MACRO STRATEGY

Machine-Learned Ranking Algorithms for Implied Volatility Prediction

July 9, 2020

Summary

Predictions of the value of the implied volatility of an FX pair are commonly used as inputs to pricing models in an FX option trading strategy. Depending on the trading strategy, however, a metric that quantifies implied volatility relatively across currencies can be of supplemental value or of more interest than level prediction for a single currency.

- Predictions of the relative magnitude of movement among the implied volatilities of FX pairs using pairwise ranking algorithms typically used for collaborative filtering and search algorithms consistently outperform predictions derived from standard implied volatility forecasts.
- Rank modeling shows that PCA components derived from equity and commodity indicators are the key drivers for both short and long-term forecasts and the change in implied volatility surfaces are of primary importance in short-term forecasts.
- The ensembling of independent forecasts of level, direction, and relative magnitude of implied volatility can be used in establishing forecast confidence and informing a trading strategy.

MetLife Investment Management

1. Introduction

One key idea of our FX Implied Volatility (IV) research is to develop independent models to predict three different targets; the level, direction of movement and relative magnitude of movement among the implied volatilities of FX pairs. If all three predictions confirm each other, it would create higher confidence about the forecasts. Combining the three forecasts can be helpful in increasing profitability of an FX option trading strategy. In our prior published papers [1,2,3] we have applied various machine learning algorithms to predict levels and directions of implied volatilities in 1 day, 1 week and 1 month forecasting horizons. In this study, we apply learning-to-rank algorithms to predict the relative magnitude of movement among the implied volatilities of eight FX pairs.

Machine-Learned Ranking, or Learning-to-Rank, is a class of algorithms that apply machine learning approaches to solve ranking problems. Ranking algorithms were originally developed for information retrieval problems. Recently, however, they have been used in a wide range of applications including recommendation systems, computational biology, and software engineering. Learning-to-rank algorithms can be categorized into three groups based on their problem formulations: pointwise approaches, pairwise approaches, and listwise approaches. The pointwise approach is to predict a quantitative score associated with each element in a list to be ranked. Pointwise approach includes Pranking [4], McRank [5] , and Ordinal Classification Support Vector Machine (OC SVM) [6]. The pairwise approach formulates the problem as a sequence of binary classifications. Pairwise approaches, while typically more computationally intensive than pointwise approaches, have the clear advantage of incorporating relationships between pairs of items. Pairwise approaches include PolyRank [7], SortNet [8], RankNet [9], and RankSVM [10]. The listwise approach is perhaps the most direct approach to the ranking problem. These algorithms seek to directly minimize loss defined by some evaluation metric as a function of observed rankings in a training dataset. Listwise approach includes ListMLE [11], ListNet [11], and AdaRank [12]. The choice of approach depends on the application. In the application of the prediction of relative magnitude of implied volatilities, we propose to use a pairwise approach, for performance and computational reasons that will be discussed in Section 2.

2. Methodology

2.1. Data

The data (source: Bloomberg) used in this study consisted of 75 points of the implied volatility surface at the daily level for eight foreign exchange currencies from January 1, 2014 till June 11, 2019. The 75 points corresponded to five values of delta: 10 Call, 25 Call, At the Money (ATM), 25 Put and 10 Put, and fifteen values of expiry: 1, 2, and 3 weeks, 1, 2, 3, 4, 6, and 9 months, 1, 1.5, 2, 3, 4 and 5 years out. The feature data consisted of 2,182 economic feature variables categorized by Commodity, Equity, Economic, Yield, Interest Rate, Currency Historical, Currency Implied Volatility, Currency Spot, EM Sector, and S&P 500 Sector data.

We first construct a training dataset for our problem by creating rankings of pairs across history. Of interest is relative, not absolute, magnitudes of movements. That is, since FOREX pairs have different mean and variance levels of volatility, we must first standardize historical values in order to compare movements on the same scale. Additionally, since the distribution of historical volatilities vary in levels of deviation from normality, we fit Box-Cox transformations to each point of every pair before calculating Z-scores to use as the quantitative value for generating historical rankings. That is, for the volatility value $y_{d,e,t}$ of a given pair for delta d, expiry e, and time t, we calculate

$$Y_{d,e,t}^{(\lambda)} = \frac{y_{d,e,t}^{\lambda}}{\lambda - 1}$$

where λ maximizes a Normal likelihood of data for a pair, delta, expiry combination. We then compute the Z-scores of the transformed variables over time and generate ranks $r_{p,d,e,t}$ by ranking the eight pairs' Z-scores for each day.

