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Quantifying Technical Analysis with AI and Machine Learning

Not all profitable trades are equal

- We introduce the relative range statistic (RR) as a potential classifier to leverage in our machine learning-based filters, and compare its characteristics with trade hit rate and volatility-adjusted returns. While the RR metric shows a high correlation to both hit rate and volatility-adjusted returns, the statistic identifies a unique feature in the data that results in a bimodal signal outcome distribution. The metric also provides a more comprehensive understanding of signal performance over the entire trade period. Initial results using the metric as a classifier show improved strategy performance on average.
- The use of relative range as a standardized classifier and an automated hyper parameter selection process also discussed in this note can help speed up the filtration of existing technical signals and new system development.
- We introduce a graphic that illustrates the differentiation between quantitative technical signal performance and random trade entry. The use of the volatility adjusted one-sigma forecast cones also provides context to show the significance of a trade signal within the market environment at the time it triggered.

Global Fixed Income and US Equity Index Technical Strategy

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Relative Range as an alternative classifier

Hit rate offers the simplest way to measure the success of a strategy. However, while easy to calculate and understand, the measure has key shortcomings. As a binary metric, there is no way to differentiate outcomes beyond profit from loss and, more importantly, that limited description only applies to the state of the trade at a specific exit time. We theorize the limited information potentially hampers classification and system development, and we offer a more comprehensive alternative to address those issues. A statistic we termed ***relative range*** **(RR)** captures more information and still distills the data down to an easy-to-understand metric. In this section we go through the statistic calculation, examine its similarities and differences to hit-rate statistics, show how market performance expressed in RR terms illustrates the statistic's promise as a classifier, and utilize one of our existing systematic strategies as an initial test case.

Exhibit 1: Rather than just using the binary outcome of a winning or losing trade over a set hold period, we use a measure we termed Relative Range, which looks at the in-the-money realized price range over a set hold period as a percentage of the total realized price range.
10-year note yield, daily bars; bp

Source: J.P. Morgan

Calculation

The metric describes the location of the theoretical entry price for a trade within the entire price range realized over a set hold period. For entry, we use the opening print for the price bar after the trade signal. The **RR** simply represents the ratio of the profitable price range in comparison to the total price range over the hold period.

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Exhibit 1 illustrates a trade signal with a high **RR**, whereas **Exhibit 2** portrays another profitable trade at exit, but a trade with a poor **RR**. The measure does not overly emphasize a single bar's closing price relationship to the entry level. Furthermore, and as the contrasting exhibits portray, the comparison of maximum unrealized gain to maximum unrealized loss over the entire hold period provides context to more properly assess risk associated with the trade signal.

Exhibit 2: While the Mar 21 10-year note sell signal also produced a profitable outcome after a 20-day hold period, the trajectory over that period was markedly different from the Mar 29 signal illustrated in Exhibit 1. A binary classifier marks these as equal outcomes, whereas the Relative Range score does not.

10-year note yield, daily bars; bp

Source: J.P. Morgan

Relative range and hit rate statistics have a good deal of overlap, but we theorize that the additional information RR provides can enhance classification

Exhibit 3 and **Exhibit 4** compare hit rate and relative range statistics for 5-day hold periods in two different ways utilizing all 10-year note outcomes over a two-decade period. **Exhibit 3** illustrates two histograms with the gray bars marking the outcomes when yields closed at lower levels after a 5-day hold period, and the blue bars when yields closed higher. Those data are separated into ten RR buckets. Both outcomes portray a linear and progressive relationship between hit rate frequency and RR. For bullish and bearish binary outcomes (hit rate), more than 60% of the occurrences fall in the 0-30% and 70-100% RR buckets, respectively. In other words, extreme relative range statistics are likely to line up with the binary hit rate outcomes for the same hold period. However, there are occurrences where that is not the case, which provides additional information within the potential classifier. Furthermore, hit rate provides only two categories for labeling, whereas RR outcomes can be parsed in multiple categories for classification, or used as a sliding scale to be modeled in a continuous form.

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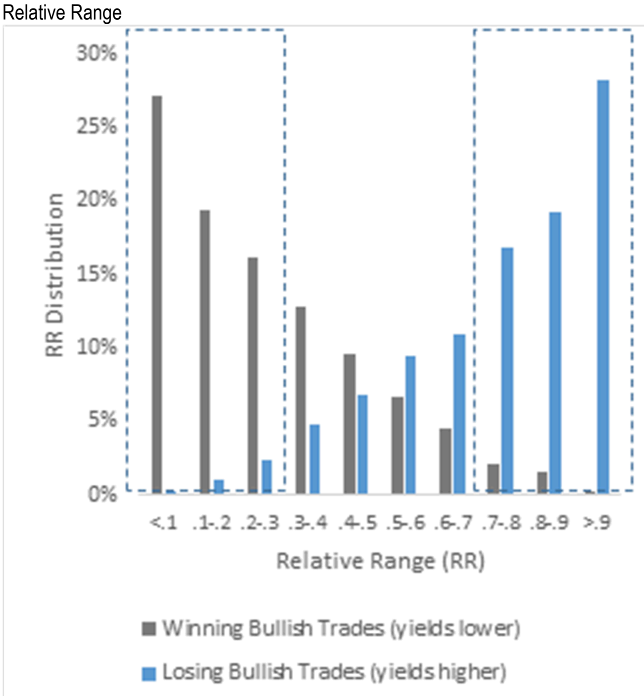
Exhibit 4 plots the 10-year note volatility-adjusted yield changes (dependent variable) against the relative range outcomes (independent variable) over 5-day hold periods. For the study, we normalized the raw 5-day yield change by the average 1-day realized volatility over the preceding quarter. As far as hit rate goes, we are only concerned with the distribution of points above/below the 0bp mark on the y-axis at a given RR as marked by the x-axis. Again, the regression shows a clear linear relationship between hit rate and RR.

Exhibit 3: The distribution of binary outcomes by RR bucket also shows a similar asymmetry at the extremes. More than 60% of the distribution for both bullish and bearish binary outcomes sits in the top/bottom 30% RR buckets.

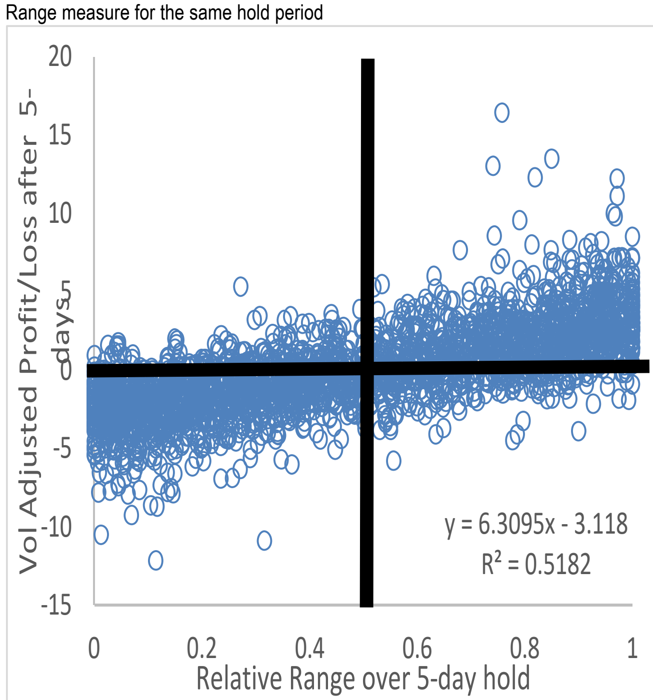
Distribution of winning/losing Bullish 10-year note trades with 5-day hold periods by Relative Range



Source: J.P. Morgan

Exhibit 4: A regression of volatility adjusted 10-year note yield changes (5-day period) against RR shows a clear linear relationship. The plot shows large hit-rate asymmetry in the top/bottom 30% RR buckets, and that is where outsized volatility events occurred as well.

