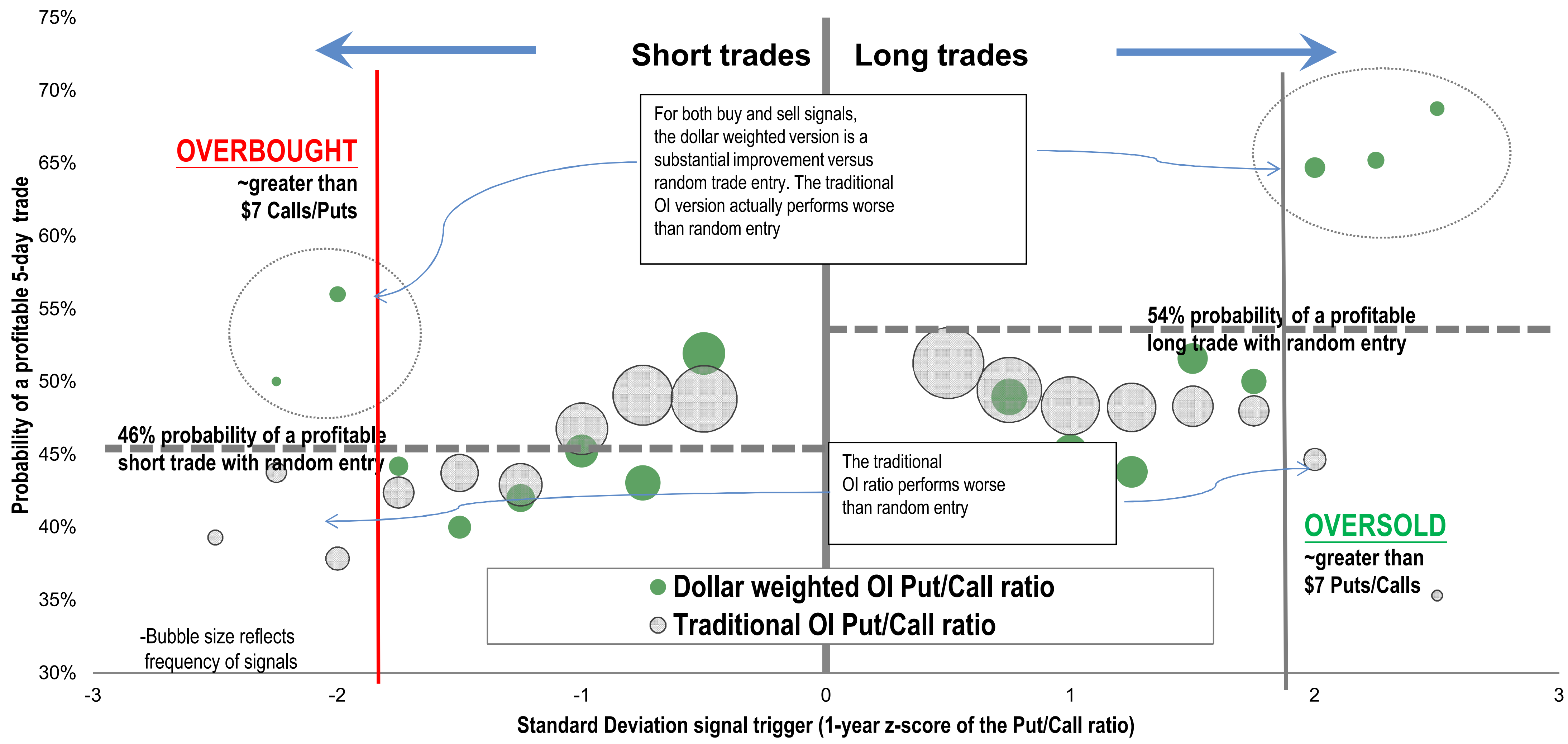


Source: J.P. Morgan, CME, CQG

J.P.Morgan

Building a better contrarian trading signal: The value of premium weighting the TY Put/Call ratio (>60% hit rate over a 5 day hold period)

Trade signal outcomes held over a 5-day period

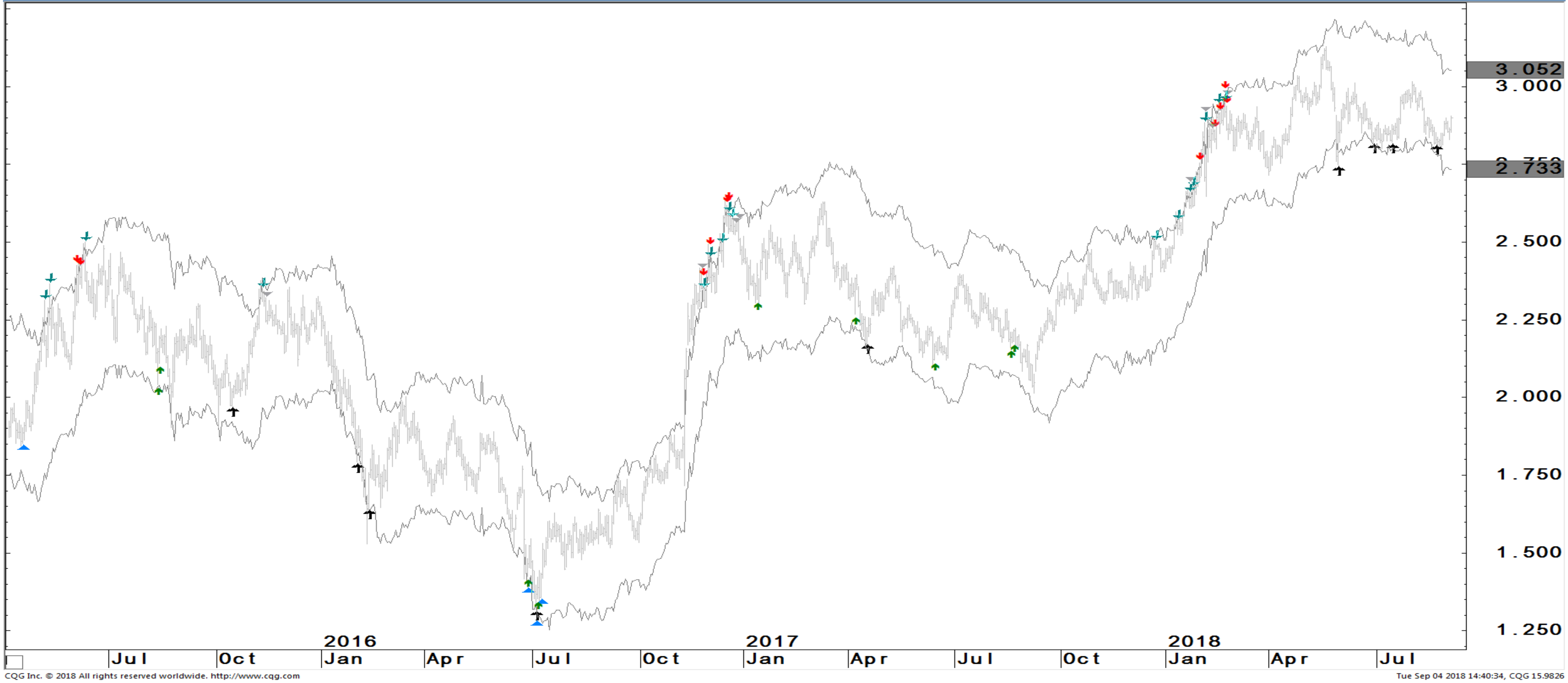


Source: J.P. Morgan, CME, CQG

J.P.Morgan

We also can estimate the approximate yield move it would take to press indicator into extreme/signal territory based on rolling beta of 1-day indicator to yield change