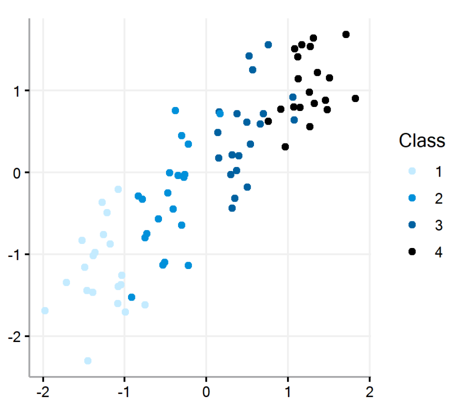
2.2. Formulation of Ranking Problem

The typical problem in implied volatility (IV) modelling is level forecasting. That is, to learning a prediction function $\hat{y}_{t+1} = f(X_t)$ that predicts future values of implied volatility given a feature space X_t associated with time t. The ranking problem, however, seeks to learn a ranking function $\hat{r}_{t+1} = f(X_t)$ that maps a list of items to a ranked list based on some quantitative context. In our application, f maps a list of exchange rates to a predicted list ordered by movement in implied volatility. Exchange rates expected to have a large relative decrease in IV will have a low rank in the prediction vector, while exchange rates expected to have large relative increase in IV will have a high rank.

2.3. Pointwise Approach

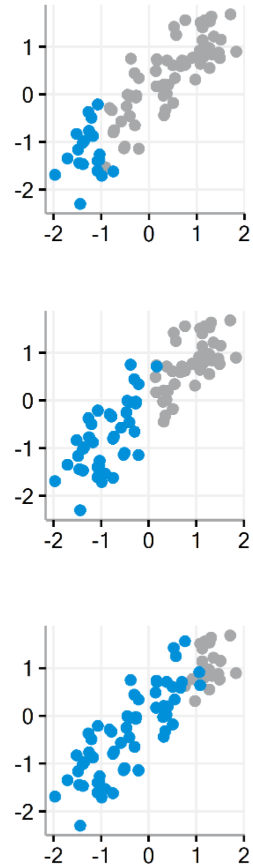
In the pointwise approach, we assume that for a point on the IV surface each currency has some numerical score associated with it depending on the date. Then the rank problem is approximated by a regression problem or by an ordinal regression problem. This assumption, of course, ignores interactions between subjects and group structure in the ranking problem. We include this approach for completion as well as an illustration of the significance of the interaction and group structure. As previously noted, there are a number of pointwise approaches to ranking, including Subset Ranking [9], McRank, Prank, and SVM. We will consider here just an ordinal classification SVM. A k-class ordinal classification problem can be transformed to $k-1$ binary classification problems. Using the methodology described in the referenced work, for a single rank prediction, we fit $k-1$ linear SVM classifications to binary responses using predictors engineered from our feature set. The features were generated via principal components analysis (PCA) dimensionality reduction. Specifically, for each category of feature, we performed a separate PCA and took the components found to be correlated with the classification labels. We discuss the variables selected to be predictive of rank in Section 2.7. The resulting ordinal classifications for each currency were used to rank the currencies. This approach to ordinal classification is visualized in Figure 1 and 2.

Figure 1: Ordinal Classification Problem



Source: MetLife Investment Management

Figure 2: Ordinal Classification as Binary Classification



Source: MetLife Investment Management

2.4. Listwise Approach

The listwise approach to ranking is to consider ranked lists as instances and to train a ranking function through the minimization of a listwise loss function. Typical loss functions are based on Kullback–Leibler divergence, mean average precision, and log-likelihood. To illustrate, we consider the ListMLE algorithm as proposed in [7]. Given observed rankings y and feature vectors x, ListMLE seeks a scoring function g by maximizing the sum of the log-likelihood functions

$$\sum_{i=1}^{n} \log \mathbf{P}(\boldsymbol{y}^{(i)}; \boldsymbol{x}^{(i)}, \boldsymbol{g})$$

where

$$\mathbf{P}(\boldsymbol{y}^{(i)}; \boldsymbol{x}^{(i)}, \boldsymbol{g}) = \prod_{i=1}^{n} \frac{\exp\left(g\left(x_{y(i)}\right)\right)}{\sum_{k=i}^{n} \exp\left(g\left(x_{y(i)}\right)\right)}$$

That is, the likelihood function of a Placket-Luce model. The scoring function is typically chosen as a linear Neural Network.