Volatility adjusted 5-day hold 10-year note yield moves plotted against Relative Range measure for the same hold period



Source: J.P. Morgan

The bimodal distribution of short-term RR outcomes emphasizes the metric's potential as a data classification tool

For most markets we tested, the average short-term RR for all days over a test period of any meaningful length does not stray too far away from 50%. For example, the two-decade 5-, 10-, and 20-day average RRs for the 10-year note yield read in the high-40s. That makes sense since yields generally fell over that period. However, the histogram of those outcomes reveals an interesting data characteristic (**Exhibit 5**). The bimodal distribution illustrates that yield had a tendency to trend one way or the other over 5-, 10-, and 20-day periods. Furthermore, the average RR of all outcomes rests in the decile with the third lowest distribution. We found similar RR distributions for other markets as well. From our perspective, the bimodal distribution emphasizes the RR potential as a classification tool.

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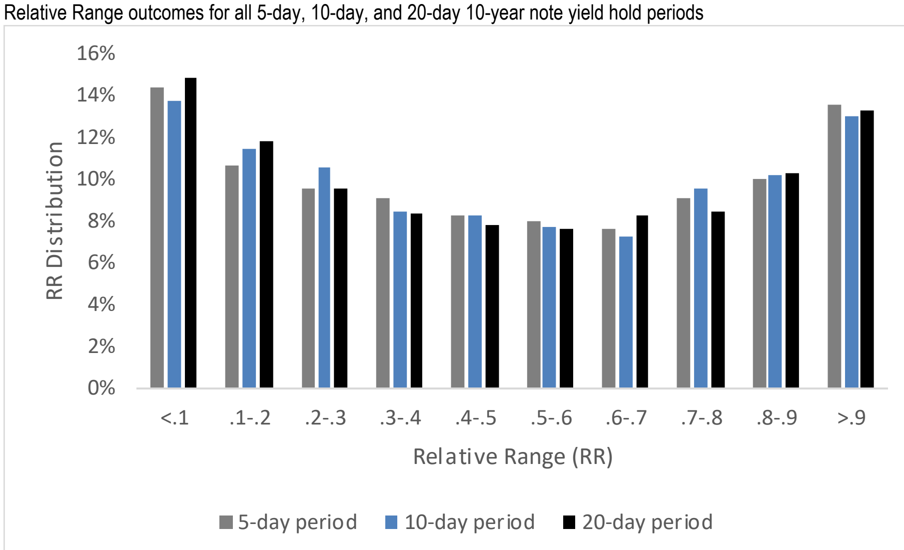
Exhibit 5: While the average 5-day, 10-day, and 20-day Relative Range measure for the 10-year note yield over a 20-year period shows a slight tendency for a bullish outcome (yields lower), the histogram's binary distribution suggests yields tend to mostly trend one way or the other over at those frequencies. That binary distribution identifies a well-defined subset of adverse outcomes and potentially allows for better data classification while using a support vector machine.

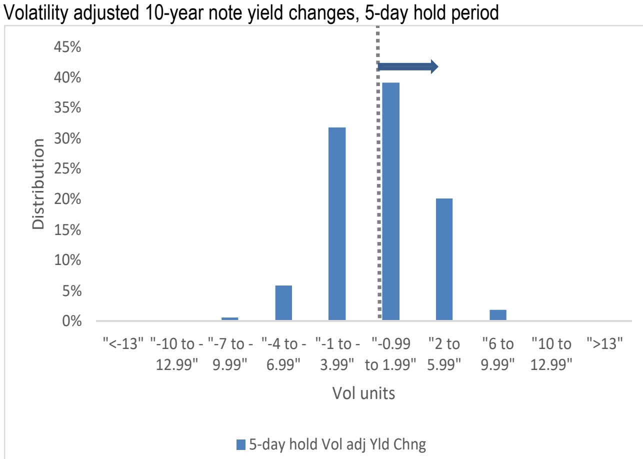
Relative Range outcomes for all 5-day, 10-day, and 20-day 10-year note yield hold periods



Source: J.P. Morgan

Exhibit 6: The side-by-side of the 5-day hold volatility-adjusted yield changes and relative range distributions emphasize how the alternative classification statistic (RR) identifies a unique data feature. The goal of the machine-learning filter is to shift the mean outcome toward the profitable end of the distribution...

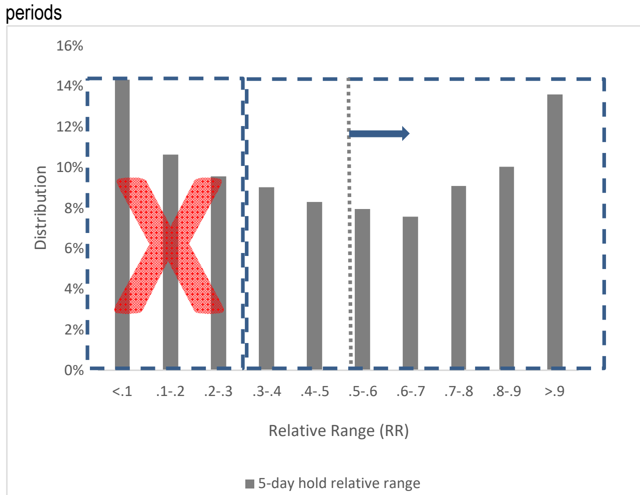
Volatility adjusted 10-year note yield changes, 5-day hold period



Source: J.P. Morgan

Exhibit 7: ... Even though both transformations are highly correlated (see Exhibit 4), the RR bimodal distribution presents a more defined subset of outcomes for the machine to identify and isolate.

Relative Range outcomes for all 5-day, 10-day, and 20-day 10-year note yield hold periods



Source: J.P. Morgan

The side-by-side comparison illustrated by the histograms in **Exhibit 6** and **Exhibit 7** further emphasize the unique data feature the RR statistic identifies. The four largest 10-year note 5-day hold period relative range deciles occupy the extremes of the distribution, and the frequency steadily falls toward more neutral outcomes. Conversely, a histogram presenting the same market in volatility-adjusted yield changes over the 5-day hold period shows a normal distribution, with the vast majority of the outcomes resting in the three deciles surrounding the mean.

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Turning theory into practice

Given our insight into why RR could be a more descriptive metric to classify successful technical signals, we move to quantify the impact of using this metric as a label in our models. In this work, we expand our previous findings that using a machine learning filter on a traditional momentum divergence signal allows us to improve the accuracy of the signal (see 6/12/18 publication here). The machine learning filter is a classifier that learns from the behavior of previous signals to identify a subset of triggers that are likely to successfully motion a divergence in the current regime. We refer to all of the instances where the base pattern recognition algorithm identifies the loss of trend momentum as the original divergence signal, given that it is the baseline on which we apply the filter. This time around, we continue to leverage the machine learning infrastructure described in our prior work, but focus on expanding the suite of metrics used to label the data for the classifier. **Our goal is to identify whether the RR metric leads to a more successful classification-based filter for the original divergence signals.**

A series of experiments allow us to further investigate the dynamics of having RR as the label to the signals as opposed to a hit rate metric. We construct a series of classification-based filters using machine learning using three kinds of data labeling approaches (see next section for the details of the mechanics):

1. **Classes defined by whether there was a continuation of the Relative Strength Index (RSI) trend after the signal** – which gives an indication that the divergence pattern materialized;

2. **Classes defined by the hit rate of the signal** – a measure of whether the signal was profitable over the hold period; and

3. **Classes defined by the RR that the signal experienced over the subsequent 5-, 10-, 20-day hold periods** – a label captures the realized price range of the signal relative to the price movement while holding the trade.

