SEE THE ADVANTAGE 〉 FACTSET

Machine Learning for Factor Investment Strategies

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Contents

Objectives

Emerging markets economies could be defined as those of developing countries that are becoming more engaged with global markets while growing. Countries to classify for Emerging Market poses some, but not all characteristics of a developed market and while investing in assets originating from there results higher yields, those are related with higher **risk** related with:

- Political instability
- Infrastructure problems
- Currency volatility
- Iliquid market

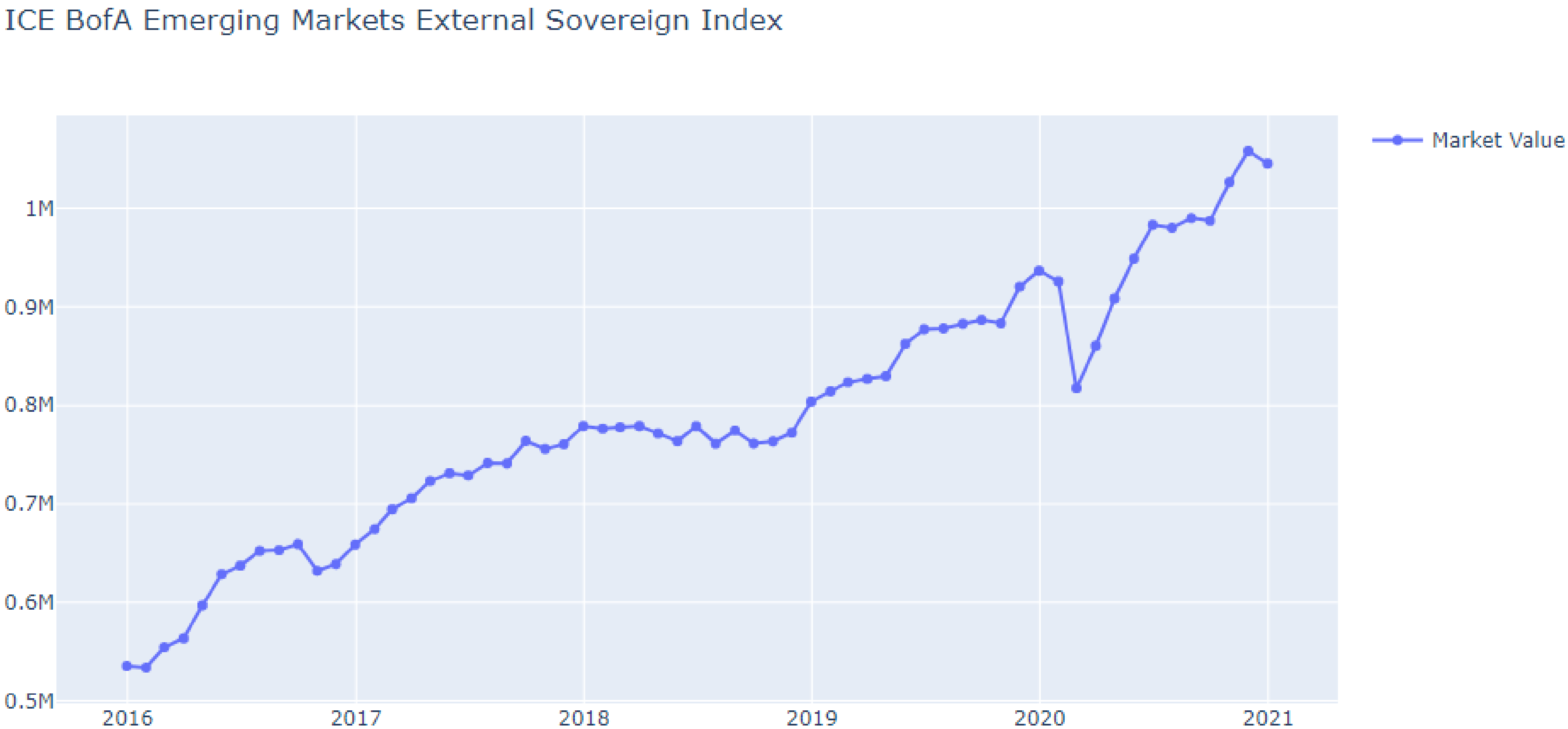
The focus of this research is to analyze systematic investment approaches in emerging markets (**EM) fixed income** space. We focus on **hard currency (USD) bonds** issued by emerging sovereign entities. Using machine learning algorithms to explore hidden non-linear patterns in data, we built cross-sectional regression models to:

- Extract a measure of value (compute the fair value of a given bond for a date specified).
- Extract a measure of sovereign quality (we extend the analysis using model interpretation library through which we compute Sovereign risk index country rankings).

Why EM?

- DM yields are very low (high yield investors alternative)
- No FX risk for investors in US (foreign high yield exposure without the associated FX exposure (quite volatile component of the portfolio))

Objectives


ICE BofA Emerging Markets External Sovereign Index
Market Value
1M
0.9M
0.8M
0.7M
0.6M
0.5M
2016
2017
2018
2019
2020
2021

Methodology and Setup

The yield of EM USD denominated debt is composed by two components:

1. Exposure to the US Treasury market
2. Country-specific spread

We would like to model both components: We model (1.) with bond-specific and (2.) with country specific factors.

Bond-specific factors:

- **Amount Outstanding (USD)**: this is meant to be a proxy for the liquidity of the instrument. The larger the amount of a given bond traded on the market, the easier it is to find buyers or sellers and the smaller is the market impact of your transactions. **Our prior: higher (lower) amount outstanding should mean lower (higher) yields as the liquidity premium is lower (higher), all else equal.** (Source: FactSet)

- **Effective duration**: bonds with longer (shorter) durations should provide a higher (lower) compensation to investors as investors are forced to lock in their capital for longer (shorter) period of time. **Our prior: longer (shorter) duration should imply higher (lower) yields, all else equal.** (Source: FactSet)

- **Time since issue**: evidence from the US Treasury market points to the observation that bonds that have been issued more recently have higher prices (lower) yields than bonds that have been issued less recently, all else equal. One explanation for this is that the supply of new issues is small, at least initially, which creates excess demand for them. Also, typically speculators use new issues to bed on interest rates creating higher demand for them. Is this a phenomenon observed in EM too? **Our prior: more (less) recent time since issue leads to lower (higher) yields.** (Source: FactSet)

Methodology and Setup

Country-specific factors:

- **GDP growth**: countries with higher expected growth can benefit in at least two ways. First, government tax revenue should increase leading to lower deficit and ultimately debt levels and giving the government greater financial resources to service its debt. Second, these countries should be more attractive for foreign capital investment that should increase foreign FX reserves of the country allowing it to service its debt more easily. **Our prior: higher (lower) GDP growth levels should lead to lower (higher) yields.** (Source: FactSet)