2.5. Pairwise Approach

In the pairwise approach, ranking is transformed into pairwise classification problem. That is, for a given delta and expiry combination, we generate a dataset of pairwise rankings $y_{i,j,t}$ where i indexes one pair, $j > i$ indexes another as

$$y_{i,j,t} = I(\text{Pair } i < \text{Pair } j)$$

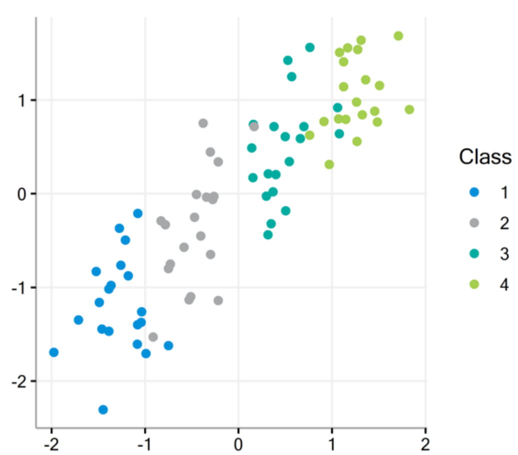
To solve such a problem, we transform our input data using the pairwise transform. That is, we form the difference of all elements in the list of items to be ranked such that our data is transformed to

$$(x'_k, y'_k) = (x_i - x_j, \text{sign}(r_i - r_j))$$

The result of the pairwise transformation is input data to a binary classification problem for each pair of currencies. In fact, for k currencies, we have $\frac{k(k-1)}{2}$ such problems. The results of a binary classification of $I(\text{Pair } i < \text{Pair } j)$ is a probability:

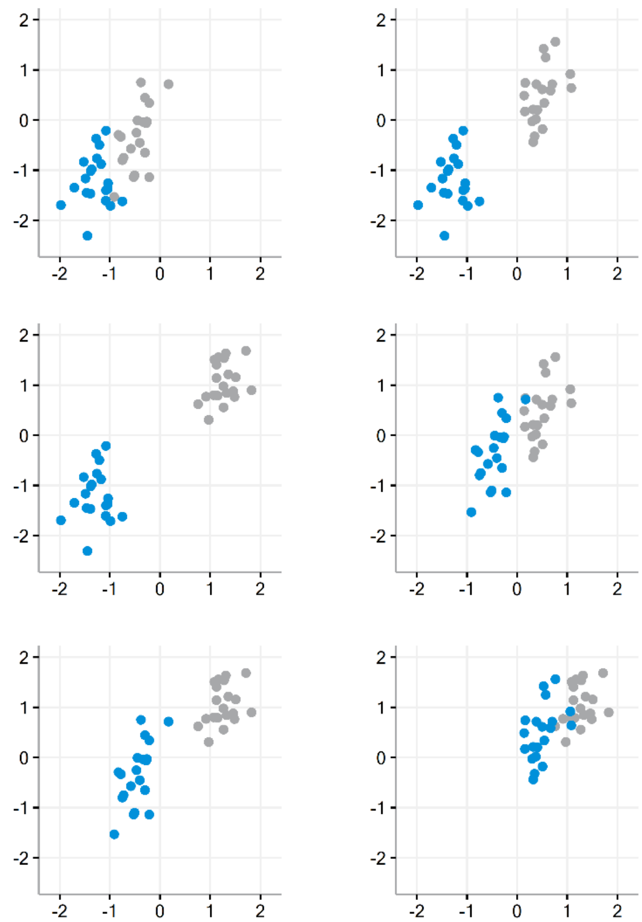
$$\begin{aligned}\hat{\pi}_{i,j,t} &= \widehat{\mathrm{P}}(y_{i,j,t} = 1)\\ &= \widehat{\mathrm{P}}(\text{Pair } i < \text{Pair } j)\end{aligned}$$

Figure 3: Pairwise Classification Problem



Source: MetLife Investment Management

Figure 4: Pairwise Classification as Binary Classification



Source: MetLife Investment Management

This approach to pairwise comparisons through binary classification is illustrated in Figure 3 and 4.

While the RankSVM uses a Support Vector Machine to fit $\hat{\pi}_{i,j,t}$, any linear model could be used. We use a logistic regression with an elastic net penalty [17] as we found it to provide better out of sample performance as well as computational performance. For a date t and delta-expiry point, we get a matrix of predicted probabilities like the one in Table 1.

Table 1: Matrix of Predicted Pairwise Probabilities

	AUDUSD	USDMXN	...	EURUSD
AUDUSD	-	$\hat{\pi}_{1,2}$	...	$\hat{\pi}_{1,8}$
USDMXN	$1-\hat{\pi}_{1,2}$	-		
...	...			
EURUSD	$1-\hat{\pi}_{1,8}$			-

Source: MetLife Investment Management

Note, that there is no clear resulting ranking from this matrix. Here, to transform these results to a ranking, we propose to fit the Bradley-Terry probability model to the matrix. That is, we make the model assumption

$$\mathrm{P}(i<j)=\frac{p_j}{p_i+p_j}$$

where p_i and p_j are positive values assigned to currency i and j respectively. That is, the probability that the movement of pair i is less than the movement of pair j is a function of two arbitrary "scores" inherent to each pair independent of the pair it is being compared to.