10-year note yield; daily bars; %

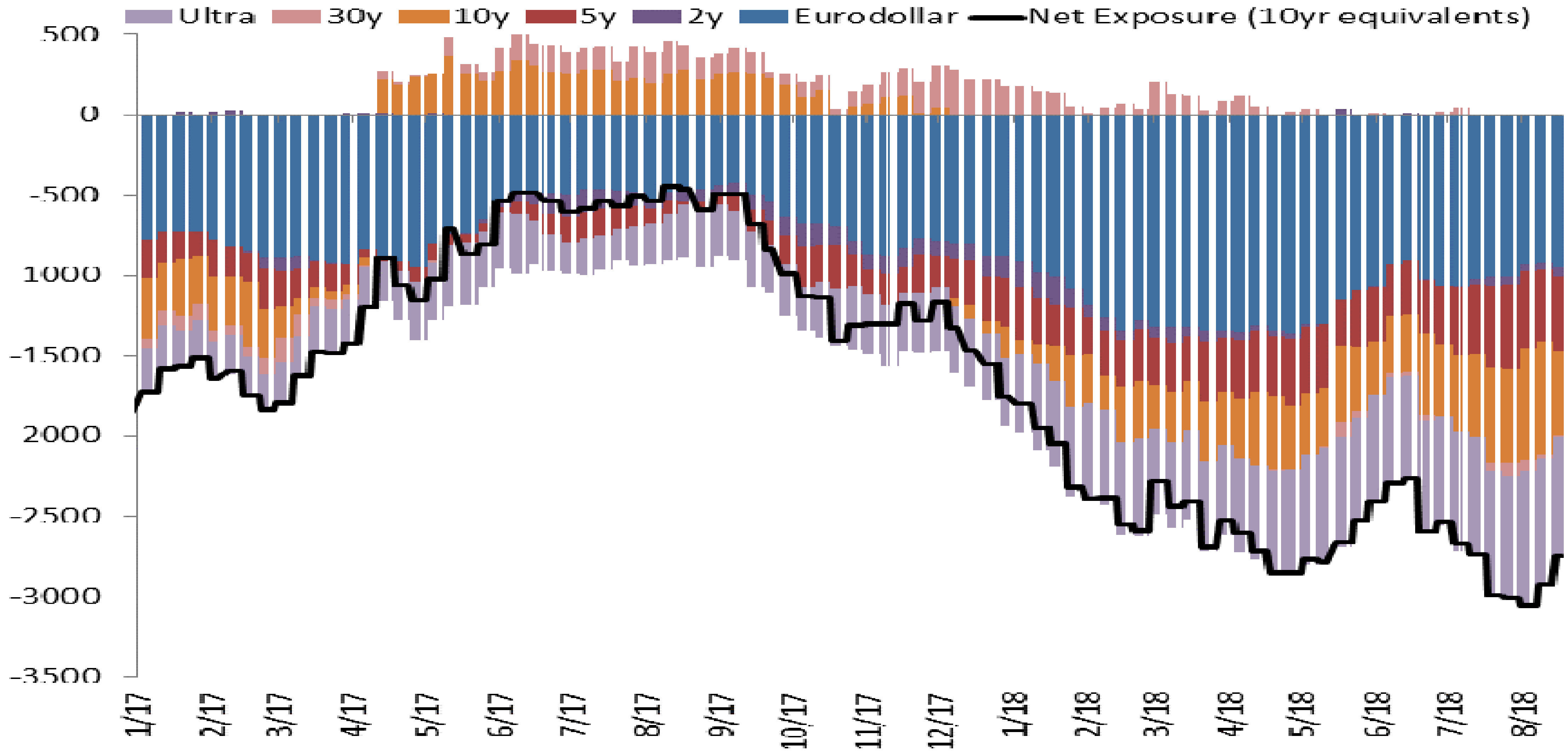


Source: J.P. Morgan, CME, CQG

J.P.Morgan

We look at the aggregated non-commercial US FI futures positions in the CFTC Commitments of Traders report (10-year equivalents)

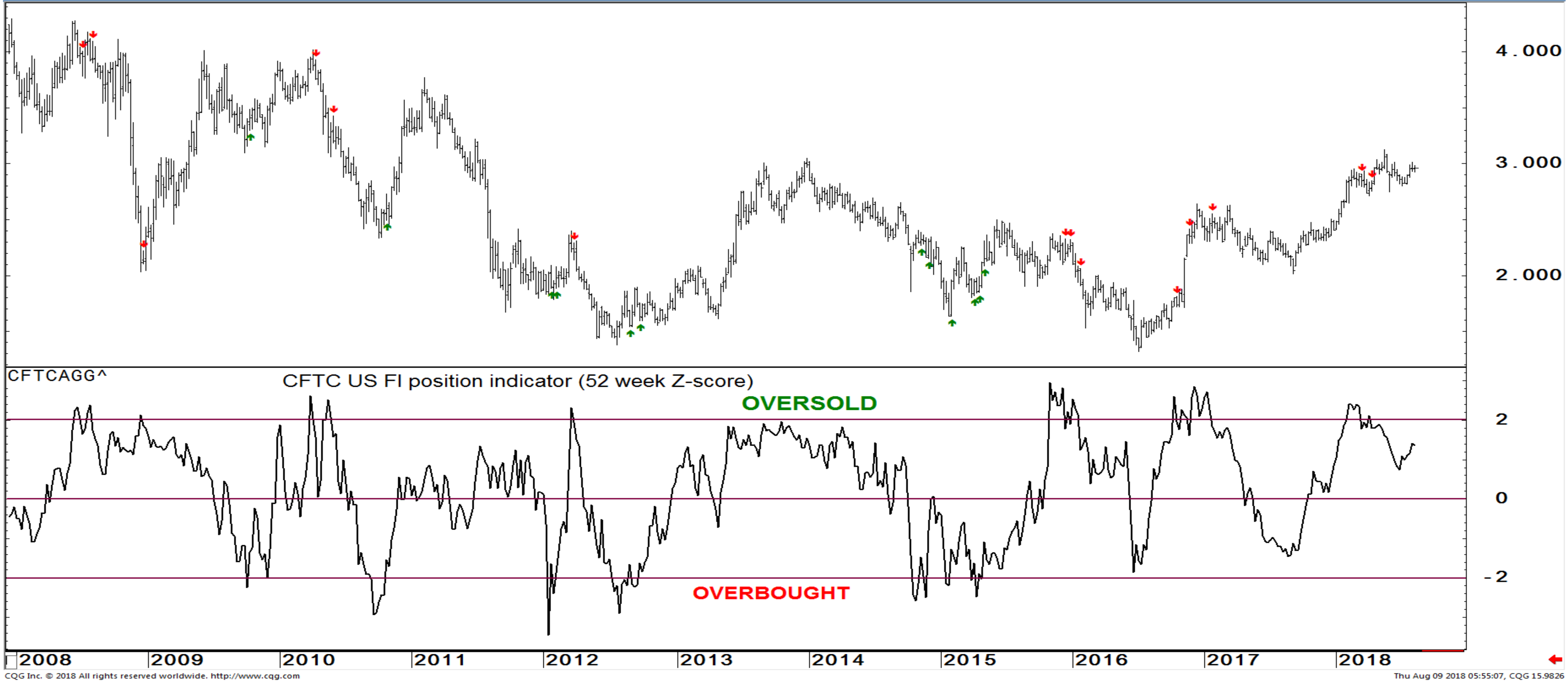
Non-commercial US FI futures positions (10-year equivalents)



Source: J.P. Morgan, CFTC

We use 1-year z-score whipsaws from extreme territory as a contrarian trade entry signal, which has worked well as a 4 week signal over the past two Fed cycles (>60% hit rate)

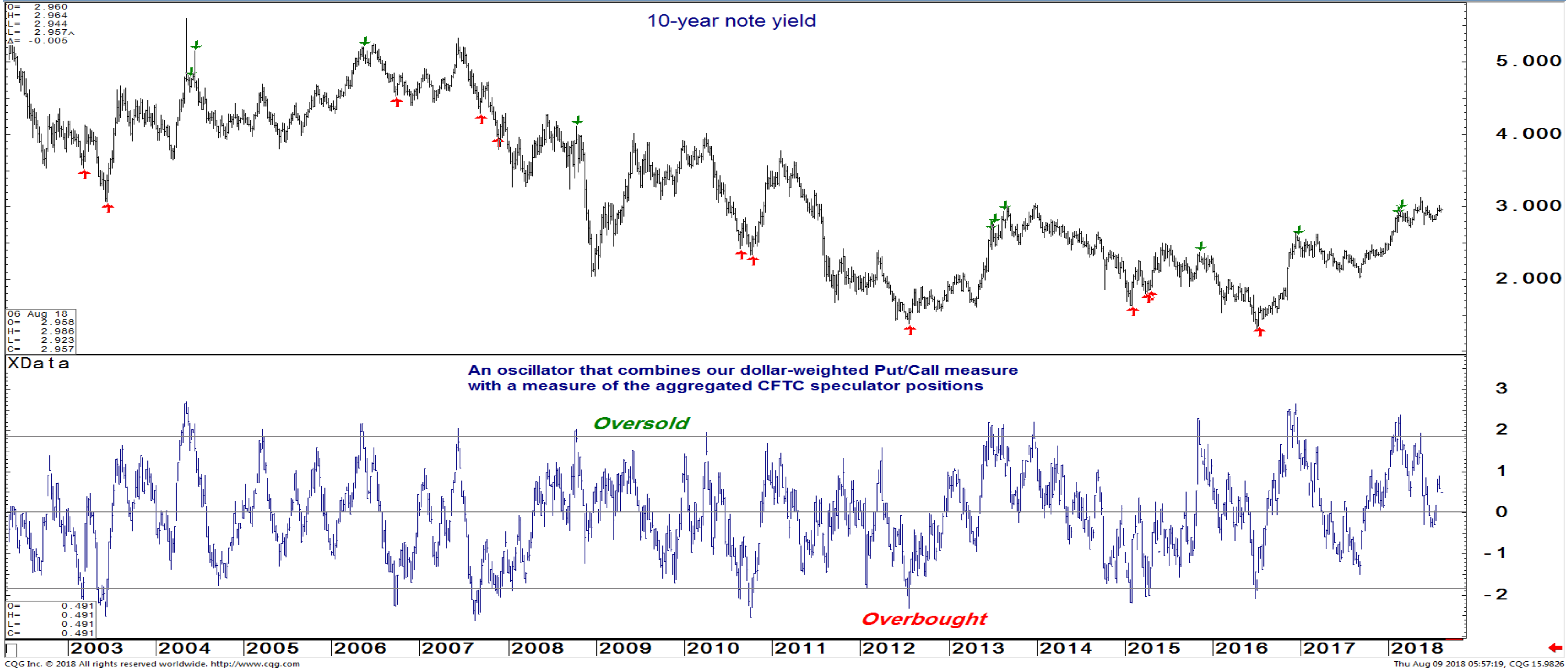
10-year note yield, weekly bars; %



Source: J.P. Morgan, CFTC, CQG

A combination of the TY weighted Put/Call ratio and CFTC position indicators produces an even better hit rate (>70% hit rate over a 4 week hold period)