- **Inflation**: in their recent paper on EM sovereign bonds AQR [*(Systematic) Investing in Emerging Market Debt, 2020*] use inflation is a general measure of the ability of the government to produce good quality economic policies, including debt management. **Our prior: higher (lower) inflation should lead to higher (lower) yields.** (Source: FactSet)

- **Fiscal deficit**: the fiscal deficit measure by how much government expenditures exceed government tax revenue. Countries that are not able to achieve a balanced budget will over time start accumulating a heavier debt burden. **Our prior: higher (lower) fiscal deficit should mean higher (lower) yields.** (Source: FactSet)

Methodology and Setup

Country-specific factors:

- **Current Account**: the current account measures if exports are above or below import. If exports exceed imports, the country increases its foreign currency reserves that allow it to service its foreign currency debt more easily. **Our prior: higher (lower) current account surplus should mean lower (higher) yields.** (Source: FactSet)

- **Short-term debt to FX reserves**: even if a country has a low USD-denominated debt relative to its GDP, if most of this debt matures in the near future it might not be able to service its debt if it does not have enough current FX reserves. **Our prior: higher (lower) short-term-debt to FX reserves ratio should mean higher (lower) yields.** (Source: IMF)

- **Institutional Strength (Rank)**: the institutional context of the country – effectiveness of government policy, accountability of government policy, strength of the legal system – are qualitative measures of the degree to which a respective sovereign borrower can be expected to implement policies and measures that are consistent with a sound management of the economy in general and of their debt obligations in particular. **Our prior: higher rank in terms of the strength and efficacy of their institutions and policy making are expected to pose a less serious sovereign credit risk.** (Source: World Bank)

Methodology and Setup

- **Jupyter Notebook** – Create and share notebooks that contain live code, visualizations, text.
- **Python kernel (3.6.9)** -High-level general purpose programming language
  - **Plotly** library – Open-source graphing library. It allows us to create visualizations, UI tools for data science, machine learning and engineering.
  - **Plotly Dash** - Open-source analytics application framework. Leading data visualization and UI tool.
  - **Scikit-Learn** – Open-source python machine learning library containing tools for data analytics.
  - **SHAP (SHapley Additive exPlanations)** - unified approach for machine learning models explanations. Allows local model explanations through game theory. Provides consistent and locally accurate additive feature attribution method based on expectations.

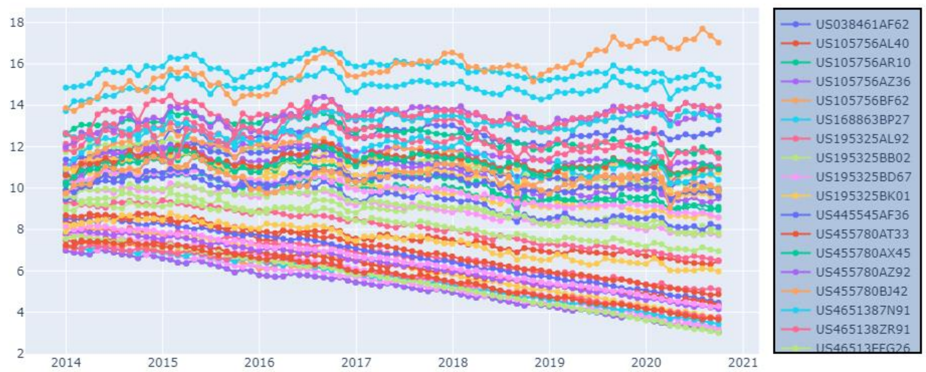
The Dataset

Dataset Summary:

- **Number of features:** 9
- **Features:**
  - Duration
  - Amount Outstanding
  - Time Since Issue
  - Inflation
  - GDP
  - Deficit to GDP
  - Current Account
  - Reserve
  - Rank
- **Date range:** 2013-12-31 to 2020-09-30, monthly data (Month-end), 82 points in time
- **Countries:** EGP (2),BRL (4),CLP (1),COP (4),HUF (1),IDR (8),ILS (5),KRW (1),MXN (4),PEN (3),PHP (8), PLN (1),RUB (4),ZAR (3),TRY (8),
- **Bonds:** 57 ISINs
- **Remaining maturity**: more than 10 years as of 2013-12-31
- **Currency**: U.S. Dollar
- **Coupon type**: Fixed
- **FactSet industry**: Government
- **Security type**: Sovereign Bond/Note
- **Issue status**: Current
- **Issue pledge status**: Unsecured
- **Callable**: No
- **Puttable**: No
- **Redemption**: No
- **Conditional Redemption**: No
- **Private placement**: No

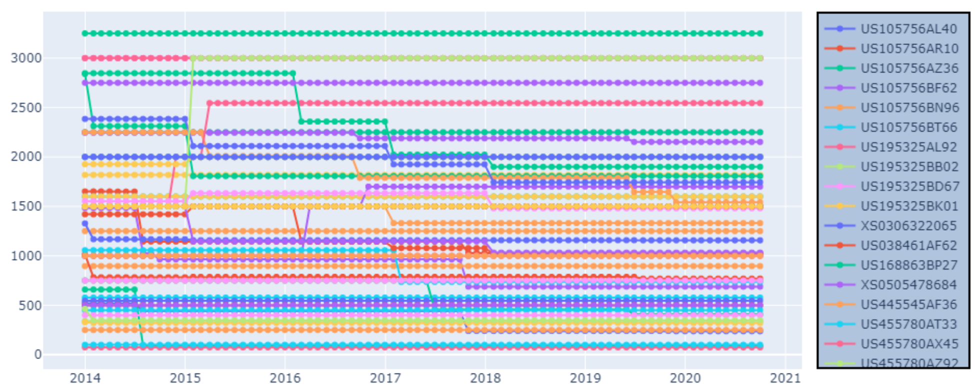
The Dataset

Durations

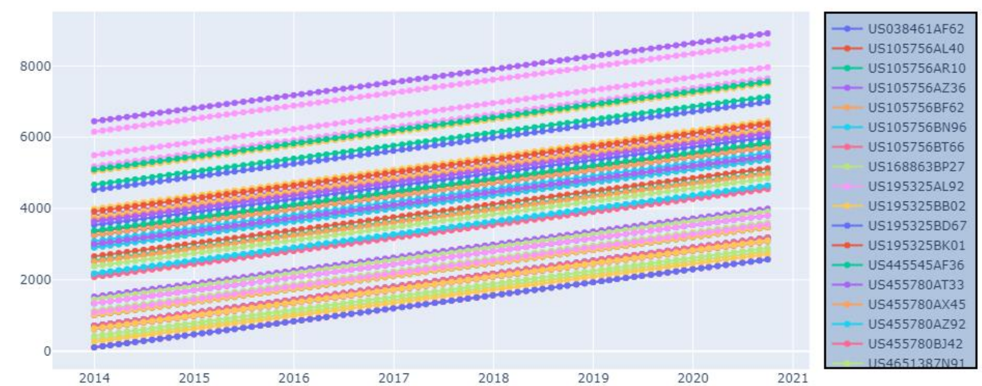


YTM

Amount Outstanding (USD)