For fitting the values of p_i, we maximize a binomial likelihood function of observed values $\mathrm{P}(i<j)$. That is, for $p=(p_1,\dots,p_k)$,

$$p=\max_{\boldsymbol{p}}\sum_{i}^{n}\sum_{j}^{n} w_{ij}\log p_i - w_{ij}\log(p_i+p_j)$$

where $w_{ij}=\sum y_{ij}$. The result is a fitted value of p_i for each pair in our matrix. The predicted rank for a given date, delta, expiry combination is thus the ordering of the scores of the pairs.

3. Results

3.1. Key Drivers

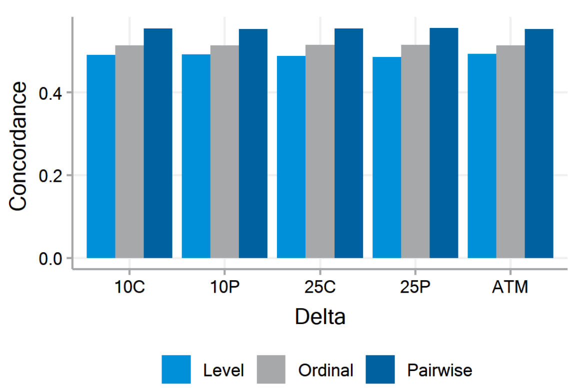
Key drivers of the rank of the list of FX currencies are identified through each of the modelling approaches. We propose the pairwise model for this application based on predictive performance and computational considerations and therefore present the variables considered by the pairwise model as the key drivers of rank. Using AUC (Area-under-curve) as a performance metric, we found the most predictive features in both the short and long-term forecasts to be PCA components derived from equity and commodity data, as well as change in implied volatility surfaces for short term forecasts. The variation in the response explained by the components generated from these sets was about equal. The components generated from the other feature sets offered no additional predictive power.

3.2. Out of Sample Performance

We now observe the out-of-sample performance of the proposed methods compared to a benchmark. The metric chosen for evaluating ranking models was percentage of concordant pairs of ranked predictions with out-of-sample actual rankings. That is, for a given hold-out date, a training dataset was generated from all data preceding the hold out date using the methods explained in the previous section, as well as a test data set from all data following the hold out date. Then for dates t following the hold out date, we have rank predictions $\hat{y}_{i,j,t}$ and out-of-sample actual predictions $\hat{y}_{i,j,t}$. In vector notation, we have two 8-dimensional vectors $\hat{y}$ and y. There are thus $\frac{8\times7}{2}=28$ pairs of two elements each from $\hat{y}$ and y. A pair is called concordant when the pairs of elements have the same ordering. To establish a benchmark model, we generate rank predictions derived from forecasts from a level model. Specifically, these benchmark predictions are derived from IV level forecasts from an order-5 Vector-Autoregression (VAR) model. To convert these level forecasts to rank predictions, we applied the same Box-Cox transformation to the level forecasts as in the generation of the training data and took their Z-scores. For each expiry-delta combination, the Z-scores corresponding to each pair were ranked, resulting in what is referred to in what follows as the level-derived rank prediction. We also generate rank predictions using both a pointwise and pairwise approach. Specifically, we use an ordinal SVM for the pointwise approach and a logistic regression with an elastic net penalty [17] for the pairwise approach. We can see a clear increase in ranking concordance and in pairwise accuracy from the benchmark to the proposed models, specifically the pairwise ranking model. We therefore propose the pairwise approach in application both for performance and for computational reasons.

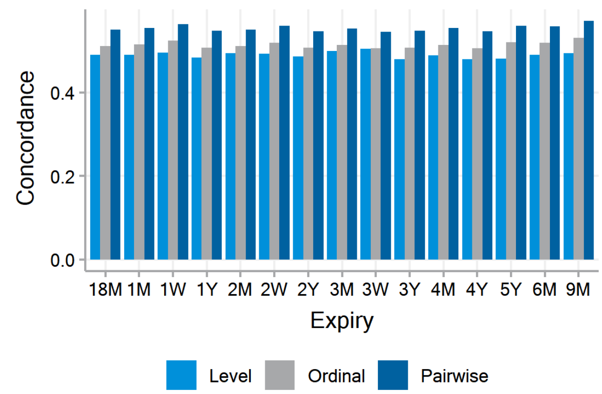
Figure 5 and 6 give the out-of-sample concordance values by delta and by expiry. Concordance here is defined the number of concordant couples of FX currencies divided by the total number of couples. Tables 2-4 give the out-of-sample pairwise comparison prediction accuracies by Expiry and days out for the ATM delta. When the pairwise ranking of two currencies is more applicable to a trading strategy, these metrics will be more insightful. The results of these tables imply no significant difference between deltas. Short term forecasts perform better than the longer-term forecasts for shorter expiries, while long term forecasts perform better than the short-term forecasts for longer expiries. Additionally, some currency pairs appear to be more easily predicted than others, e.g. the GPBUSD and USDBRL pair.