10-year note yield, weekly bars; %

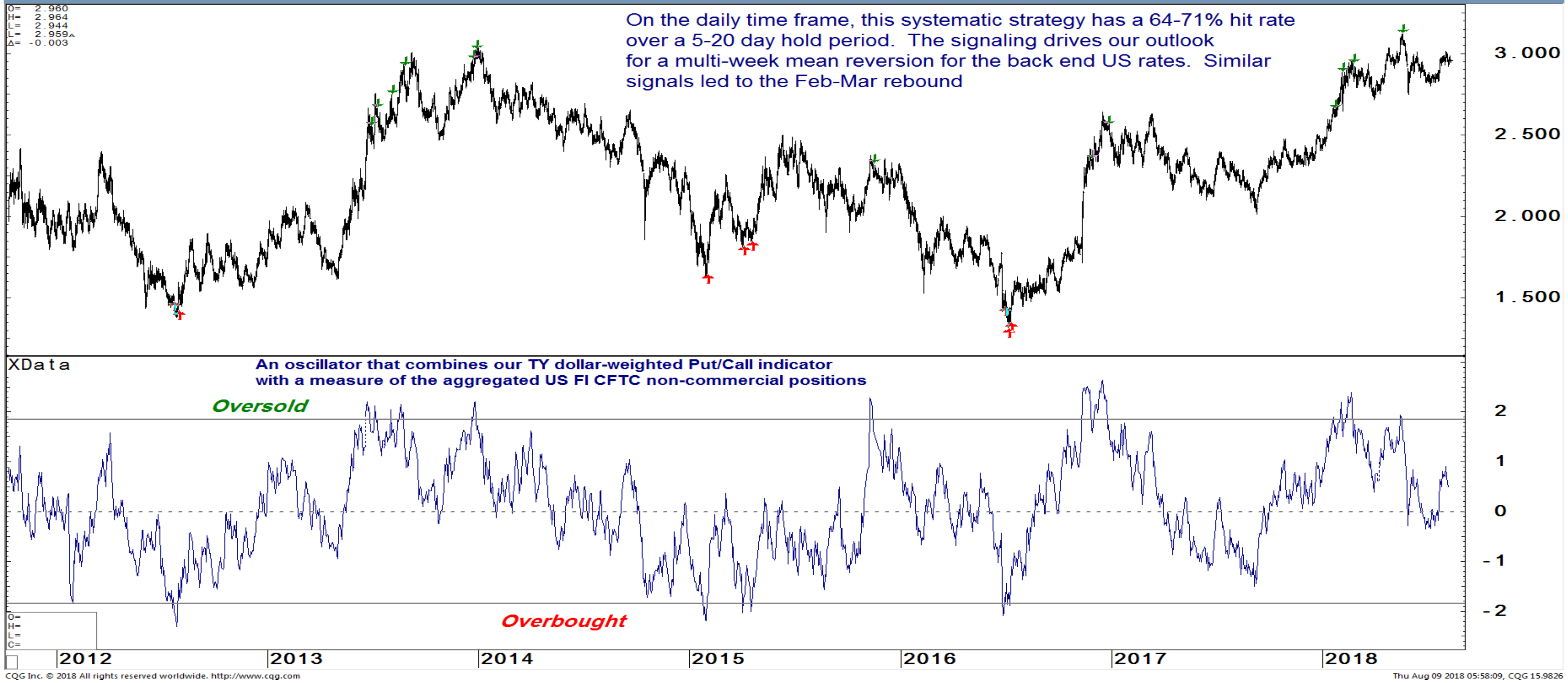


Source: J.P. Morgan, CME, CFTC, CQG

J.P.Morgan

Transforming the signal to work on the daily time frequency allows for more signals and only lowers the hit rate by a small amount

10-year note yield, daily bars; %

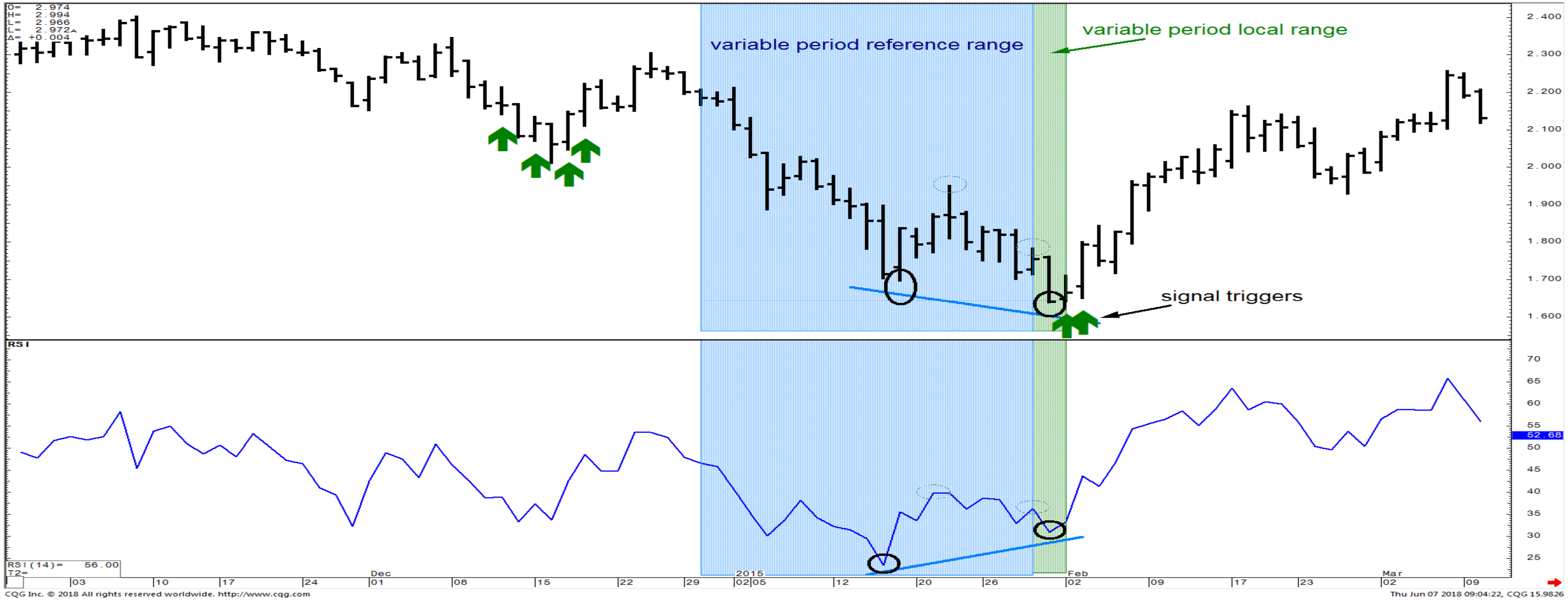


Source: J.P. Morgan, CME, CFTC, CQG

JASON HUNTER - GLOBAL FI & EQUITY TECHNICAL STRATEGY

J.P.Morgan

Momentum divergences increase the probability of mean reversion and potential for broader trend reversals. A very tactical indicator in a trending environment but could be used as a medium-term signal in a range-bound environment



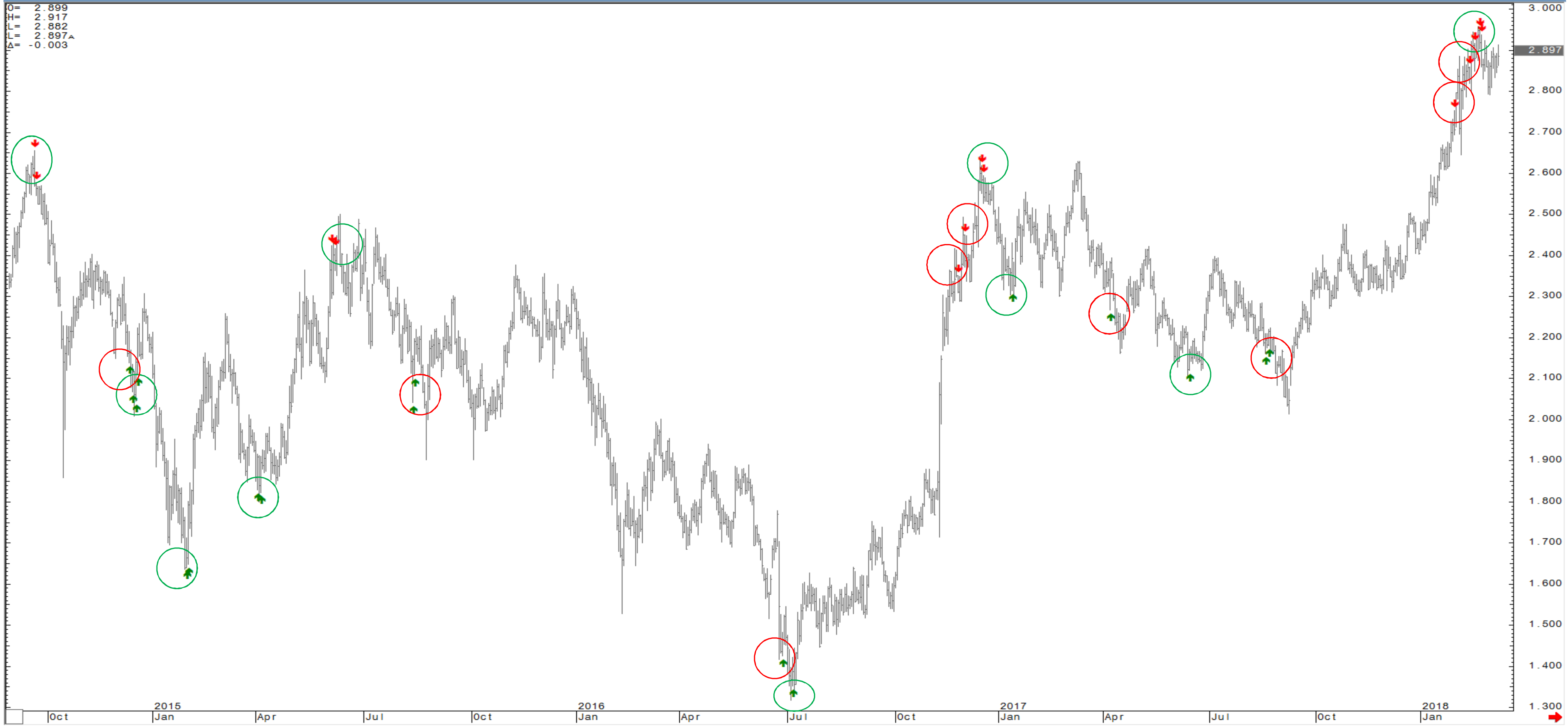
Signal derived from a logic string run across nine price and indicator parameters. Eight of the parameters are maximum and minimum price/indicator values gathered from variable period LOCAL and REFERENCE ranges. The ninth parameter is the most recent change in the RSI indicator.