In each of the trials above, we measure success of the classification methodology by comparing the metrics of our filtered signals against a random strategy as well as against a strategy that follows the original divergence signals directly. We define a random strategy as one that executes an always long or always short position, and the original strategy as one that executes a trade on the baseline unfiltered original divergence signals. A successful classification-based filter is one that is able to beat both the random approach and the original divergence signal strategy.

Running the grid of experiments to find the right contender across multiple labeling possibilities

The following shows our experiment grid to analyze the prediction options for the signal filters:

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Signal Classification Options

RSI Trend Continues	Signal Hit Rate	RR
Two options: RSI continues to increase, RSI continues to decrease	**Two options:** in the money, out of the money	**Definition of Buckets:** - **Two buckets:** RR <=50% vs >50% - **Three buckets:** RR in (0, 33%], (30%, 66%], (66%, 100] - More buckets customized

Performance measured across 5, 10, 20 day hold period

Source: J.P. Morgan

In each of the three types of classification methodologies, the data are labeled using the performance that the signal experiences in the subsequent days (assuming a 5-, 10-, and 20-day hold period). For the label based on the RSI trend, the binary class is defined as the next-day behavior of the RSI, where an original divergence signal is successful when it experiences a continued increase/decrease in RSI the following day. Here, the increase/decrease depends on whether it is a positive or negative signal. To label the signal using hit rate, we review the price of the signal at the end of the set of hold periods and use a binary class on whether the difference in price leads to an in-the-money or out-of-the-money trade. Finally, to construct the RR-based label, we review the price that the security experiences at the end of the hold period as well as the price extrema observed while holding the position. This allows us to construct a continuous RR value for the signal, which we then bucket into a predefined range. The default approach we use is a binary label whereby an RR >=50% is a successful signal and RR <50% is unsuccessful. The analysis on historical data for the SPX index and US 10-year note runs from 1998 to 2019, with the strategy results shown from 2009 to 2019. We give our models the time frame from 1998 to 2008 to train, and begin to predict out-of-sample in 2009 (for the in-/out-of-sample mechanics see next section).

The first classification-based filter we explore is the RSI trend continuation classifier. Our prior work has shown that the continuation of the RSI trend is an indication of good signal performance (see 6/12/18 publication here). **Exhibit 8** shows that leveraging the RSI trend as a label for the signals allows us to improve the results of the strategy on average over the original divergence and the random strategy. **Across all hold periods, for SPX we see an average improvement of 4% on relative range and 3.1% on hit rate to the original strategy (this includes positive/ negative signals).** Compared with the random strategy, the performance increase is more significant with an excess relative range and hit rate of 7.8% and 6.3%, respectively. **The 10-year note shows average improvement over the original strategy of 1.1% excess relative range and 0.5% excess hit rate.** The 10-year note still maintains a lead over the random strategy with an average 4.1% excess relative range and 6% excess hit rate. We note that the lower gain of performance in the 10-year note is mainly driven by the negative signal metrics across all hold periods, where the improvement to the original strategy is lower, but we still outperform random.

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Exhibit 8: The RSI trend continuation label shows an increase in performance against both the original signal strategy and the random strategy.

The results of running a strategy that executes on a trading signal determined by the RSI trend label in the classification-based filter

Hold Period	Positive Divergence Signal				Negative Divergence Signal			
	Original Strategy		*Random Strategy*		*Original Strategy*		*Random Strategy*	
	Avg % Excess in RR	Avg % Excess Hit Rate	Avg % Excess in RR	Avg % Excess Hit Rate	Avg % Excess in RR	Avg % Excess Hit Rate	Avg % Excess in RR	Avg % Excess Hit Rate
SPX Index								
5	4.5	6.2	7.7	10.6	3.1	4.5	6.0	7.4
10	4.9	4.7	10.6	7.4	4.3	3.0	7.4	7.4
20	5.1	1.2	11.6	8.1	2.0	-0.9	3.1	-3.0
USGG10YR Index								
5	7.3	8.8	8.9	10.9	0.3	1.8	3.2	7.4
10	2.4	-1.3	3.8	2.2	0.0	1.2	4.2	6.4
20	-3.5	-7.3	0.0	3.2	0.1	0.1	4.2	5.9

Source: J.P. Morgan

We find that the RSI trend label provides a good indication of the price direction that the signal will experience over the next few days, leading to a strategy that meets our success criteria. However, over a 5-, 10-, and 20-day hold period we see that the hit rate can start to degrade and the trend of the relative range is not steady (the strongest RR gain is dependent on ticker and hold period). **Using the RSI trend as the classification allows us to capture a strong indication of future price move, but mechanically we are only able to leverage a single day of future performance in the label. The single day of performance as input to the signal label limits the classifier's ability to capture the longevity of the signal, which can explain the strategy success decreases over time.**

The natural next step is to incorporate the hold period performance into the classification process. In this case, the hit rate metric allows us to define a label for the data that incorporates whether a signal resulted in a profitable trade during a given hold period. We label the data by looking at the entry price for the security once the signal triggers and determine whether the trade resulted as in-the-money or out-of-the-money after a 5-, 10-, and 20-day hold period. **Exhibit 9** shows the performance of a strategy using the hit rate–based labeling technique.

Exhibit 9: The results of running a strategy that executes on a trading signal determined by a hit rate–based classification filter show improvement in the strategy performance over the baseline signal and the random strategy. The hit rate for the filtered signals is strong and carries with it a good relative range.

The results of running a strategy that executes on a trading signal determined by hit rate as a label in the classification-based filter

Hold Period	Positive Divergence Signal				Negative Divergence Signal			
	Original Strategy		Random Strategy		Original Strategy		Random Strategy	
	Avg % Excess in RR	Avg % Excess Hit Rate	Avg % Excess in RR	Avg % Excess Hit Rate	Avg % Excess in RR	Avg % Excess Hit Rate	Avg % Excess in RR	Avg % Excess Hit Rate
SPX Index								
5	5.5	4.6	8.7	9.0	0.7	5.4	3.6	8.2
10	9.0	10.0	14.7	12.8	-0.5	-4.7	2.6	-0.3
20	1.2	2.5	7.7	9.5	6.2	5.2	7.3	3.0
USGG10YR Index								
5	5.3	6.0	6.9	8.2	-7.8	-1.8	-5.0	3.8
10	5.1	6.9	6.5	10.4	8.7	10.4	13.0	15.7
20	7.6	13.1	11.1	23.5	0.0	3.4	4.2	9.2

Source: J.P. Morgan

Overall, using hit rate as a label in our classification-based filter leads to an average improvement of 3.7% on relative range and 3.8% on hit rate for the SPX against the original signal strategy. The SPX hit rate–based filter continues to outperform the random strategy on overage with over 7% average excess relative range and hit rate. **The performance of the 10-year note also improves that of the RSI-based classifier, with an average relative range improvement of 3.1% over**