Figure 5: Out-of-Sample Concordance by Delta



Source: MetLife Investment Management

Figure 6: Out of Sample Concordance by Expiry



Source: MetLife Investment Management

Table 2: 1 day out pairwise prediction performance for the ATM delta

1 Day Out	1W	1M	3M	6M	1Y	3Y	5Y
AUDUSD>USDKRW	0.57	0.59	0.59	0.61	0.58	0.62	0.62
AUDUSD>GBPUSD	0.64	0.61	0.65	0.63	0.63	0.6	0.6
AUDUSD>EURUSD	0.64	0.63	0.62	0.63	0.64	0.64	0.62
AUDUSD>USDCAD	0.58	0.6	0.51	0.61	0.55	0.55	0.57
AUDUSD>USDJPY	0.61	0.68	0.64	0.62	0.57	0.58	0.6
AUDUSD>USDMXN	0.61	0.61	0.62	0.57	0.62	0.6	0.59
AUDUSD>USDBRL	0.52	0.52	0.52	0.5	0.52	0.53	0.49
USDKRW>GBPUSD	0.56	0.58	0.55	0.57	0.56	0.53	0.57
USDKRW>EURUSD	0.62	0.63	0.65	0.63	0.62	0.59	0.62
USDKRW>USDCAD	0.55	0.56	0.58	0.56	0.58	0.54	0.58
USDKRW>USDJPY	0.55	0.59	0.62	0.6	0.57	0.58	0.58
USDKRW>USDMXN	0.61	0.62	0.58	0.61	0.51	0.57	0.59
USDKRW>USDBRL	0.74	0.75	0.73	0.72	0.6	0.68	0.69
GBPUSD>EURUSD	0.67	0.74	0.7	0.69	0.64	0.6	0.63
GBPUSD>USDCAD	0.62	0.59	0.58	0.62	0.57	0.54	0.59
GBPUSD>USDJPY	0.7	0.72	0.71	0.73	0.68	0.65	0.63
GBPUSD>USDMXN	0.62	0.65	0.59	0.62	0.55	0.51	0.55
GBPUSD>USDBRL	0.78	0.75	0.72	0.71	0.75	0.67	0.67
EURUSD>USDCAD	0.67	0.69	0.64	0.67	0.67	0.65	0.64
EURUSD>USDJPY	0.59	0.66	0.63	0.66	0.65	0.5	0.58
EURUSD>USDMXN	0.69	0.73	0.67	0.7	0.69	0.68	0.63
EURUSD>USDBRL	0.55	0.65	0.59	0.61	0.63	0.7	0.61
USDCAD>USDJPY	0.52	0.57	0.55	0.56	0.55	0.55	0.51
USDCAD>USDMXN	0.63	0.63	0.66	0.62	0.62	0.64	0.6
USDCAD>USDBRL	0.6	0.65	0.6	0.63	0.06	0.63	0.57
USDJPY>USDMXN	0.52	0.58	0.55	0.56	0.56	0.56	0.57
USDJPY>USDBRL	0.62	0.62	0.59	0.62	0.62	0.66	0.61
USDMXN>USDBRL	0.56	0.54	0.49	0.54	0.55	0.55	0.54