Source: J.P. Morgan, CQG

J.P.Morgan

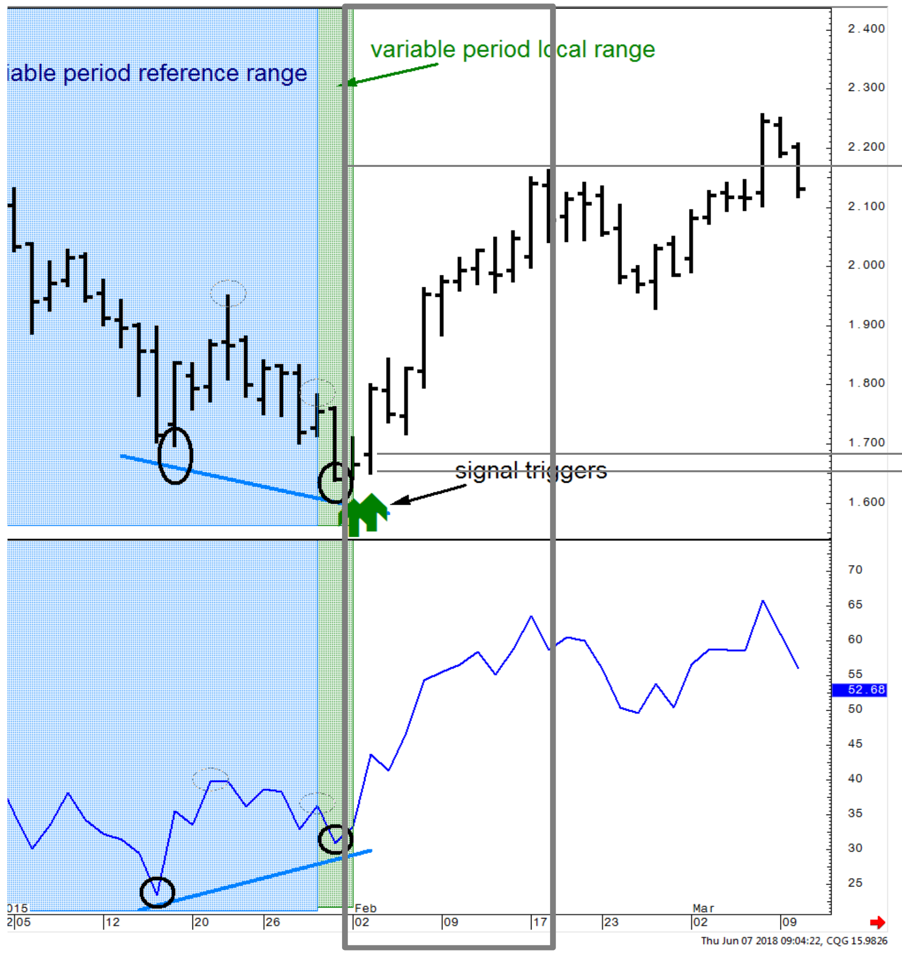
Momentum divergence signal in action

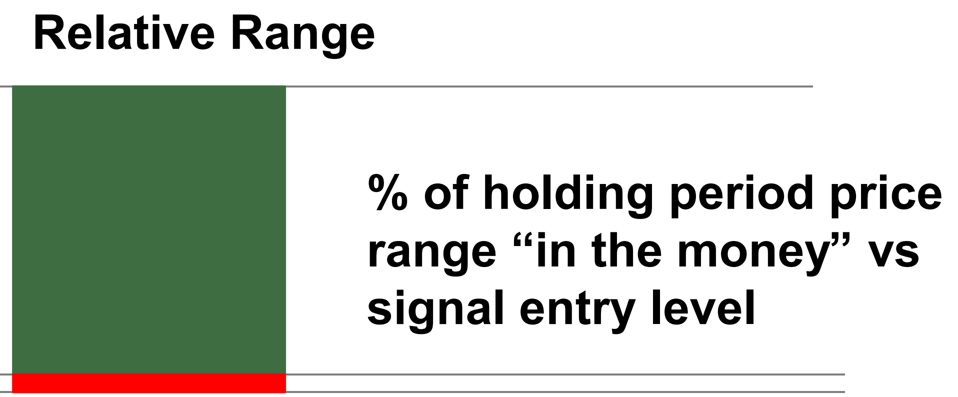
10-year note yield, daily bars



Wed Sep 05 2018 12:00:42, CQG 15.9826

We used two different measures of success: 1) simple hit rate: trades that finished with a profit, and 2) a more complex relative range: measure that looks at ratio of the hold period price range that is “in the money” versus the signal entry level (next period open price).

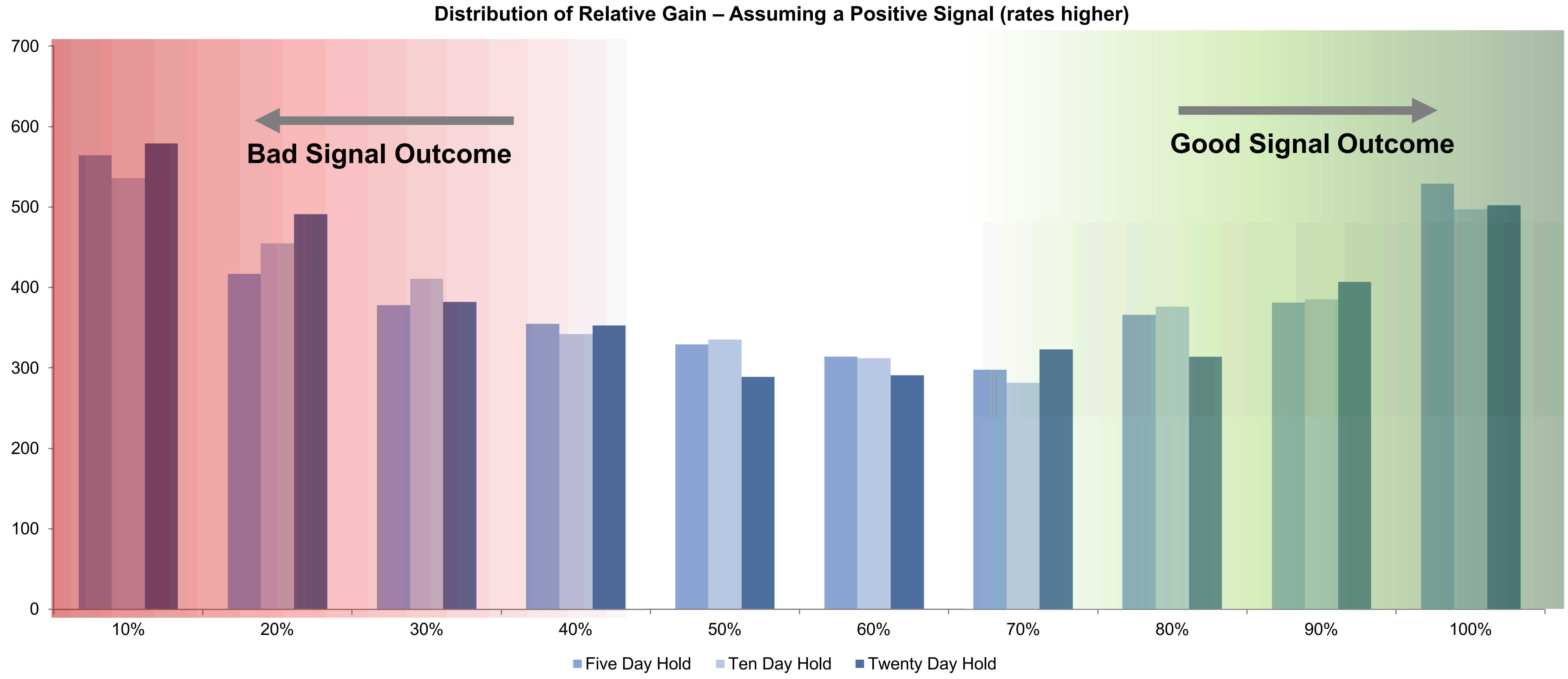




Source: J.P. Morgan, CQG

To understand the behavior of the momentum divergence indicator, we look at the distribution of the relative range for all signals produced for the 10-year note across our test period