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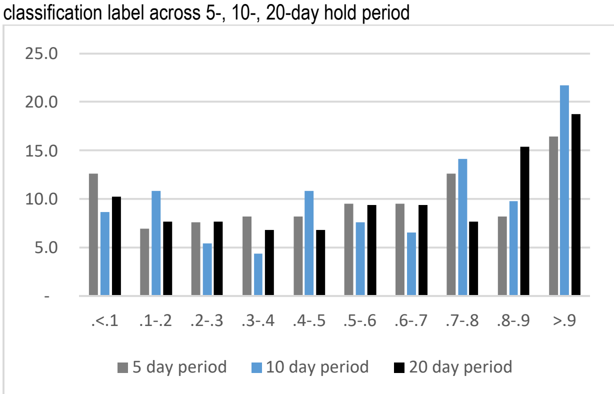
the original strategy and 6.1% over the random strategy. The hit rate improvement in this case is 6.3% over the original strategy while showing a strong 11% average improvement over the random strategy. We find that the hit rate–based classifier is, on average, filtering out more signals than the RSI-based one, meaning that this labeling methodology leads to a classifier that is more accurately selecting signals that will experience a larger profit in the hold period. We do see a weakness in the hit rate–based filter when dealing with negative signals for the 10-year note, with the 5-day hold period performing negatively against the original and random strategies.

Exhibit 10: Running a strategy based on SPX filtered signals that leverage hit rate as the classification label. The histogram shows the distribution of the relative range experienced by the signals triggered by the strategy. The average of the distribution is shifted to higher relative range.

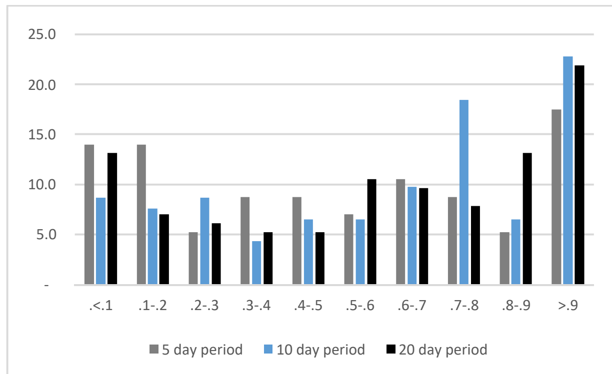
Relative range % distribution of SPX filtered signals using hit rate as the classification label across 5-, 10-, 20-day hold period



Source: J.P. Morgan

Exhibit 11: Running a strategy based on US 10-year note filtered signals that leverage hit rate as the classification label. The strategy leads to a set of signals that display an increase in the average relative range.

Relative range % distribution of the US 10-year note filtered signals using hit rate as the classification label across 5-, 10-, 20-day hold period



Source: J.P. Morgan

As expected, the hit rate–based classifier leads to a strong percentage of in-the-money trades, carrying with them a solid excess in relative range. As we have described earlier in this note, the hit rate and RR metric are strongly related as they are direct measures of price change in the given holding period. **Exhibit 10** and **Exhibit 11** show that using the hit rate–based filter also leads to capturing the expected RR bimodal distribution we found in **Exhibit 5**. The histograms show that while the classifier searches for profit or loss in the signals, it simultaneously shifts the center of the relative range distribution for the strategy toward a higher value (on average across the positive and negative signals).

Overall, using hit rate as the label in our classifier allows us to capture further future performance of the signal in the hold period, which improves our view of the RSI-based classification methodology. However, this label is limited to a binary class: profit or loss. If we wanted to filter a target spectrum of signal performance, the gain/loss of the signal would need to be standardized in some way. Also, as we theorize above, the hit rate does not pack enough information about the path that the trade takes through its holding period, which we theorize is valuable insight. **We continue the search of a classification metric that will be more robust and standard across different instruments and regimes.**

The last method that we employ to classify our signals is the RR metric. The RR-based filter gives us the flexibility to define classes that split the range of 0-100% into as many buckets as we choose, or to model it as a continuous variable. We start by evaluating the RR-based filter as a binary label, where a threshold of 50% is used to define our classes. **Exhibit 12** shows the results of using an RR-based classifier across all hold periods.

Exhibit 12: The RR classifier using 50% as the boundary of classes, marking a successful signal as one that experienced a higher than 50% RR in the holding period. We see strong performance in the SPX using this label, while the negative signals in the US 10-year note show weakness.

The results of running a strategy that executes on a trading signal determined by RR using 0-50% and 50%-100% as the label in the classification-based filter

Hold Period	Positive Divergence Signal				Negative Divergence Signal			
	Original Strategy		Random Strategy		Original Strategy		Random Strategy	
	Avg % Excess in RR	Avg % Excess Hit Rate	Avg % Excess in RR	Avg % Excess Hit Rate	Avg % Excess in RR	Avg % Excess Hit Rate	Avg % Excess in RR	Avg % Excess Hit Rate
SPX Index								
5	9.2	12.3	12.4	16.7	-0.9	-0.1	2.0	2.8
10	3.1	5.0	8.9	7.7	1.9	5.2	5.0	9.6
20	3.8	5.7	10.4	12.7	11.2	12.5	12.3	10.4
USGG10YR Index								
5	0.2	-3.3	1.8	-1.1	-6.1	-5.6	-3.2	0.1
10	5.3	7.7	6.7	11.2	-5.8	-9.0	-1.5	-3.7
20	4.2	12.0	7.7	22.4	3.1	1.0	7.2	6.8

Source: J.P. Morgan

The RR 50% boundary label shows that on average across all hold periods, the SPX performs the best over RSI and ITM based methods. The strategy leads to an improvement over the relative range in the original strategy of 4.7% and the associated hit rate of close to 6.8%. For the SPX, the area of weakness is the 5-day hold period in the negative SPX signal, but even then the filter is outperforming the random strategy. The performance of the US 10yr Treasury positive signals show an average improvement of 3.2% and 5.5% on relative range and hit rate, respectively, over the original strategy (while continuing improvement over the random strategy). However, we see a similar weakness in this classifier in the US 10-year note negative signal, as it improves some over a random strategy but fails to improve the original strategy.

We can improve the weakness of this classifier in the US 10-year note by leveraging another configuration of the RR labels. In this case, we maintain binary classes but target to identify the buckets that are [0-70%) and [70%-100]. Essentially, we are now deploying our classifier to identify whether a signal is expected to experience a high relative range. Using a targeted spectrum of RR improves the performance of our strategy significantly, the results by hold period are shown in **Exhibit 13**.

Exhibit 13: A different configuration of the RR classifier that leverages 70% as the boundary of classes. In this case, we are interested in capturing only those positive and negative signals that are expected to experience a high relative range during the hold period. This configuration improves the weakness shown by the 50% class boundary.