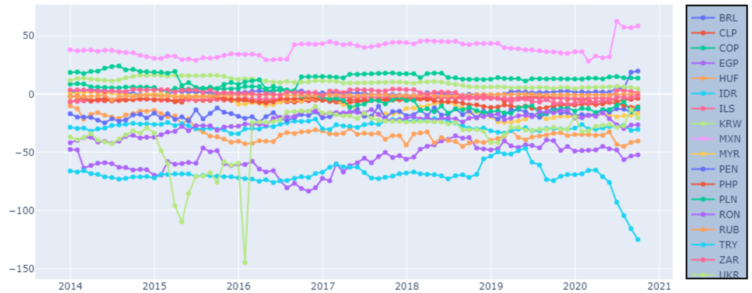


Time Since Issue

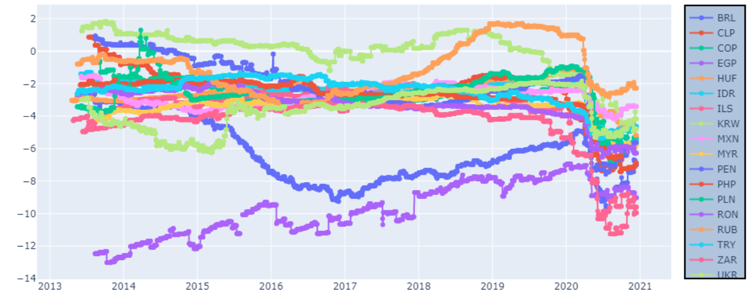


The Dataset

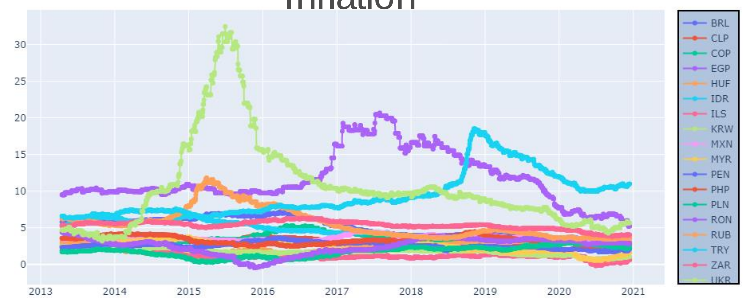
Reserve



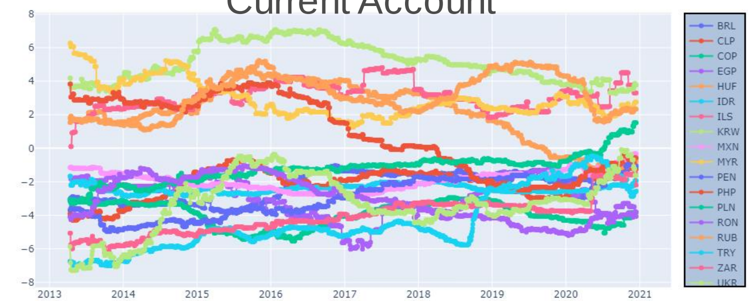
Deficit to GDP



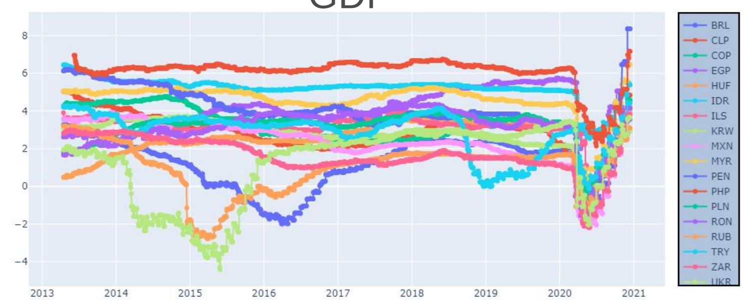
Inflation



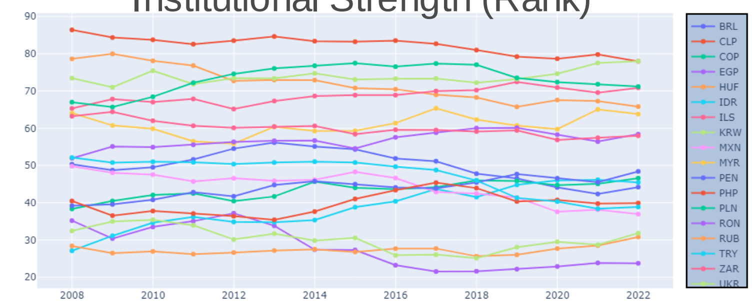
Current Account



GDP



Institutional Strength (Rank)



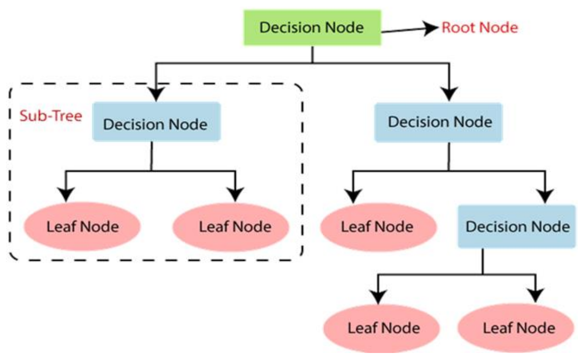
Using Random Forests

What is Random Forest?

Random Forest algorithm is a machine learning method that can be described as a meta estimator that fits a number of decision trees (estimators) on varios sub-samples of data to control the overfitting and uses averaging to improve the prediction accuracy. Random Forests for regression use tree predictor h(x, θθ) which takes on numerical values. Usually, Random forest perform great on data which includes features with non-linear relationships.

Why Random Forest?

- It could catch non-linear patterns in the data.
- Control overfitting – number of features, sub-sample of data.



Using Random Forests

RandomForestRegressor hyperparameters:

•**max_features** -> maximum number of features that the model can try in individual tree.
Note: the search for a split does not stop until at least one valid partition of the node samples is found, even if it requires to effectively inspect more than max_features features.
•**n_estimators** -> number of trees in the forest.
•**max_depth** -> maximum depth of a single tree in the forest.
•**min_samples_split** -> minimum samples required to split a single node.
•**criterion** -> mse (mean squared error) - penalizes the largest errors
•**bootstrap** -> use bootstraped samples to build a tree. Do not include all train samples.
•**random_state** -> controls the randomness of the bootstraping and the sampling of features when looking for best split. *Use a new random number generator seeded by the given integer. Using an int will produce the same results across different calls.*
•**oob_score** -> use out-of-bag samples to estimate the generalization accuracy. (mean r2 for all estimators)

```
for k in range(self.noutputs): self.oobscore += r2_score(y[:, k], predictions[:, k])
self.oobscore /= self.noutputs
```

•**min_samples_leaf** -> minimum number of samples required to be at a leaf node. (Usually, this parameter is used to reduce complexity and grow smaller trees in the forest. In our case we do not have many features (9) and the computation time is acceptable, so set this to 1).
•**warm_start** -> reuse the solution of the previous call to fit and add more estimators to the ensemble. Useful when maximizing performance with grid search - it allows to use aspects of the model fitted with the previous set of parameters.
•**max_samples** -> controls the subsample size when bootstrap is used. In our case we use about randomly selected 2/3 of the dataset for each bootstrap.
•**ccp_alpha** -> controls the size of a tree by cost complexity pruning. Larger values increase the number of pruned nodes.