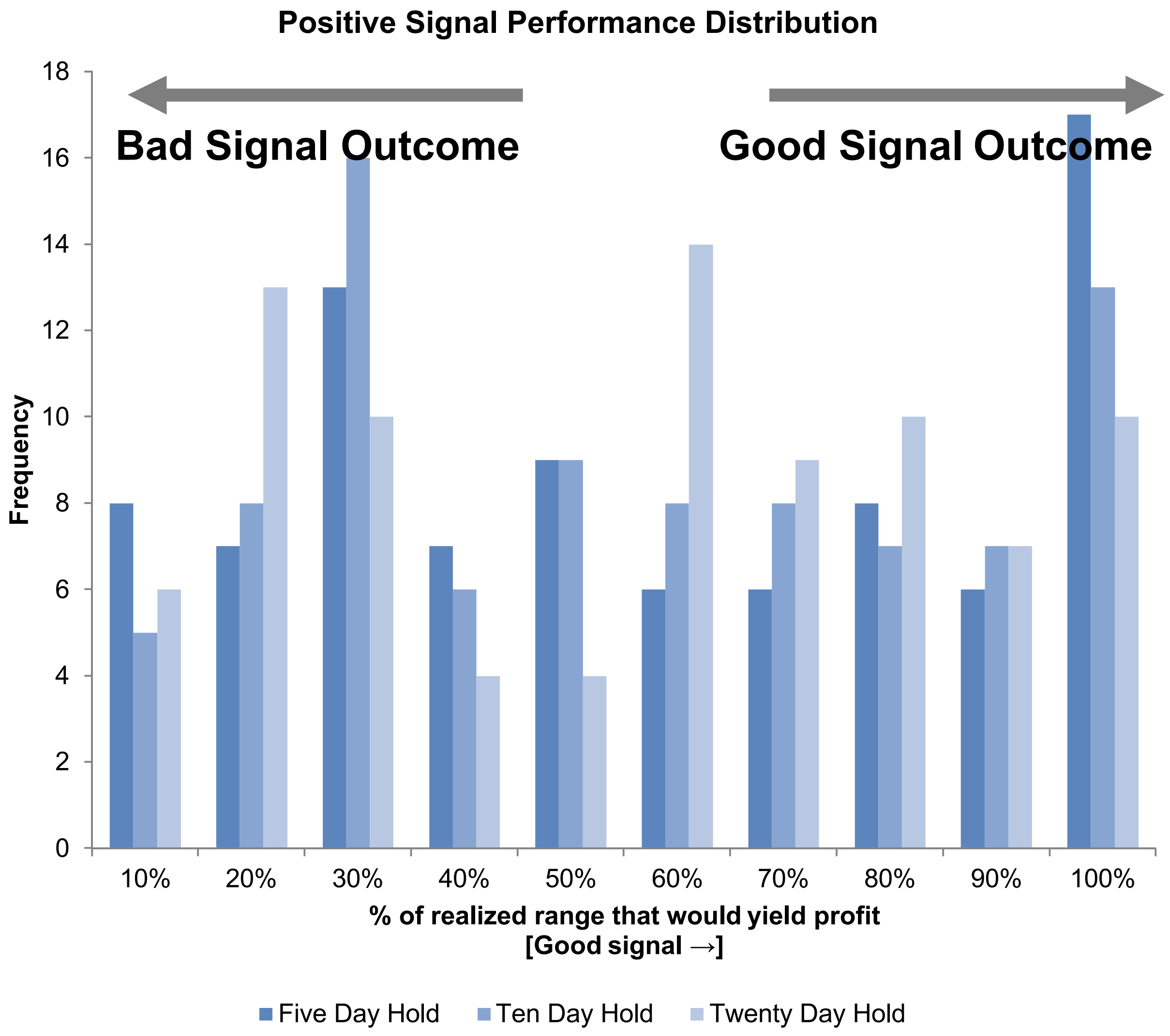
All 10-year note 5, 10, and 20 day performance distribution

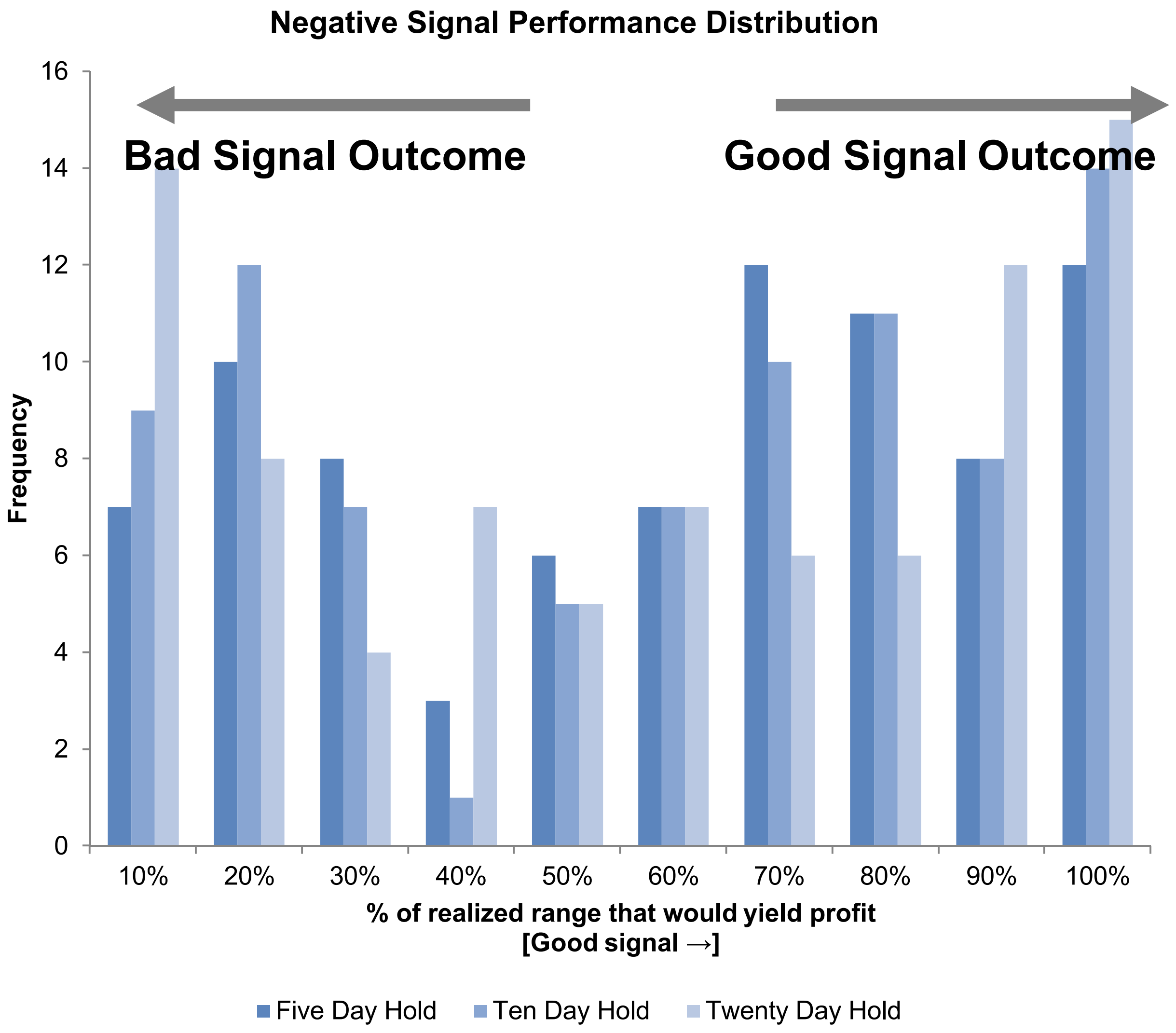


Source: J.P. Morgan

Base momentum divergence algo signal outcomes. The goal is to reduce the bimodal nature and end up with a heavily skewed distribution to the right (positive relative range outcomes)

Original momentum indicator signal performance distribution





Source: J.P. Morgan

Results of momentum divergence indicator base algorithm across different securities using a daily time frequency. Results measured as hit rate.

Success measured as the percentage of signals resulting in the expected move of price activity

2008-2018	Hold Period (Days)	Positive Signal: Reference Strategy (Always Long) (%)	Positive Signal: Momentum Indicator Hit Rate (%)	Positive Signal: Increase Over Reference (%)	Negative Signal: Reference Strategy (Always Short) (%)	Negative Signal: Momentum Indicator Hit Rate (%)	Negative Signal: Increase Over Reference (%)
US Treasuries							
USGG10YR Index	5	47.4	52.0	4.5	52.4	59.6	7.2
	10	48.5	50.0	1.5	51.1	52.8	1.7
	20	48.5	58.8	10.3	50.8	53.9	3.2
USGG2YR Index	5	49.8	49.5	-0.3	49.8	43.9	-5.9
	10	49.2	51.6	2.5	50.3	53.3	3.0
	20	50.9	58.2	7.4	48.1	57.0	8.9
USGG5YR Index	5	48.1	48.4	0.3	51.7	45.8	-5.9
	10	48.4	52.5	4.1	51.3	50.5	-0.8
	20	48.7	51.6	2.9	50.5	53.3	2.7
USGG30YR Index	5	47.0	44.1	-2.9	52.6	51.5	-1.1
	10	49.1	56.9	7.7	50.5	43.3	-7.2
	20	48.6	57.8	9.3	50.7	48.5	-2.3
Equities							
SPX Index	5	58.8	59.4	0.6	41.0	43.5	2.4
	10	61.1	59.4	-1.7	38.5	43.5	4.9
	20	64.2	69.6	5.4	35.0	31.4	-3.6
SVX Index	5	56.8	64.0	7.2	43.1	46.4	3.3
	10	58.1	62.7	4.5	41.5	38.6	-2.9
	20	60.9	65.3	4.4	38.3	39.2	0.8
SGX Index	5	59.6	63.3	3.7	40.2	41.5	1.3
	10	61.1	56.7	-4.4	38.6	41.5	2.9
	20	65.7	66.7	1.0	33.6	30.2	-3.4
RTY Index	5	55.8	63.4	7.6	44.1	48.7	4.6
	10	57.2	57.3	0.1	42.5	48.0	5.6
	20	59.8	65.9	6.0	39.4	41.4	2.0

Source: J.P. Morgan

Results of momentum divergence indicator base algorithm across different securities using a weekly time frequency. Results measured as hit rate.