The results of running a strategy that executes on a trading signal determined by RR using 0-70% and 70%-100% as the label in the classification-based filter

Hold Period	Positive Divergence Signal				Negative Divergence Signal			
	Original Strategy		Random Strategy		Original Strategy		Random Strategy	
	Avg % Excess in RR	Avg % Excess Hit Rate	Avg % Excess in RR	Avg % Excess Hit Rate	Avg % Excess in RR	Avg % Excess Hit Rate	Avg % Excess in RR	Avg % Excess Hit Rate
SPX Index								
5	7.8	0.6	11.0	5.0	1.8	7.1	4.9	11.5
10	1.9	7.5	7.6	10.3	5.3	1.8	6.5	-0.3
20	5.0	1.2	11.5	8.1	0.4	7.4	4.2	13.0
USGG10YR Index								
5	7.5	25.4	9.2	27.6	-6.9	-1.1	-4.0	4.6
10	-1.2	-7.8	0.2	-4.3	4.7	13.2	8.9	18.5
20	5.0	9.4	8.6	19.8	3.5	10.2	7.6	16.0

Source: J.P. Morgan

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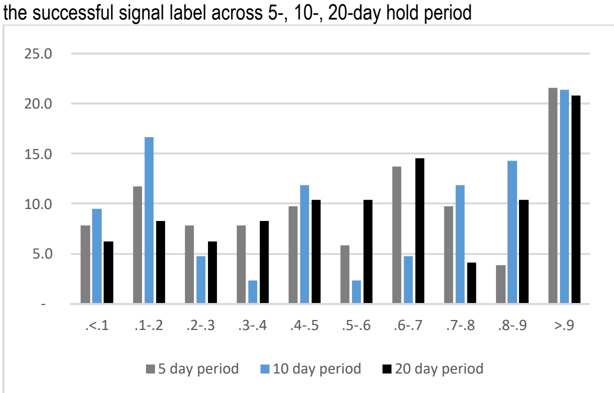
The 70%-100% range allows the performance of the US 10-year note to increase significantly relative to the 50-50% classifier, and improves the average negative signal metrics over the RSI-based and hit rate–based classifiers. For this ticker, we now see an average increase in the relative range of 2.1% over the original strategy and 8.2% over the random strategy (for positive and negative signals). The increase in relative range over the random strategy is 5.1% and 13.7% on hit rate. This classifier reduces the total number of signals filtered (as expected) but allows only those with strong RR to be part of the strategy. We continue to see that the SPX maintains a strong performance against the RSI-based and hit rate–based classifiers.

Exhibit 14: SPX performance of a strategy based on labeling successful signals as those experiencing an RR of 70% or more. The signals triggered by the strategy show that the filter is capturing the upper end of the expected bimodal RR distribution.

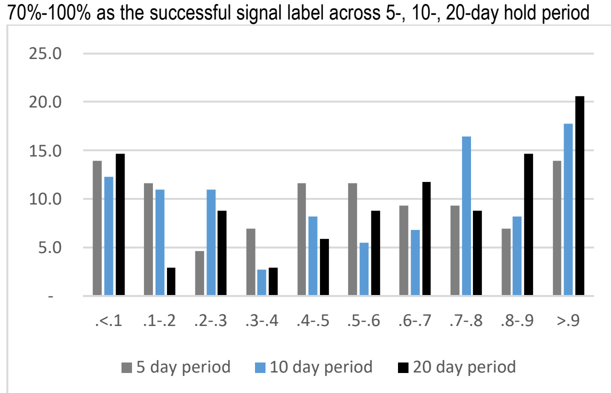
Relative range % distribution of SPX filtered signals using a RR 70%-100% as the successful signal label across 5-, 10-, 20-day hold period



Source: J.P. Morgan

Exhibit 15: US 10-year note performance of a strategy based on labeling successful signals as those experiencing an RR of 70% or more. The strategy results in a set of signals whose RR distribution has a higher average.

Relative range % distribution of US 10-year note filtered signals using a RR 70%-100% as the successful signal label across 5-, 10-, 20-day hold period



Source: J.P. Morgan

The distribution of relative range for the signals resulting from this RR-based classifier also experiences a shift to a higher relative range against the original signal (on average across all hold periods). The histograms in **Exhibit 14** and **Exhibit 15** show this shift for both the SPX and US 10-year note.

Is RR then our new classification metric of choice?

RR-based filtering methods are definitely strong contenders that we will continue to use as part of our work moving forward. **We find that the flexibility that using RR provides in the definition of the classification is critical, since it can improve the results of the filtered strategy and allow us to focus on a target performance range.** In addition, the RR-based filter naturally extends to multi-label classification, which we did not explore in this note due to the sparsity of data but will continue to explore in the future. Aggregating the results of our experiments across the different hold periods, we see the RR strategy perform strongly for the SPX index as well as the US 10-year note (see **Exhibit 16** and **Exhibit 17**).

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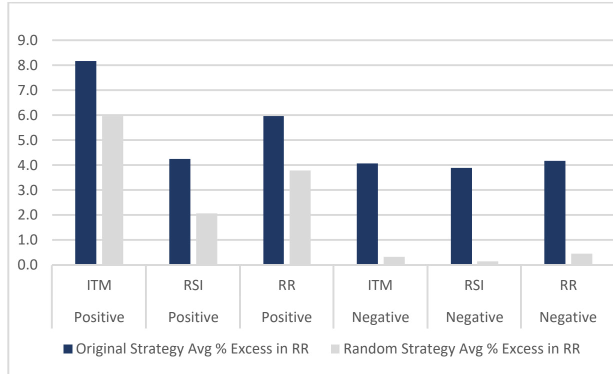
Exhibit 16: For the SPX we see improvement in the strategy by using filters in the original signal. The RR and hit rate (ITM) classifiers can improve the performance of the strategy.

Average relative range % for the SPX filtered signals using RR-based, hit rate-based, and RSI-based classification labels

Source: J.P. Morgan

Exhibit 17: For the US 10-year note we also see improvement in the strategy by using filters in the original signal. The RR and hit rate (ITM) classifiers show strategy improvement.

Average relative range % for the SPX filtered signals using RR-based, hit rate-based, and RSI-based classification labels



Source: J.P. Morgan

From **Exhibit 16** and **Exhibit 17** we can clearly draw two important conclusions. First, our machine learning filters on traditional technical signals improve the average performance of a strategy built on them. **Across all different classification labels and sides of the market, the filter signals improve *both* the random and original strategy. As we continue this series of analysis of quantifying technical analysis with AI and machine learning, this conclusion shows that there is value to enhancing our work using these techniques**. **Second, there is value in the enhancement of the classification labeling using the path of the price series over the hold period. From the results above, we see that RSI is the laggard in performance (except for the negative SPX signals), which indicates that the other two metrics provide more explanatory value.** This will continue to be explored and further tested as we scale our filters to multiple asset classes.

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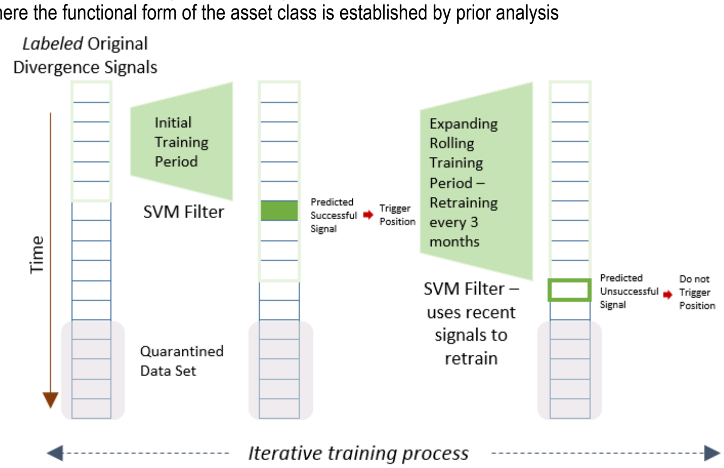
Automating our SVM framework to scale the build of filter models

Tackling multiple issuers in an automated fashion

To scale our process of model construction across different tickers and markets, we have standardized and automated our filter creation process. The drivers in our models are a combination of price-based measures that we have empirically found to offer some value, all of which are characteristics of price trend behavior before the signal event (see 6/12/18 publication here). Note that in this exercise we assume that the set of drivers are constant and measure the impact of the classification label on the strategy that follows from it. While we understand that the combination of drivers and label may be a factor in the success of the model, our analysis targets to understand whether more valuable labels for our signals exist past the work that we completed in our prior note. All of the labeling methodologies proposed are a direct function of price, so we expect the drivers to be sufficient in explaining different variations in our predicted variable.