Source: MetLife Investment Management

Table 3: 5 day out pairwise prediction performance for the ATM delta

5 Day Out	1W	1M	3M	6M	1Y	3Y	5Y
AUDUSD>USDKRW	0.6	0.64	0.63	0.62	0.6	0.61	0.63
AUDUSD>GBPUSD	0.62	0.64	0.66	0.61	0.62	0.59	0.6
AUDUSD>EURUSD	0.66	0.66	0.66	0.63	0.6	0.62	0.56
AUDUSD>USDCAD	0.58	0.59	0.56	0.63	0.58	0.59	0.58
AUDUSD>USDJPY	0.58	0.63	0.67	0.63	0.56	0.6	0.59
AUDUSD>USDMXN	0.61	0.57	0.61	0.6	0.58	0.58	0.58
AUDUSD>USDBRL	0.55	0.55	0.57	0.54	0.54	0.55	0.58
USDKRW>GBPUSD	0.57	0.58	0.55	0.58	0.53	0.5	0.54
USDKRW>EURUSD	0.62	0.61	0.63	0.59	0.6	0.59	0.56
USDKRW>USDCAD	0.5	0.54	0.61	0.58	0.56	0.65	0.55
USDKRW>USDJPY	0.6	0.67	0.57	0.59	0.61	0.58	0.59
USDKRW>USDMXN	0.6	0.65	0.55	0.59	0.53	0.6	0.57
USDKRW>USDBRL	0.69	0.71	0.63	0.69	0.68	0.68	0.63
GBPUSD>EURUSD	0.65	0.72	0.6	0.69	0.63	0.58	0.6
GBPUSD>USDCAD	0.56	0.55	0.62	0.57	0.56	0.56	0.57
GBPUSD>USDJPY	0.7	0.68	0.62	0.71	0.65	0.63	0.62
GBPUSD>USDMXN	0.59	0.63	0.72	0.61	0.54	0.55	0.57
GBPUSD>USDBRL	0.74	0.75	0.7	0.72	0.69	0.63	0.66
EURUSD>USDCAD	0.65	0.68	0.57	0.7	0.61	0.64	0.63
EURUSD>USDJPY	0.62	0.63	0.64	0.65	0.6	0.58	0.59
EURUSD>USDMXN	0.7	0.71	0.7	0.71	0.67	0.62	0.66
EURUSD>USDBRL	0.56	0.63	0.61	0.64	0.62	0.67	0.63
USDCAD>USDJPY	0.55	0.55	0.51	0.53	0.53	0.51	0.47
USDCAD>USDMXN	0.62	0.61	0.62	0.61	0.6	0.61	0.55
USDCAD>USDBRL	0.62	0.63	0.63	0.59	0.6	0.64	0.6
USDJPY>USDMXN	0.51	0.58	0.52	0.57	0.57	0.59	0.53
USDJPY>USDBRL	0.6	0.61	0.6	0.59	0.6	0.63	0.63
USDMXN>USDBRL	0.54	0.55	0.5	0.58	0.54	0.56	0.55

Source: MetLife Investment Management

Table 4: 21 day out pairwise prediction performance for the ATM delta

21 Day Out	1W	1M	3M	6M	1Y	3Y	5Y
AUDUSD>USDKRW	0.61	0.65	0.6	0.63	0.61	0.61	0.62
AUDUSD>GBPUSD	0.62	0.62	0.65	0.61	0.59	0.58	0.55
AUDUSD>EURUSD	0.62	0.63	0.62	0.64	0.55	0.59	0.52
AUDUSD>USDCAD	0.59	0.6	0.57	0.59	0.55	0.56	0.53
AUDUSD>USDJPY	0.63	0.68	0.6	0.61	0.59	0.61	0.58
AUDUSD>USDMXN	0.6	0.59	0.64	0.6	0.56	0.55	0.55
AUDUSD>USDBRL	0.53	0.54	0.56	0.51	0.56	0.59	0.56
USDKRW>GBPUSD	0.5	0.53	0.55	0.54	0.56	0.57	0.55
USDKRW>EURUSD	0.63	0.56	0.62	0.59	0.54	0.55	0.52
USDKRW>USDCAD	0.54	0.55	0.68	0.57	0.54	0.54	0.57
USDKRW>USDJPY	0.55	0.62	0.68	0.58	0.58	0.56	0.59
USDKRW>USDMXN	0.63	0.68	0.69	0.6	0.59	0.6	0.58
USDKRW>USDBRL	0.67	0.68	0.69	0.69	0.64	0.63	0.65
GBPUSD>EURUSD	0.65	0.69	0.59	0.63	0.6	0.57	0.58
GBPUSD>USDCAD	0.59	0.59	0.69	0.57	0.53	0.55	0.57
GBPUSD>USDJPY	0.66	0.69	0.68	0.73	0.65	0.61	0.64
GBPUSD>USDMXN	0.64	0.68	0.71	0.66	0.65	0.59	0.55
GBPUSD>USDBRL	0.77	0.71	0.75	0.73	0.67	0.58	0.65
EURUSD>USDCAD	0.69	0.68	0.68	0.67	0.63	0.6	0.64
EURUSD>USDJPY	0.6	0.6	0.64	0.67	0.65	0.57	0.58
EURUSD>USDMXN	0.71	0.73	0.7	0.72	0.66	0.62	0.6
EURUSD>USDBRL	0.61	0.63	0.6	0.57	0.58	0.65	0.62
USDCAD>USDJPY	0.54	0.57	0.55	0.59	0.51	0.57	0.54
USDCAD>USDMXN	0.61	0.61	0.6	0.59	0.58	0.56	0.56
USDCAD>USDBRL	0.61	0.61	0.61	0.59	0.6	0.62	0.59
USDJPY>USDMXN	0.52	0.55	0.55	0.55	0.54	0.57	0.53
USDJPY>USDBRL	0.56	0.59	0.59	0.59	0.59	0.62	0.6
USDMXN>USDBRL	0.56	0.59	0.59	0.57	0.53	0.57	0.55