Success measured as the percentage of signals resulting in the expected move of price activity

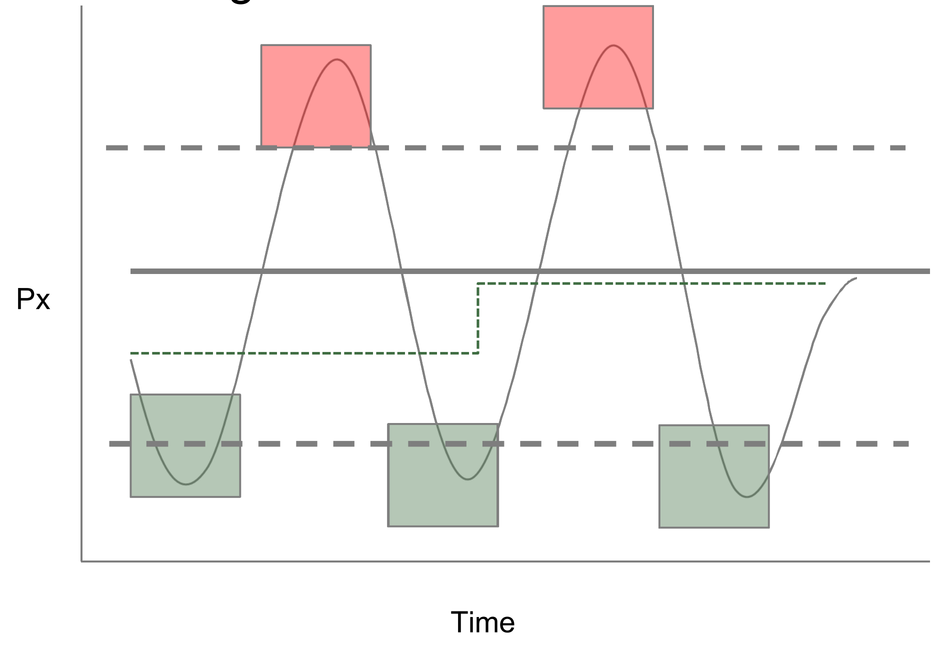
2008-2018	Hold Period (Days)	Positive Signal: Reference Strategy (Always Long) (%)	Positive Signal: Momentum Indicator Hit Rate (%)	Positive Signal: Increase Over Reference (%)	Negative Signal: Reference Strategy (Always Short) (%)	Negative Signal: Momentum Indicator Hit Rate (%)	Negative Signal: Increase Over Reference (%)
US Treasuries							
USGG10YR Index	5	47.4	52.2	4.8	52.4	70.3	17.9
	10	48.5	52.2	3.7	51.1	64.9	13.7
	20	48.5	51.1	2.6	50.8	77.0	26.3
USGG2YR Index	5	49.8	55.7	6.0	49.8	60.2	10.4
	10	49.2	62.3	13.1	50.3	57.1	6.8
	20	50.9	59.0	8.1	48.1	49.0	0.8
USGG5YR Index	5	48.1	55.9	7.8	51.7	60.8	9.1
	10	48.4	53.9	5.5	51.3	59.8	8.5
	20	48.7	50.0	1.3	50.5	69.1	18.5
USGG30YR Index	5	47.0	49.5	2.4	52.6	63.5	10.8
	10	49.1	39.2	-10.0	50.5	63.5	12.9
	20	48.6	27.8	-20.7	50.7	65.4	14.7
Equities							
SPX Index	5	58.8	62.3	3.6	41.0	40.0	-1.0
	10	61.1	77.9	16.8	38.5	38.5	-0.1
	20	64.2	74.0	9.8	35.0	28.5	-6.6
SVX Index	5	56.8	53.9	-2.8	43.1	46.0	2.9
	10	58.1	63.2	5.0	41.5	42.4	0.9
	20	60.9	59.2	-1.7	38.3	36.6	-1.7
SGX Index	5	59.6	63.5	3.9	40.2	34.8	-5.4
	10	61.1	75.0	13.9	38.6	35.9	-2.7
	20	65.7	71.2	5.5	33.6	30.0	-3.6
RTY Index	5	55.8	67.8	12.0	44.1	50.7	6.6
	10	57.2	79.7	22.5	42.5	56.0	13.5
	20	59.8	79.7	19.8	39.4	41.1	1.7

Source: J.P. Morgan

SVM inputs: 20, 40, 60, and 120 period price/yield returns/changes, and r2 values (rough measure of trend linearity over those periods)

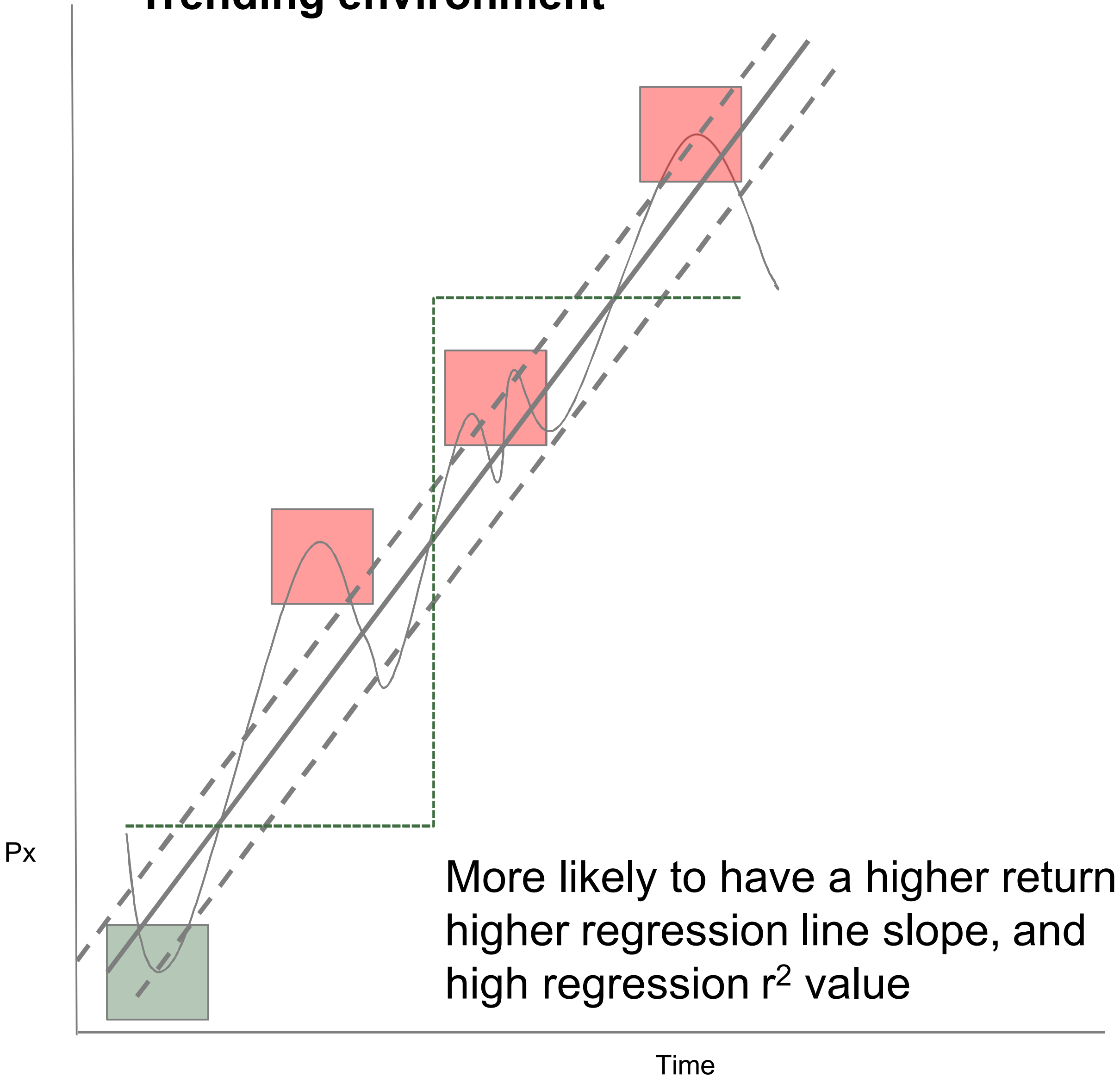
Range-bound environment

More likely to have a lower return, smaller regression line slope, and low regression r^2 value