Exhibit 18: Automatic training process to build filters on the original divergence signal: we use an expanding rolling window that categorizes the next signal based on the information from signals in the past.

High-level overview of the training and retraining process of our filters, Hyper parameters are found in an offline process where the functional form of the asset class is established by prior analysis



Source: J.P. Morgan

Exhibit 18 shows an overview of the training process for each filter. The model calibration and training process is done in multiple stages, starting with a grid search to define of the model parameters (hyper parameters) for each security. Our machine learning tool of choice for categorization is an SVM. To define the hyper parameters, we perform a search over the decision boundary type (kernel), its coefficient (gamma) and the regularization parameter (cost). We measure the success of the parameters by leveraging cross-validation and use a weighted f1 score as one of the metrics of success in order to account for unbalanced classes in the sample. This scoring metric also easily enables the usage of multiple labels in the RR methodology if we choose to do so. We stick to a fully automated search of optimal gamma and cost, but given our prior work have the predefined functional form for US Treasuries (a third-degree polynomial), and equities (an RBF model).

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We set aside over three-and-a-half years of data in our sample as quarantine (data not used for the initial model selection and training).

Once the model parameters are determined, the training process for the classifier employs an expanding training window of three months, starting with ten years of history (1998 to 2008). Note that in an expanding training window the model is retrained every three months incorporating the signals that were recently observed as additional training data. The results we show in this note are the outcome of executing a strategy that leverages the out-of-sample prediction of the model as a trigger. The iterative training process is described in **Exhibit 18**.

To measure the stability of our filter-base classifiers, we review the usual metrics for the performance out-of-sample. In this case, we mean out-of-sample as those triggers that executed based on the model training window before their date. We leverage an f1-weighted score for the automation of the training but still see that the accuracy (the percent labels predicted successfully), precision and recall (measures of true positives and false negatives) across the different filters are reasonable. The worst-performing models are generally the RSI-based filters, another reason for us to explore moving away from this metric. The results for the period of signals between 2009 and 2016 are shown in **Exhibit 19**.

Exhibit 19: Average metrics to measure the performance of the filter-based classifiers for this analysis show that the automatic selection of parameters leads to good models, particularly for RR-based classifiers.

Average classifier performance out-of-sample - signals triggered between 2009 and 2016

	Average across all hold periods		
	Accuracy	**F1_Score**	**AUC**
SPX Index			
RR	59.9	53.7	58.3
Hit rate	60.1	52.5	56.1
RSI	54.6	56.5	55.5
USGG10YR Index			
RR	61.1	72.0	53.3
Hit rate	57.4	59.4	59.1
RSI	51.6	50.4	49.9

Source: J.P. Morgan

Average across all hold periods

When looking at the performance of purely the quarantined data set, which represents those signals that were not used for the training of any hyper parameters (the period from 2016 to August 2019), we see indication of decent classifier performance for the RR-based filters. This is shown in **Exhibit 20**.

Exhibit 20: Average metrics to measure the performance of the filter-based classifiers during the quarantine period. This is the period where no data interfered with model parameter calibration.

Average classifier performance in the quarantine period - signals triggered between 2016 and August 2019

	Positive	**Accuracy**	**AUC**	**Negative**	**Accuracy**	**AUC**
SPX Index	RR	68.3	60.7	RR	55.5	53.5
	Hit rate	63.5	55.4	Hit rate	62.3	53.0
	RSI	61.9	62.3	RSI	53.9	53.6
USGG10YR Index	RR	58.7	63.1	RR	*43.6*	*39.7*
	Hit rate	58.1	54.1	Hit rate	*41.0*	*37.6*
	RSI	53.5	55.8	RSI	*46.2*	*47.5*

Source: J.P. Morgan

As we have seen throughout this note, the US 10-year note models show weakness in the negative signals – the classifier struggles to properly address this sample. We continue to explore ways to improve this classifier (including modifying the driver set) but otherwise, we see promise in our automated model selection elsewhere in our experiment set. We will extend the framework above to cover more tickers and asset

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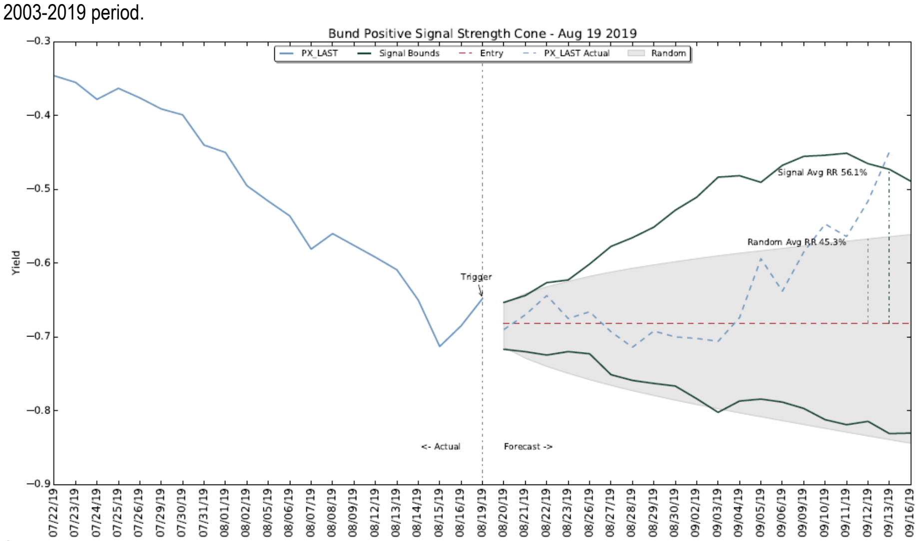
classes in an automated fashion. **This process is an example of using machine learning to scale our filters and creating a self-learning ecosystem.**

Forecast cones offer a way to comprehensively illustrate signal outcomes and compare them with random trade entry

Just as we theorize a simple hit rate provides limited information for a data classification exercise, we also feel the statistic fails to comprehensively describe signal outcomes. To address the issue, we developed a forecast cone illustration that allows comparison of the signal subset to the overall data set in normalized terms (**Exhibit 21**). The illustration not only allows the user to compare the relative cone symmetry around the theoretical entry level to determine a directional bias; the competitive cone widths also provide a volatility forecast as well.

Exhibit 21: We developed a forecast cone illustration to quickly portray the differential between past signal outcomes and all outcomes within the test period (a measure of random entry) and put those statistics in the context of the current market environment. We normalize past outcomes by a level of realized volatility when the signal was triggered. The average and standard error statistics of the two data sets are used to create the normalized forecast cones. Those cones are then rescaled by the same measure of realized volatility at the most recent signal.