Using Random Forests

Our Setup for RandomForestRegressor hyperparameters:

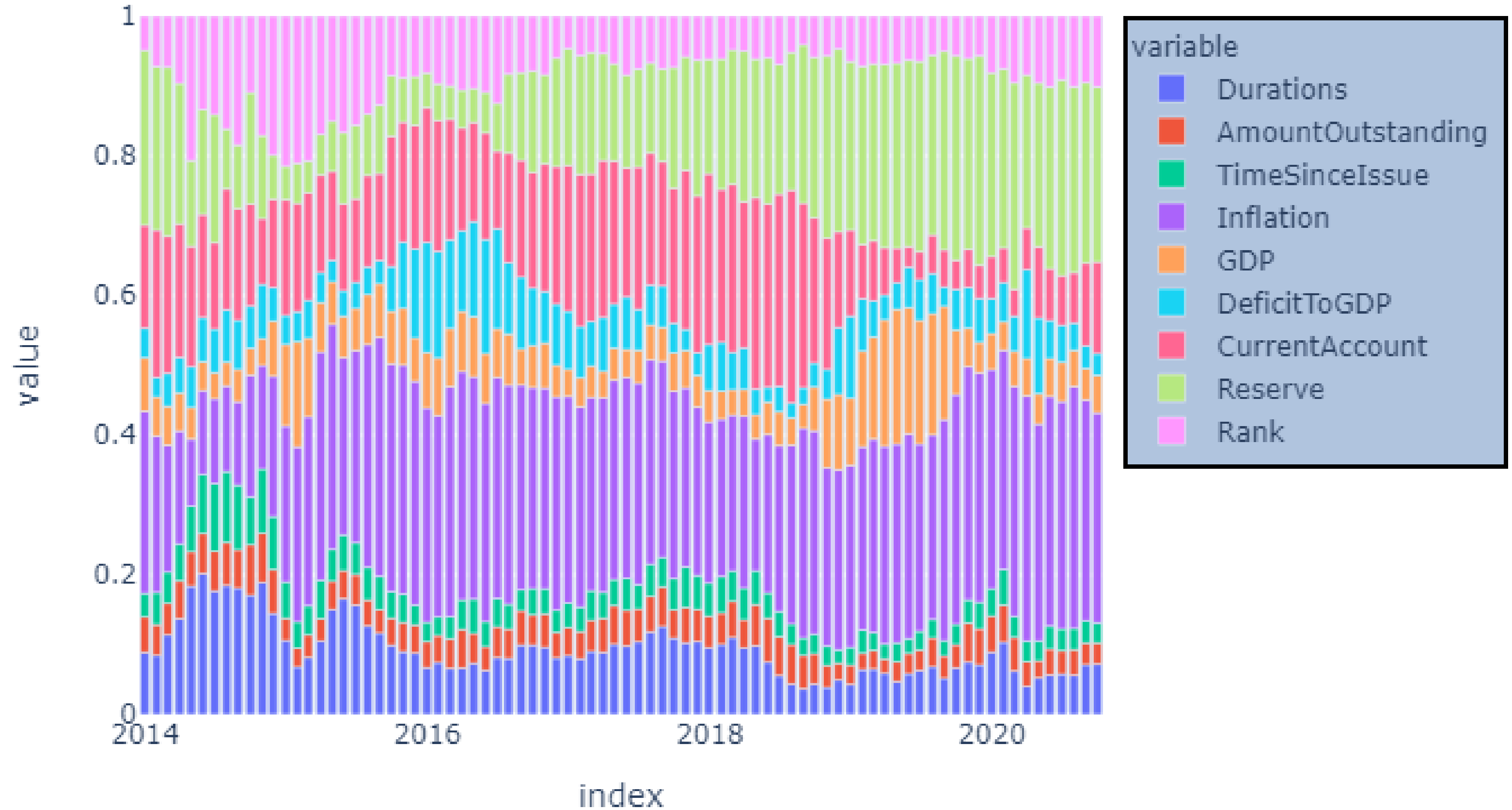
•**max_features** = sqrt
•**n_estimators** =100
•**max_depth** = None
•**min_samples_split** = 2
•**criterion** = mse (mean squared error) - penalizes the largest errors
•**bootstrap** = True
•**random_state** = 0
•**oob_score** = True
•**min_samples_leaf** = 1
•**warm_start** = False
•**max_samples** = None In our case we use about randomly selected 2/3 of the dataset for each bootstrap.

Use RandomForestRegressor for Cross-sectional data analysis:

Cross-sectional data analysis is when we want to analyze the data at a fixed single point in time.
We fit a RandomForestRegressor for every Month-End with bootstrapped data, then we predict on the full dataset and calculate R2 for the model and Out-of-bag R2 which tells us how averagely weak is every estimator in the ensamble. **The two are not comparable to each other.**

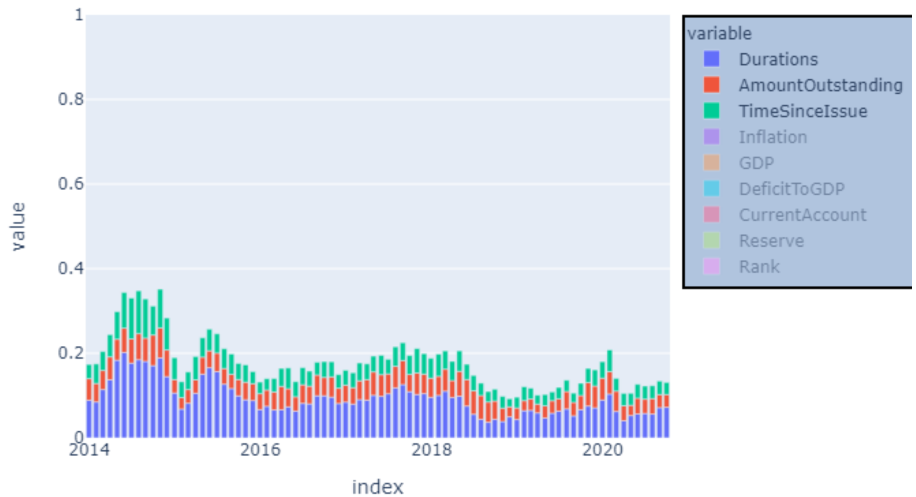
Results and Conclusion

Models Feature Importance:

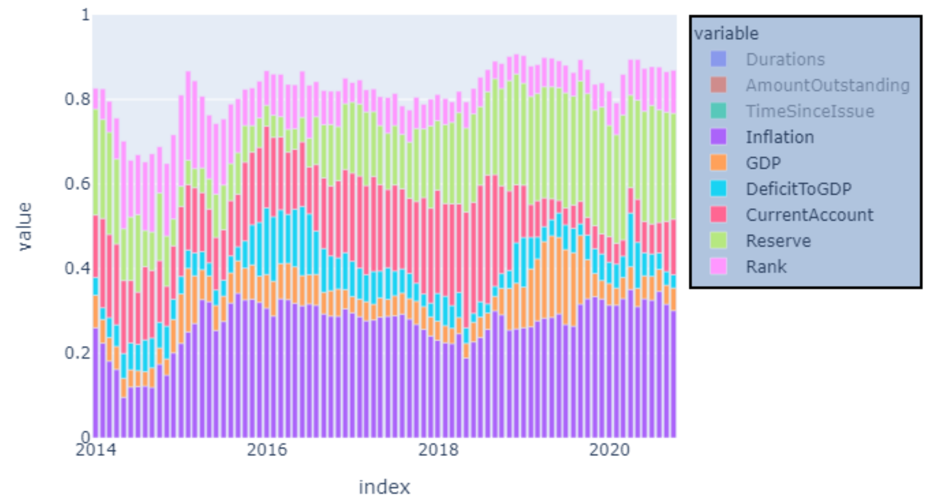


Results and Conclusion

Models Bond-specific Feature Importance:



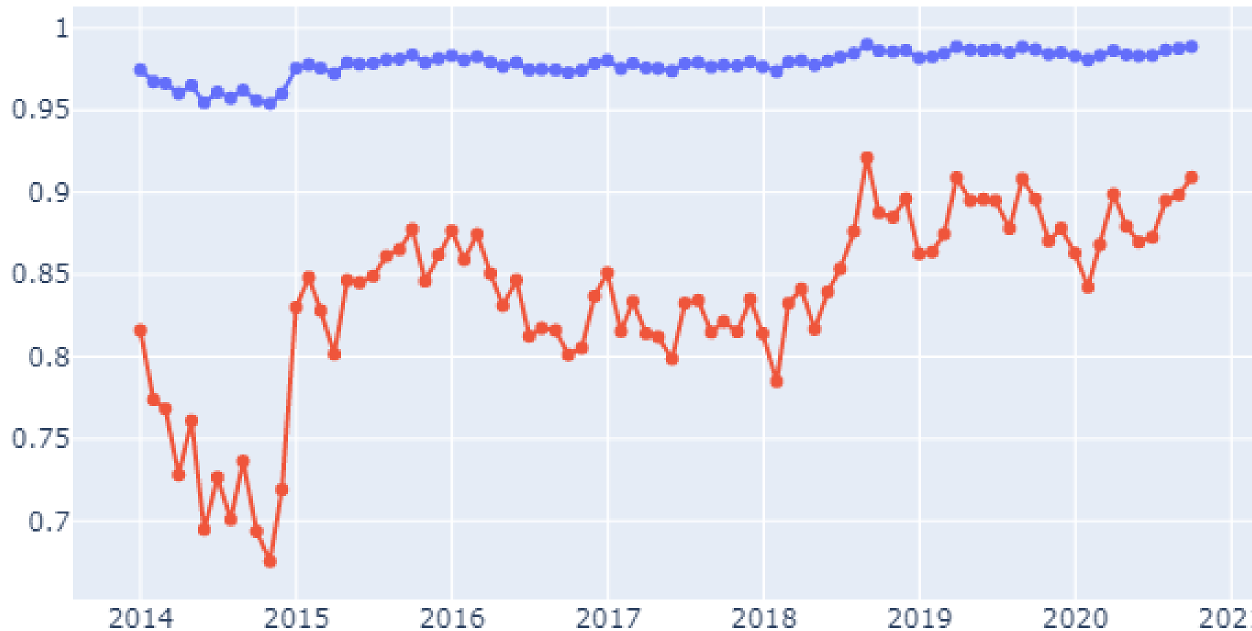
Models Country-specific Feature Importance:



We note that relative to the number of features in each group, the sum of the feature importances for the bond-specific factors is lower than the sum of features for the country-specific factors for most of the points in time. We also note that the importance of the bon-specific features goes lower with the time while the country-specific features importance rises.

Results and Conclusion

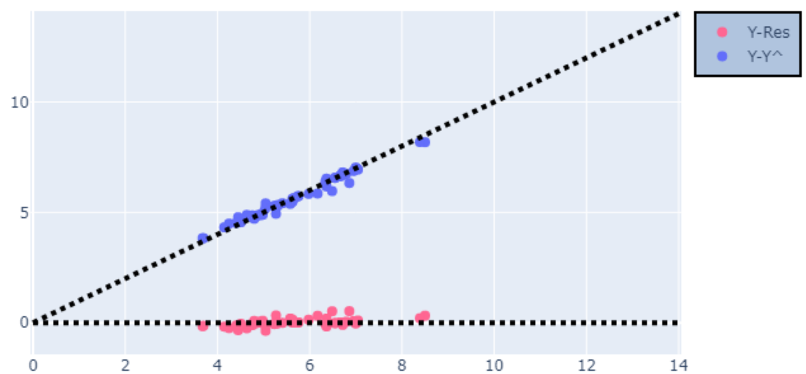
R2 (mean R2 for OOB is `0.835`)