Source: J.P. Morgan

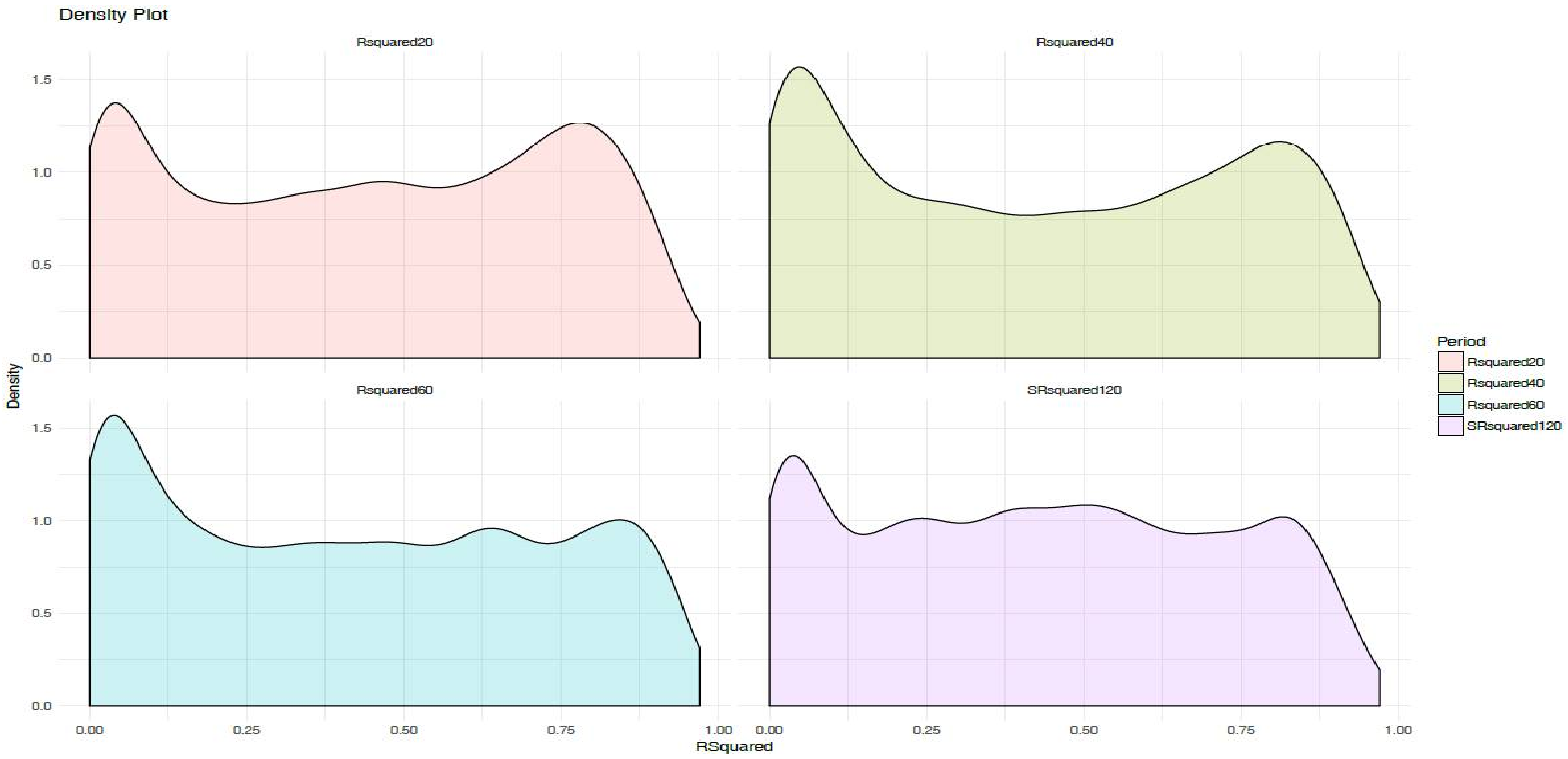
Trending environment



More likely to have a higher return, higher regression line slope, and high regression r^2 value

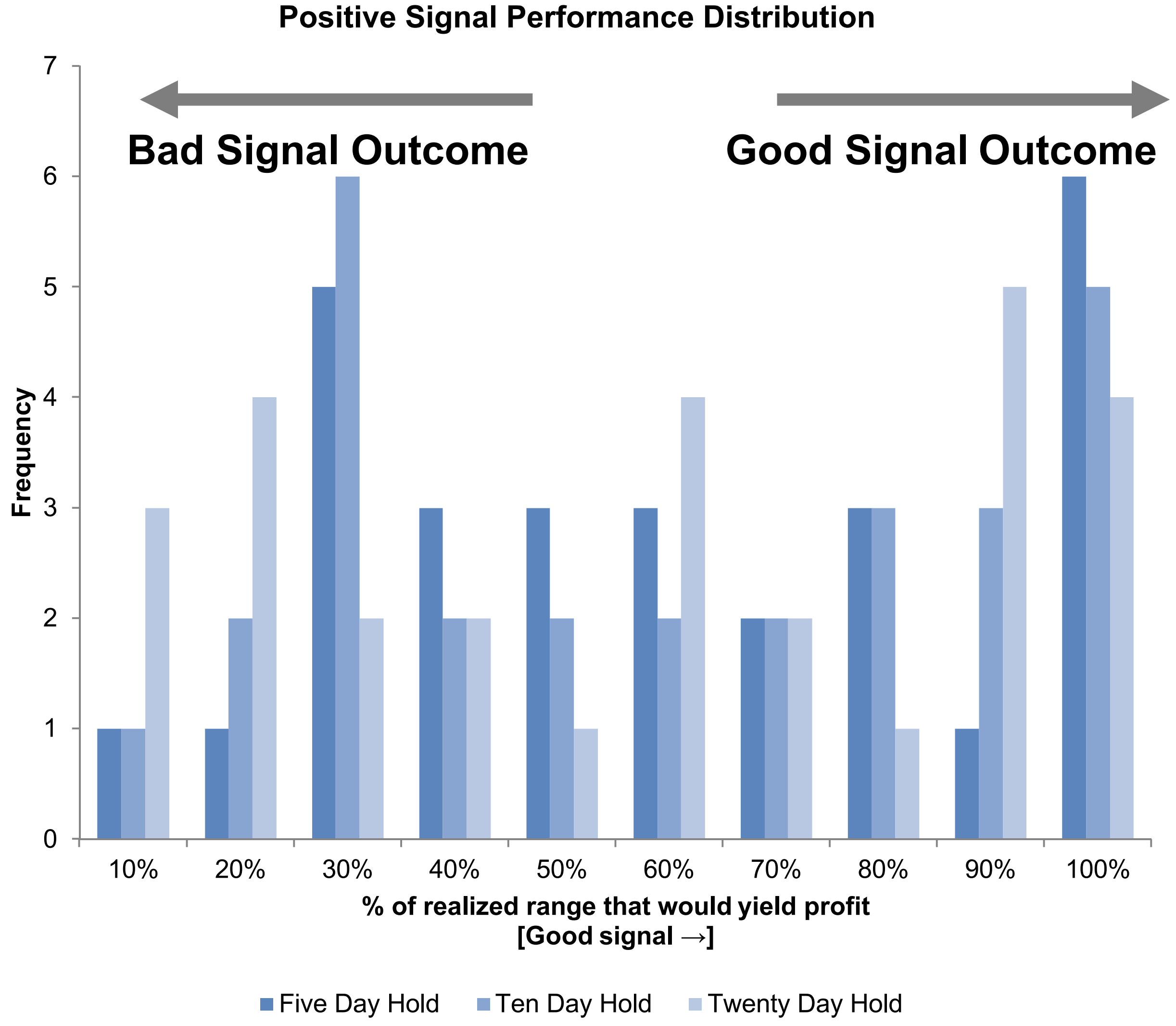
Bimodal distribution of r-square values suggests markets have a tendency to trade in mean-reverting and more range-bound environments, or in aggressive trend environments