10-year Bund yield, most recent RX dollar-weighted Put/Call ratio sell signal, theoretical entry level, 1-sigma cone derived from all price action in the 2003-2019 period, 1-sigma forecast cone derived from past sell signals win the 2003-2019 period.



Source: J.P. Morgan

Construction

Rescaling outcomes by a measure of realized volatility at the time of trade entry

While developing the forecast cone illustration, we quickly realized a data normalization mechanism was required to properly calculate most of the elements portrayed in **Exhibit 21**. Markets have wildly different betas to each other, and even within a single market, volatility regimes shift regularly. To properly utilize any aggregation of past outcomes as a potential forecast signal within a single market, or

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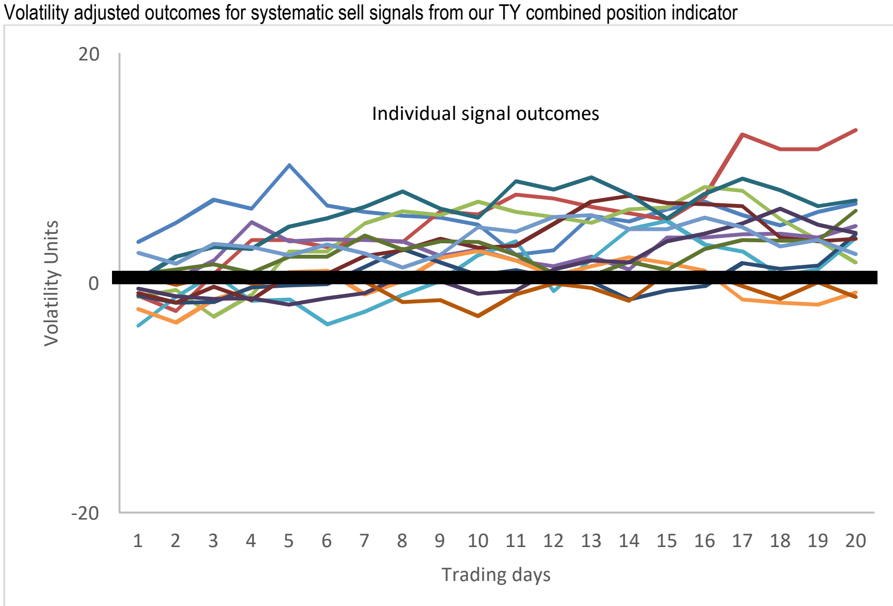
to study behaviors across different markets and asset classes, we rescale the outcome by the realized volatility at the time of trade signal. To do this, we simply divide the bp change or price percentage change from the trade entry level (next period Open) by the average of absolute 1-period changes over the 60-periods before the trade signal.

Cone creation

The graphic in **Exhibit 21** contains five key elements: price history before the trade signal, realized price trajectory after the signal, entry level, 1-sigma forecast cone, 1-sigma cone for random trade entry (assumes trade entry on every period within the data set). The market price information is self-explanatory. We are initially using Close data, but intend to incorporate full Open, High, Low, Close price bars in the future. For trade entry, we use the Open price for the period after the systematic trade signal was triggered. The 1-sigma signal forecast and random trade entry cones are constructed in the same fashion, but the signal cones only use the subset of data identified by the systematic strategy employed. The random cone utilizes all data within the study period.

Exhibit 22: The version of our system that combines CFTC position data and the TY dollar-weighted Put/Call ratio that runs on a weekly time frame produced a handful of sell signals since 2002. The infrequent signals provide an ideal example to illustrate the steps for forecast cone construction. This exhibit portrays all of the signal outcomes in volatility-adjusted terms...

Volatility adjusted outcomes for systematic sell signals from our TY combined position indicator

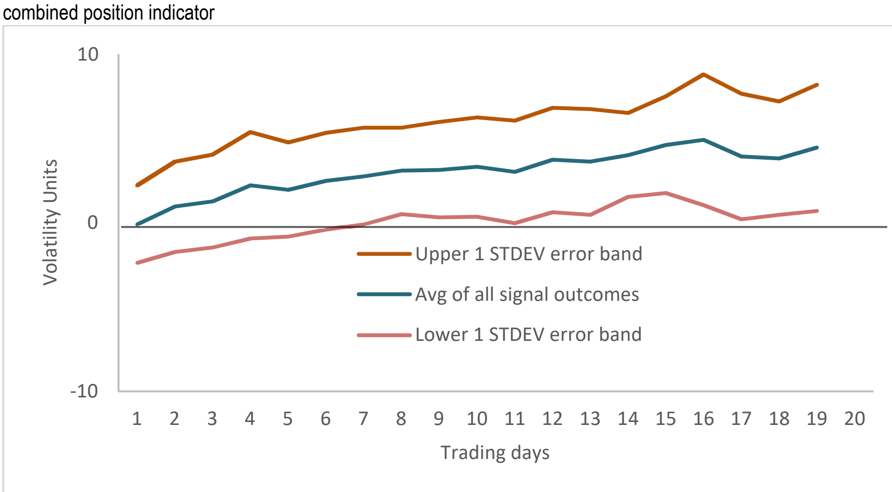


Source: J.P. Morgan

To construct the forecast cone, we average the volatility-adjusted outcomes for each day of the hold period. The one standard deviation bands surrounding that average create the cone over the 20-period window. **Exhibit 22** shows the volatility adjusted outcomes for sell signals from our TY combined position indicator strategy. **Exhibit 23** illustrates the average of all signal trajectories within the subset from **Exhibit 22** and the one standard deviation bands.

Exhibit 23: ... The forecast cone represents the daily average of those outcomes +/- 1 standard deviation. While this cone is still in volatility adjusted terms, it can easily be rescaled by the same measure of realized volatility on any of the signal triggers to put it in the context of the market at that time.

Daily average and 1 standard deviation range of volatility adjusted outcomes for systematic sell signals from our TY combined position indicator



Source: J.P. Morgan

Analysis

Signal subset differentiation from full data set (random entry)

As noted in the section describing Relative Range as a classifier, the bimodal distribution of outcomes for most markets over 5-day, 10-day, and 20-day hold periods tended to yield an average that sat not too far away from the 50% mark. The cone illustration of full data set outcomes for most markets we looked at showed a similar characteristic insofar as the cone distribution surrounding the theoretical entry level did not stray too far from 50:50 (in the money: out of the money). By design, the cone is also as much a study of the average historical realized volatility profile as it is a study of the slight bullish or bearish bias within that market over the test period. Using the full data set cone as a representation of random entry statistics, algorithmically identified technical states that produce signal cones with substantial differentiation from the random cone offer potential trade signals. Graphically, the cone illustration presents a type of Venn diagram, where we are not only concerned with the unique and common areas, but we are also referencing the cone distributions surrounding the theoretical entry level.

The upper panel of **Exhibit 24** shows the TY combined position indicator sell signal forecast cone rescaled to the level of realized volatility at the time of the last signal and anchored to the theoretical entry yield level. The grayed cone in that exhibit portrays the random entry cone. The lower panel shows two statistics over the life of the trade hold period, the cone differential and hit rate differential. The cone differential represents the in-the-money percentage of the signal forecast cone minus the in-the-money percentage of the random cone on a specific day during the hold period. The hit-rate differential is simply the signal success rate minus the random success rate on a specific day during the hold period.