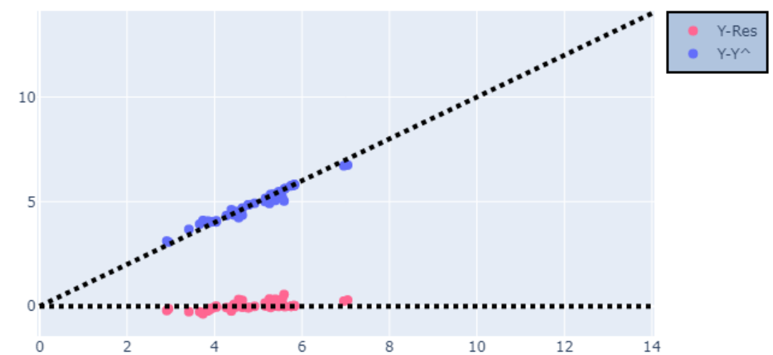
Results and Conclusion

Y-Y^ and Y-Residuals

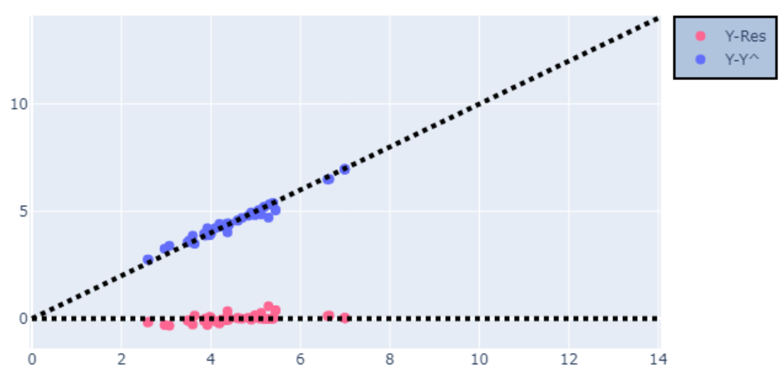
12.2013



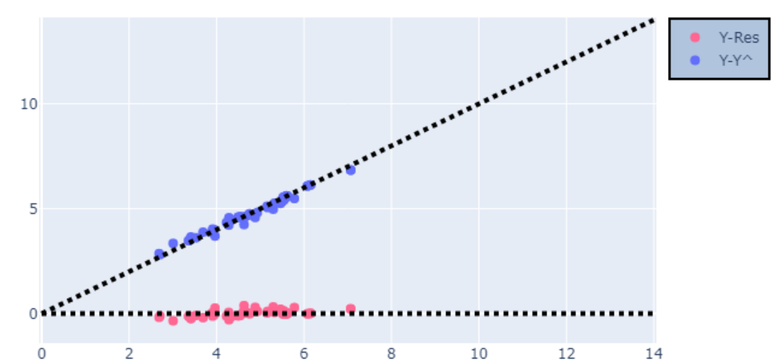
06.2014



12.2014



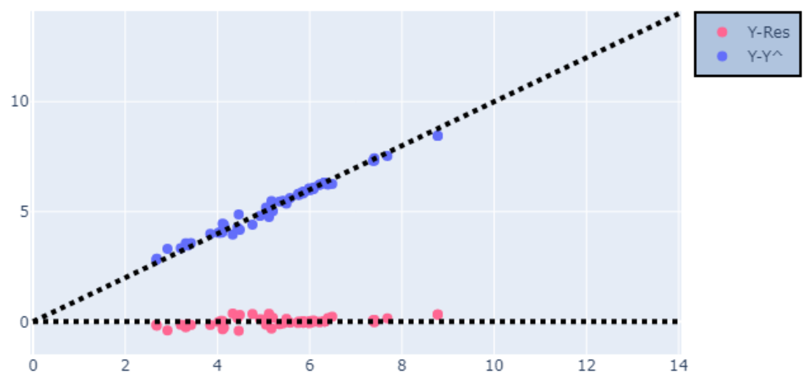
06.2015



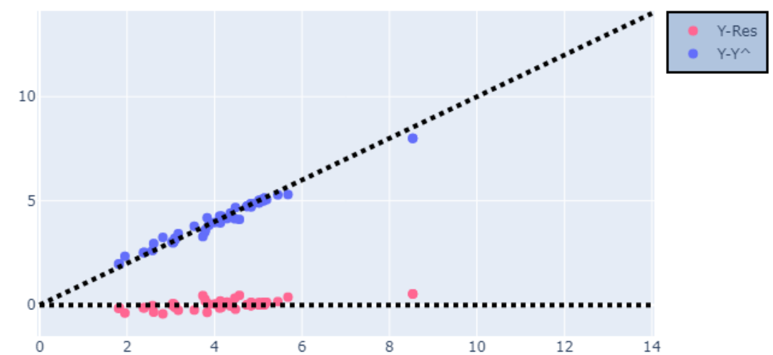
Results and Conclusion

Y-Y^ and Y-Residuals

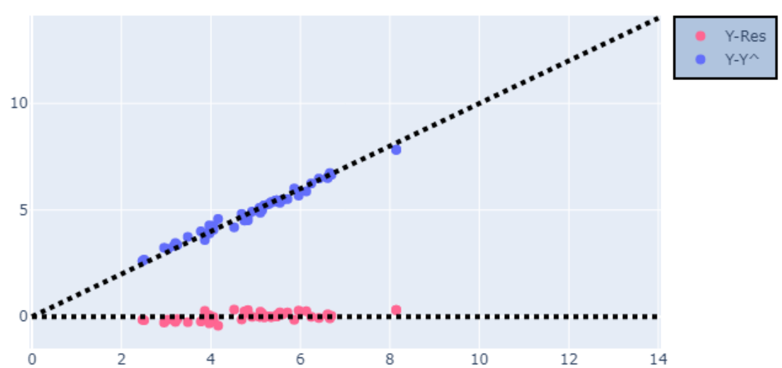
12.2015



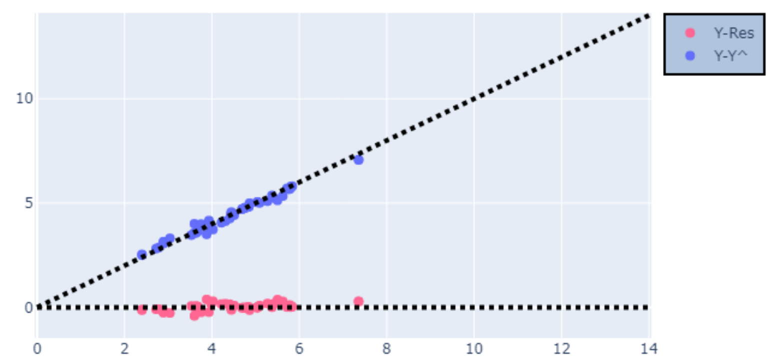
06.2016



12.2016



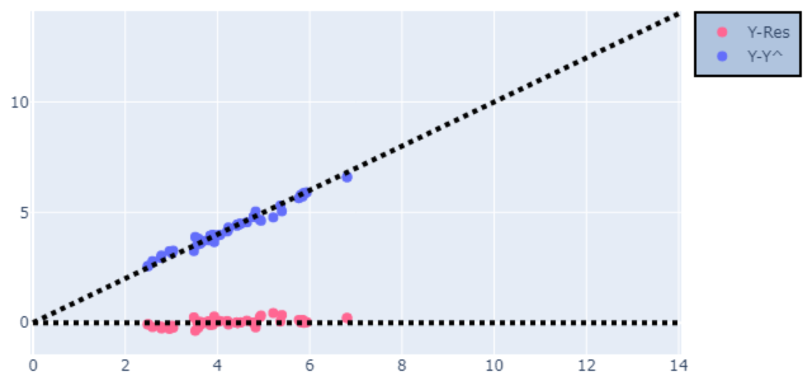
06.2017



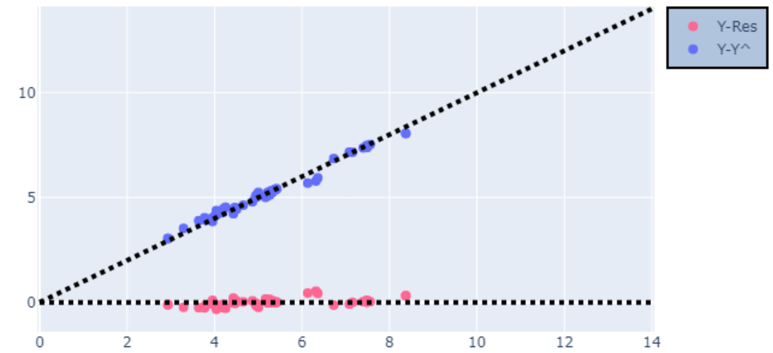
Results and Conclusion

Y-Y^ and Y-Residuals

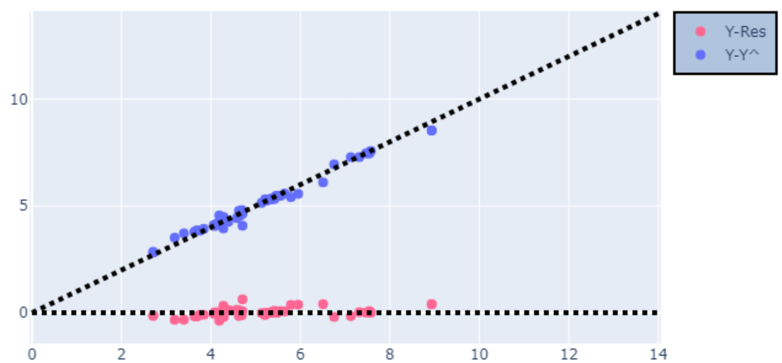
12.2017



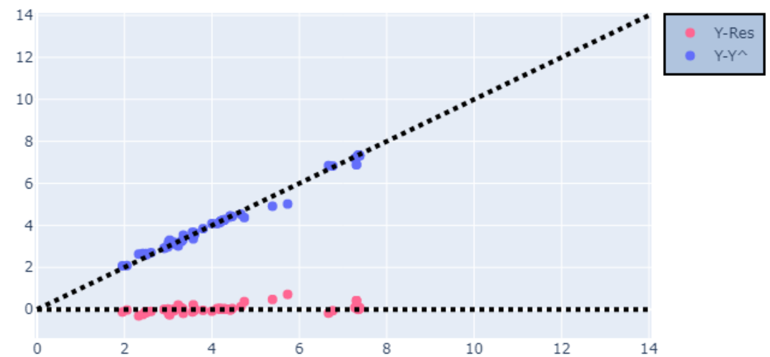
06.2018



12.2018