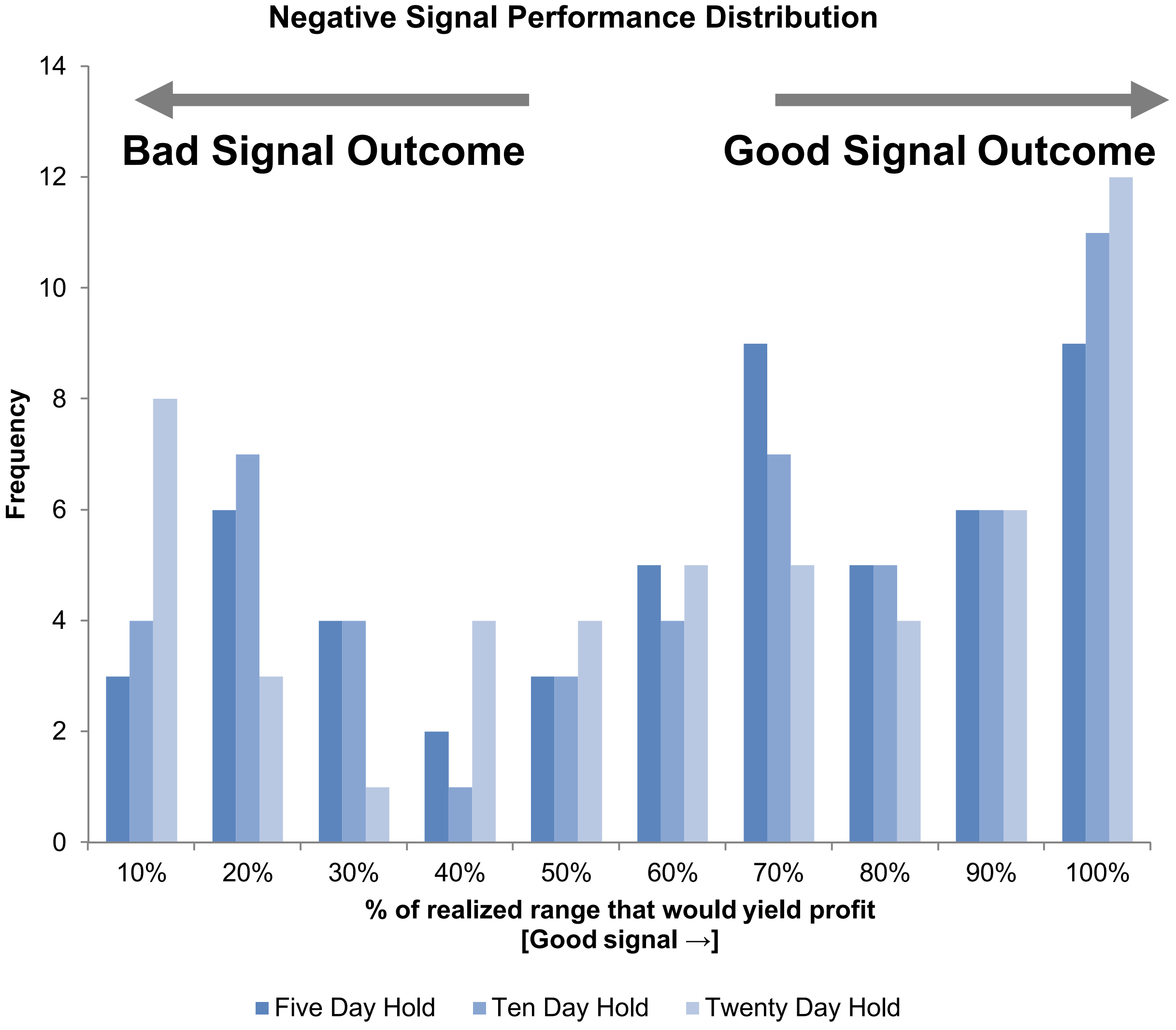
Density plot of 10-year note yield trend R^2 values over 20, 40, 60, and 120 periods



Results after SVM filter was applied to the subset of divergence signal outcomes

Momentum divergence indicator with SVM filter signal performance distribution





Source: J.P. Morgan

Results of momentum divergence indicator with SVM as a filter across different securities using a daily time frequency. Results measured as hit rate.

Success measured as the percentage of signals resulting in the expected move of price activity

2008-2018	Hold Period (Days)	Positive Signal – Hit rate Increase Over Reference (%): Original Momentum Divergence Indicator	Positive Signal – Hit rate Increase Over Reference (%): Momentum Divergence Indicator *With SVM Filter*	Negative Signal - Hit rate Increase Over Reference (%): Original Momentum Divergence Indicator	Negative Signal - Hit rate Increase Over Reference (%): Momentum Divergence Indicator *With SVM Filter*
US Treasuries					
USGG10YR Index	5	4.5	4.2	7.2	7.6
	10	1.5	3.1	1.7	7.0
	20	10.3	16.0	3.2	14.7
USGG2YR Index	5	-0.3	-3.6	-5.9	50.2
	10	2.5	4.7	3.0	49.7
	20	7.4	3.0	8.9	51.9
USGG5YR Index	5	0.3	3.9	-5.9	-9.6
	10	4.1	7.6	-0.8	-3.9
	20	2.9	19.3	2.7	17.9
USGG30YR Index	5	-2.9	3.0	-1.1	5.1
	10	7.7	8.0	-7.2	-8.2
	20	9.3	22.9	-2.3	-0.7
Equities					
SPX Index	5	0.6	6.4	2.4	10.4
	10	-1.7	4.1	4.9	4.5
	20	5.4	14.1	-3.6	-3.1
SVX Index	5	7.2	11.2	3.3	-1.2
	10	4.5	5.9	-2.9	-10.4
	20	4.4	11.1	0.8	3.6
SGX Index	5	3.7	10.4	1.3	17.4
	10	-4.4	3.9	2.9	21.1
	20	1.0	4.3	-3.4	6.8
RTY Index	5	7.6	7.0	4.6	4.4
	10	0.1	-0.3	5.6	3.0
	20	6.0	4.9	2.0	1.5

Source: J.P. Morgan

Results of momentum divergence indicator with SVM as a filter across different securities using a daily time frequency. Results measured as relative range.

Success measured as the percentage of "in the money" range versus total realized price range

2008-2018	Hold Period (Days)	Positive Signal – Average Relative range Increase Over Reference (%): Original Momentum Divergence Indicator	Positive Signal – Average Relative range Increase Over Reference (%): Momentum Divergence Indicator *With SVM Filter*	Negative Signal - Average Relative range Increase Over Reference (%): Original Momentum Divergence Indicator	Negative Signal - Average Relative range Increase Over Reference (%): Momentum Divergence Indicator *With SVM Filter*
US Treasuries					
USGG10YR Index	5	3.2	4.3	3.4	6.2
	10	2.4	3.1	3.7	6.6
	20	3.3	4.1	2.6	7.1
USGG2YR Index	5	3.7	9.4	-1.3	26.5
	10	3.9	9.1	-2.0	31.1
	20	6.2	10.5	-0.1	39.1
USGG5YR Index	5	3.9	13.1	-5.7	0.5
	10	2.1	7.7	-3.1	1.1
	20	2.0	9.3	-2.0	11.0
USGG30YR Index	5	-2.4	-1.5	-4.2	1.0
	10	-0.5	2.2	-3.1	4.6
	20	2.4	12.0	-1.6	8.5
Equities					
SPX Index	5	-2.6	6.2	1.6	3.0
	10	-0.8	9.0	2.6	3.3
	20	1.2	9.7	0.1	1.8
SVX Index	5	3.3	6.2	0.8	-4.8
	10	2.1	4.6	0.6	-2.5
	20	4.6	9.1	0.7	-2.6
SGX Index	5	0.2	0.1	0.9	12.3
	10	-0.3	0.5	1.8	15.2
	20	0.2	0.3	-1.0	10.8
RTY Index	5	5.0	8.8	1.9	3.0
	10	4.9	6.0	4.4	4.3
	20	4.4	4.6	4.6	1.7

Source: J.P. Morgan

We use machine learning techniques, and specifically a Support Vector Machine (SVM), as a filter applied to the momentum divergence indicator in order to strengthen the predictive capacity of the base algorithm

Using an SVM filter reduces the number of triggers and improves average signal performance

		Average Relative range (%) - Difference Over Reference		Number of Signals	
		Original Momentum Divergence Indicator	Momentum Divergence Indicator *With SVM Filter*	Original Momentum Divergence Indicator	Momentum Divergence Indicator *With SVM Filter*
Day	Positive Signals	2.2	6.2	703	202
	Negative Signals	0.2	7.9	1121	366
Week	Positive Signals	2.3	6.2	614	261
	Negative Signals	4.6	8.1	1353	286

Source: J.P. Morgan

J.P. Morgan Fixed Income Quantitative and Systematic Strategies

Do androids dream of electric bonds?: Machine learning in interest rate markets

November 22, 2017

Generating a systematic approach to trading duration, spreads and volatility using techniques from machine learning and over a decade of J.P. Morgan's global market data.

Munier Salem, Joshua Younger, Zhan Zhao

Quantifying Technical Analysis with AI and Machine Learning

June 12, 2018

This note introduces a series of papers that will explain the systematic application of existing concepts in technical analysis, look to enhance the forecast value of those signals through machine learning techniques, and eventually use a collection...

Jason Hunter, Veronica Mejia Bustamante, Alix Tepper

TradeRunner: Ensemble learning-driven systematic trading in interest rate markets

August 16, 2018

We revisit and expand our analysis of systematic trading signals in U.S. interest rate markets generated via machine learning techniques, this time focusing on ensemble methods Gradient boosting machines (GBM) clearly outperform other classical...

Munier Salem, Joshua Younger, Jimmy (Guanjie) Huang

Liquid lunch: Exploring drivers of liquidity in the U.S. Treasury market

April 6, 2018

We explore price impact and its relationship to a host of quantitative descriptors of market microstructure. Working with granular, order-level data from the interdealer 10-year Treasury note market we reconstruct a 10-year history of the live...

Munier Salem, Joshua Younger, Zhan Zhao

Drivers of price impact and the role of hidden liquidity

January 13, 2017

U.S. Fixed Income Markets - Interest Rate Derivatives provides summary on Interest Rate Derivatives for the weekly and also details out Market views, Options and Trade recommendations. This report also gives details of Closed trades in the year.

Joshua Younger, Devdeep Sarkar, Munier Salem

Anatomy of a flash rally: Cash versus futures at the extremes of volatility

February 25, 2016

In recent years, changes in market structure have led to Treasury futures being increasingly more liquid and actively traded than cash. As the risk of extreme price action and liquidity-driven events in Treasury markets has increased, to the extent...

Joshua Younger, Jay Barry

24 hour party people: Tracking global liquidity in U.S. Treasuries

October 23, 2015

The market for U.S. Treasuries has evolved into one of the deepest, most actively traded in the world and with more than half of all high grade debt securities now denominated in USD, they are a truly global asset. We find that market depth is the...

Joshua Younger, Jay Barry, Alex Roever

Building a better contrarian trading signal: The value of premium-weighting the traditional OI Put/Call ratio

March 26, 2015

For over a decade, we have used a T-note dollar-weighted put/call ratio as an enhanced variant of the more traditional (unweighted) OI ratio. In this note, we show that the inclusion of premium into the indicator calculation greatly improves the...

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