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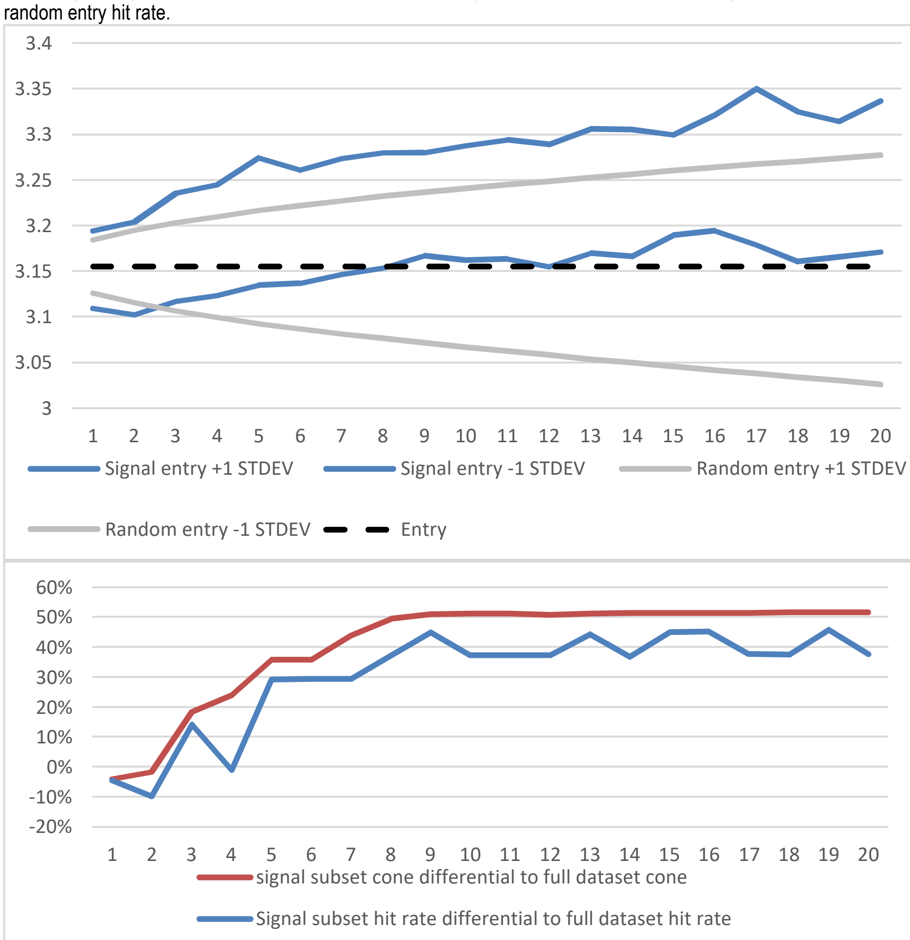
Exhibit 24: We focus on the percentage of the forecast cone that exists above the theoretical entry level and compare that signal cone statistic with the random entry cone. The more traditional hit-rate statistic seems to correlate with that measure.

Upper panel: 1 sigma cone from Exhibit c rescaled by the realized volatility measure as of the last sell signal, and a 1 sigma forecast cone that assumes trade entry for every period within the full dataset. Lower panel: Daily profitable percentage of signal forecast cone minus profitable percentage of random entry cone. Daily signal entry hit rate minus random entry hit rate.



Source: J.P. Morgan

The TY combined position indicator sell signal statistics illustrated in **Exhibit 24** show substantial differentiation from random outcomes through most of the 20-day hold period. From day 5 through 20, both cone and hit rate show 30% or more differentiation. Most systematic technical strategies we have developed do not come close to that level of differentiation, and we suspect the statistics for that particular strategy will moderate over time as more signals occur. The example below provides differential statistics that are more representative of the majority of entry signal algorithms we have developed (**Exhibit 25**). The signal forecast cone represents past outcomes from our bearish momentum divergence signal for the 10-year note with a Machine Learning filter that utilizes lower-frequency trend characteristics as drivers. The signal and random entry cone have nearly 80% in common, which visually offers little differentiation. However, it's important to note that even subtle cone differentiation can have a meaningful impact on more commonly used trade statistics like hit rate. In this case, that which appears to look like a small bias on the cone chart provides a roughly 15% improved hit rate over randomly entered short trades through much of the 20-day hold period.

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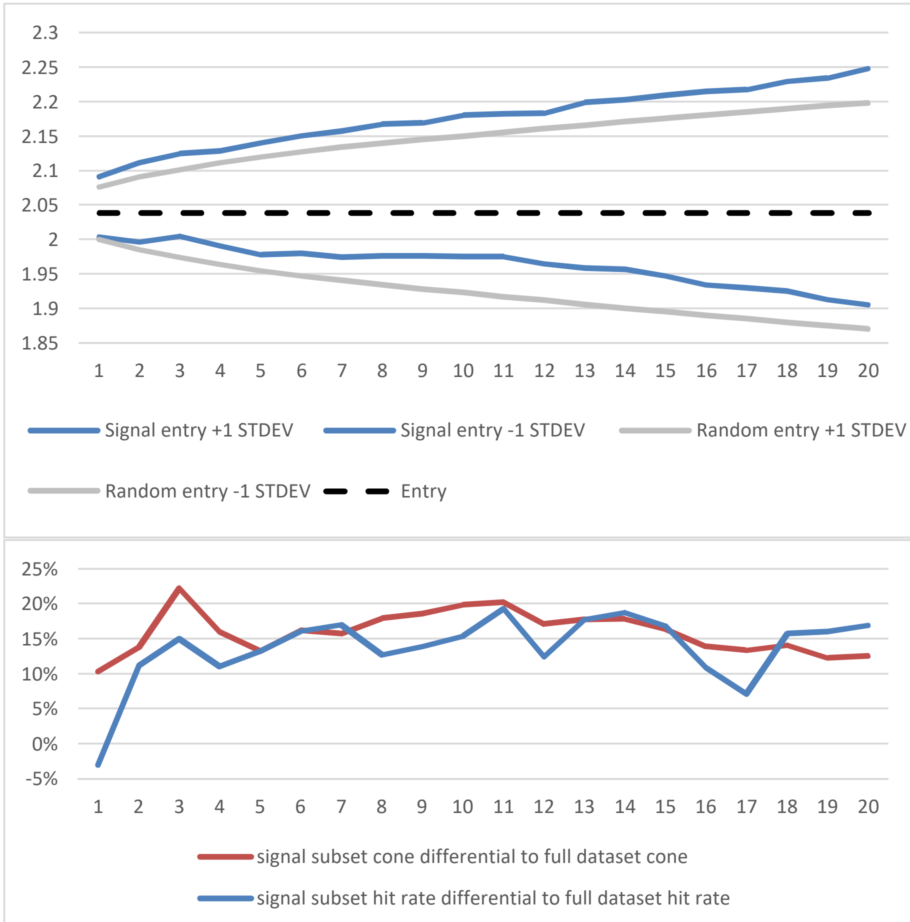
Exhibit 25: Large-scale visual separation between the signal and random cones presents a high hurdle. Even what appears to look like a marginal separation generated by this signal corresponds with a 10-15% improved hit rate through most of the 20-day hold period.

Upper panel: 1 sigma cone for 10-year note momentum divergence sell signal (w/ SVM filter) rescaled by the realized volatility measure as of the last sell signal, and a 1 sigma forecast cone that assumes trade entry for every period within the full dataset. Lower panel: Daily profitable percentage of signal forecast cone minus profitable percentage of random entry cone. Daily signal entry hit rate minus random entry hit rate.



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