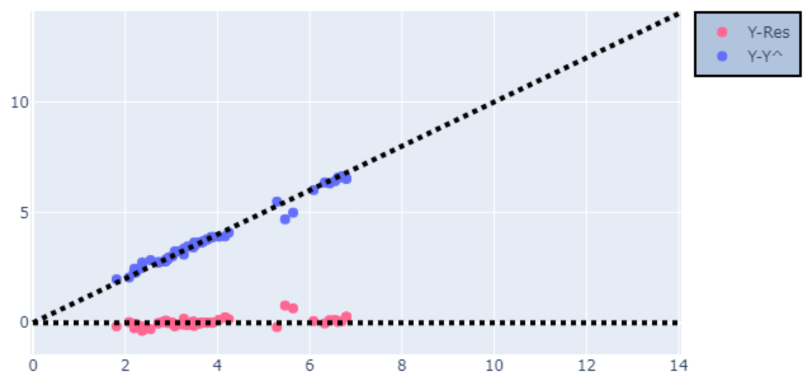
06.2019



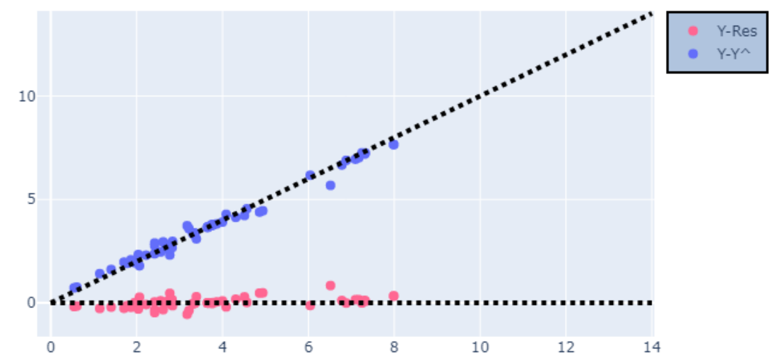
Results and Conclusion

Y-Y^ and Y-Residuals

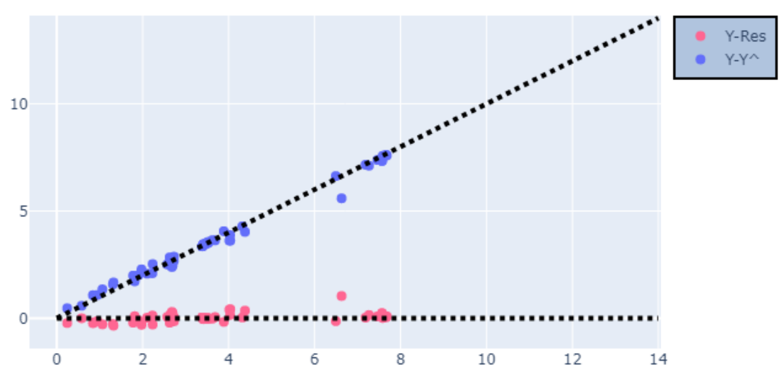
12.2019



06.2020



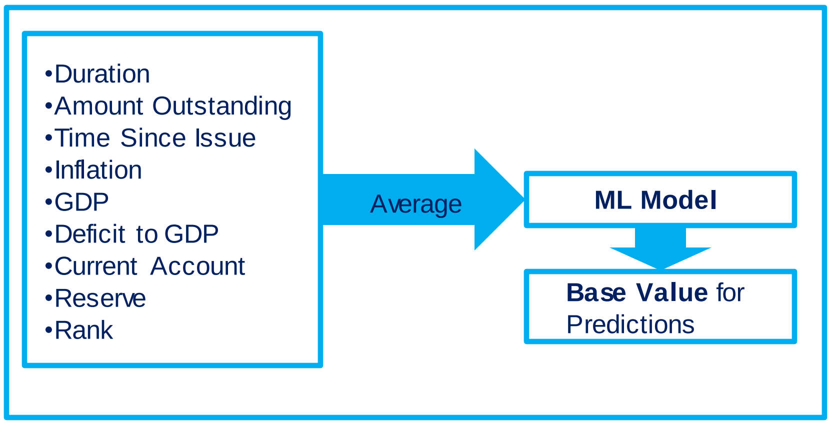
09.2020



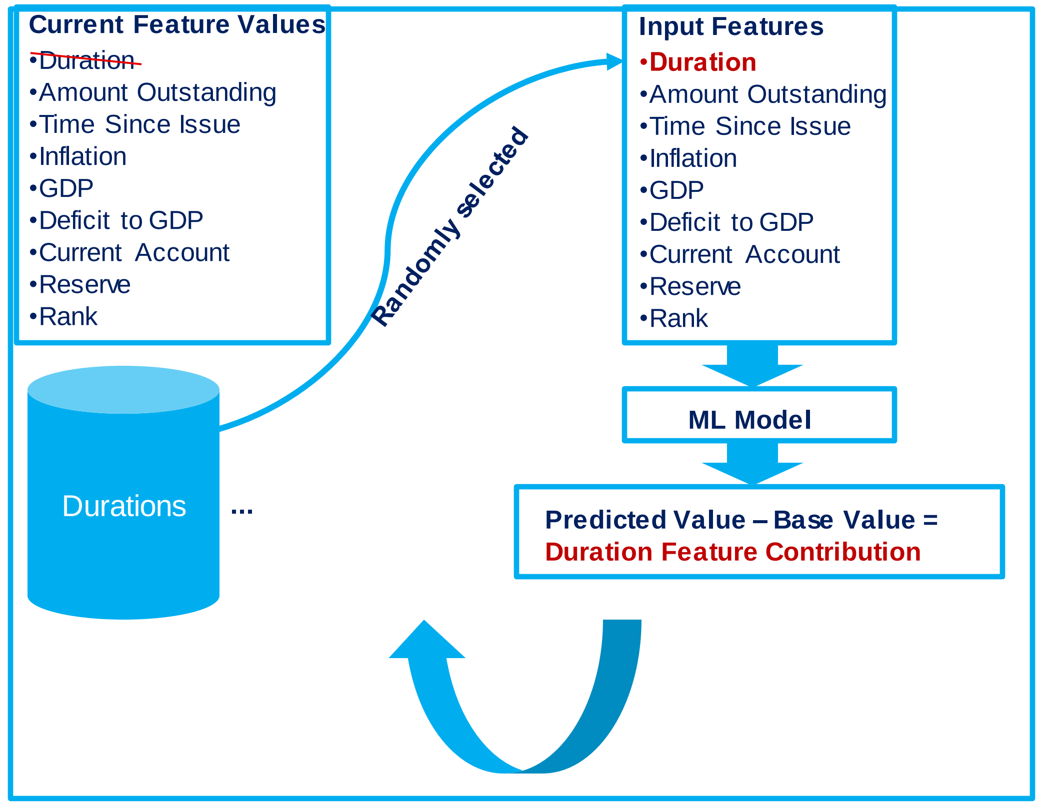
Results and Conclusion

Shap (SHapley Additive exPlanations) - from game theory to machine learning explanation

Model Averaging



How to explain prediction?



Results and Conclusion

Shap

ISIN: US46513EJX13, **Issuer**: Government of Israel, **Currency**: U.S. Dollar, **Issue Date**: 2004-04-26, **Maturity Date**: 2024-04-26
ISIN: US195325AL92, **Issuer**: Government of Colombia, **Currency**: U.S. Dollar, **Issue Date**: 1997-02-24, **Maturity Date**: 2027-02-15