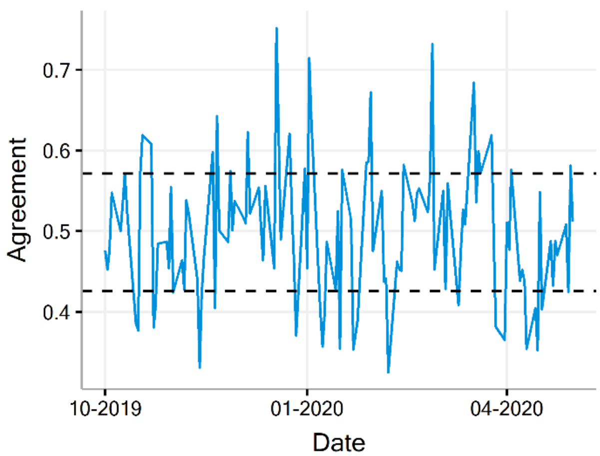
Source: MetLife Investment Management

4. Forecast Agreement

In this and previous articles, we have proposed methods of forecasting three targets of implied volatility: IV level, direction, and relative magnitude [1,2,3]. While each prediction is valuable in its own right, the ensembling of the three forecasts can establish a measure of confidence in the aggregate forecast, and provide indication of good buy/sell opportunities. We propose here a simple method of such an ensemble.

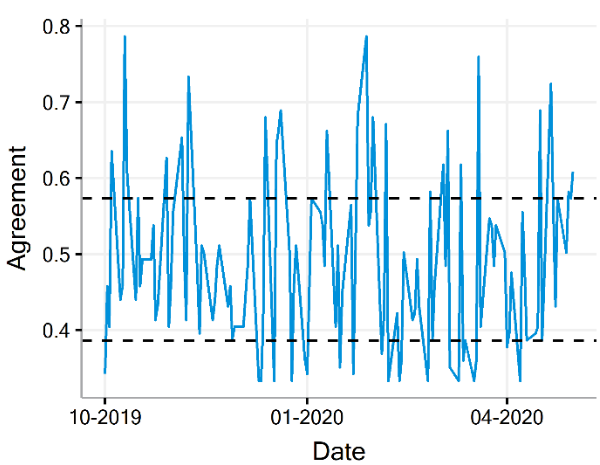
Rank forecasts can be derived from both level and direction forecasts simply by ranking the predicted values for each currency resulting in three predictions of currency rankings for any given day. Across the three rank forecasts, the pairwise concordance can be calculated, resulting in three concordance numbers for any given day. The agreement metric we propose is the mean of these three concordances. In periods of high agreement, one should be more confident in trades in contrast to periods of low forecast agreement. The forecast agreement over one year for the 1 day out forecast is plotted in Figure 7. The 10% and 90% quantiles are also indicated. These may serve as indicators given a trading strategy.

Figure 7: Forecast Agreement over all Pairs



Source: MetLife Investment Management

Figure 8: 1 day out Forecast Agreement over AUDUSD and EURUSD



Source: MetLife Investment Management

Forecast agreement for a subset of pairs may be of more interest than all currencies to a trader. In this case, the agreement can be computed by calculating the concordance over a subset of interest. The forecast agreement and quantiles for the AUDUSD and EURUSD pairs are given in Figure 8 for the 1 day out forecast. The distribution of the agreement values for the 5 and 21 day out forecasts are similar as well as for other pairs of currencies.

5. Conclusions

FX Implied volatility is essential to understanding the behaviour of option prices and to implementing profitable trading strategies. Methods of forecasting level values of implied volatility have been well studied. In the series of articles containing this entry, the forecasting of implied volatility through the combination of forecasts of multiple metrics has been proposed and explored. With this approach to the ensembling of forecasts, we can increase our confidence on timing the markets and making directional bets for Foreign Exchange options trading and hedging. In this entry, we discussed the rank target for measuring the relative magnitude of movement among the implied volatilities of FX pairs. We showed its predictability and observed the performance of models developed to forecast the rank with backtesting. Finally, we discussed a method of using the forecasted values for establishing confidence in a forecast of implied volatility values.

6. Future Work

We have provided results for a pairwise ranking model applied to predict relative magnitude of movement among the implied volatilities of FX pairs. The models used for pairwise classifications were all linear models. We anticipate that the use of nonlinear models such as neural networks would lead to better signal recovery given the depth of the feature space of our problem. Additionally, due to computational constraints, the listwise approach was not tested for out-of-sample performance. As the listwise approach to ranking is the most advanced, it may also provide better predictive power than the models tested.

References

[1] Weaver, Caleb, et al. Functional PCA for Implied Volatility Surface Prediction. s.l. : MetLife, Inc., 2020.

[2] Weaver, Caleb, et al. Surface Classification for Direction Predictions of the Foreign Exchange Implied Volatility Surface. s.l. : MetLife, Inc., 2020.

[3] Meoded, Erez, et al. Applying an Embedded Ridge Model to Forecast the Implied Volatility Surface for Foreign Exchange. s.l. : MetLife, Inc., 2020.

[4] Crammer, Koby & Singer, Yoram. (2002). Pranking with Ranking. Adv Neur In. 14.

[5] Li, Ping & Burges, Christopher & Wu, Qiang. (2007). McRank: Learning to Rank Using Multiple Classification and Gradient Boosting. Advances in Neural Information Processing Systems.

[6] Crammer, Koby & Singer, Yoram. (2002). Pranking with Ranking. Adv Neur In. 14.

[7] Crammer, Koby & Singer, Yoram. (2002). Pranking with Ranking. Adv Neur In. 14.

[8] Li, Ping & Burges, Christopher & Wu, Qiang. (2007). McRank: Learning to Rank Using Multiple Classification and Gradient Boosting. Advances in Neural Information Processing Systems.

[9] Crammer, Koby & Singer, Yoram. (2002). Pranking with Ranking. Adv Neur In. 14.

[10] Shashua, A., Levin, A., 2003. Ranking with large margin principle:Two approaches. Advances in Neural Information Processing Systems 15, 937 944.

[11] Leonardo Rigutini, Tiziano Papini, Marco Maggini, Franco Scarselli, "SortNet: learning to rank by a neural-based sorting algorithm", SIGIR 2008 workshop: Learning to Rank for Information Retrieval, 2008

[12] Burges, Christopher &Shaked, Tal & Renshaw, Erin & Lazier, Ari & Deeds, Matt & Hamilton, Nicole & Hullender, Gregory. (2005). Learning to Rank using Gradient Descent. ICML 2005 -Proceedings of the 22nd International Conference on Machine Learning. 89-96. 10.1145/1102351.1102363.

[13] Joachims, T. (2002), "Optimizing Search Engines using Clickthrough Data", Proceedings of the ACM Conference on Knowledge Discovery and Data Mining

[14] Xia, Fen & Liu, Tie-Yan & Wang, Jue & Zhang, Wensheng & Li, Hang. (2008). Listwise approach to learning to rank - Theory and algorithm. Proceedings of the 25th International Conference on Machine Learning. 1192-1199. 10.1145/1390156.1390306.

[15] AdaRank: a boosting algorithm for information retrieval. Proceedings of the30th annual international ACM SIGIR conference on research and development in information retrieval. 391-398. 10.1145/1277741.1277809.

[16] Frank, Eibe & Hall, Mark. (2001). A Simple Approach to Ordinal Classification. Lecture Notes in Computer Science. 2167. 145-156. 10.1007/3-540-44795-4_13.development in information retrieval. 391-398. 10.1145/1277741.1277809.

[17] Zou, Hui, and Trevor Hastie (2005). Regularization and variable selection via the elastic net. Journal of the royal statistical society: series B (statistical methodology) 67.2 301-320.

Authors

Caleb Weaver, Ben Perryman, Jun Jiang, Alex Chien, Erez Meoded, Al Kirk

About MetLife Investment Management

MetLife Investment Management (MIM),[1] MetLife, Inc.'s (MetLife's) institutional investment management business, serves institutional investors by combining a client-centric approach with deep and long-established asset class expertise. Focused on managing Public Fixed Income, Private Capital and Real Estate assets, we aim to deliver strong, risk-adjusted returns by building tailored portfolio solutions. We listen first, strategize second, and collaborate constantly as we strive to meet clients' long-term investment objectives. Leveraging the broader resources and 150-year history of the MetLife enterprise helps provide us with deep expertise in navigating ever changing markets. We are institutional, but far from typical.

For more information, visit: **investments.metlife.com**

[1] MetLife Investment Management ("MIM") is MetLife, Inc.'s institutional management business and the marketing name for the following affiliates that provide investment management services to MetLife's general account, separate accounts and/or unaffiliated/third party investors: Metropolitan Life Insurance Company, MetLife Investment Management, LLC, MetLife Investment Management Limited, MetLife Investments Limited, MetLife Investments Asia Limited, MetLife Latin America Asesorias e Inversiones Limitada, MetLife Asset Management Corp. (Japan), and MIM I LLC.

MetLife
Investment
Management

One MetLife Way | Whippany, New Jersey 07981