isin

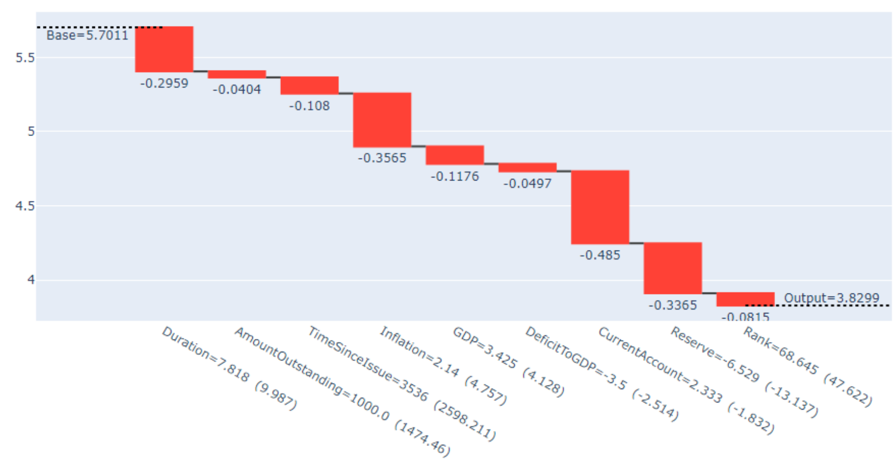
US46513EJX13

date

2013-12-31

Feature force plot

US46513EJX13 (3.8299) Base value: 5.7011 :



isin

US195325AL92

date

2013-12-31

Feature force plot

US195325AL92 (5.9652) Base value: 5.7011 :

Results and Conclusion

Shap

ISIN: US46513EJX13, **Issuer**: Government of Israel, **Currency**: U.S. Dollar, **Issue Date**: 2004-04-26, **Maturity Date**: 2024-04-26
ISIN: US195325AL92, **Issuer**: Government of Colombia, **Currency**: U.S. Dollar, **Issue Date**: 1997-02-24, **Maturity Date**: 2027-02-15

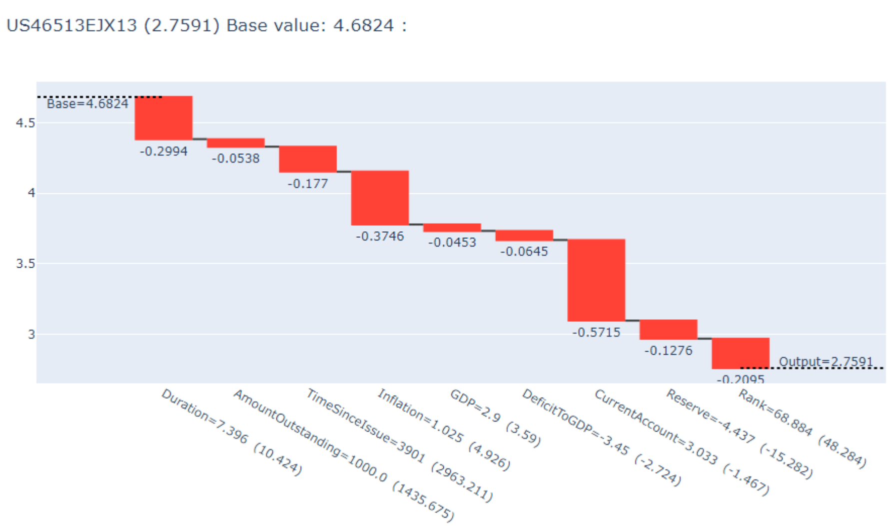
isin

US46513EJX13

date

2014-12-31

Feature force plot



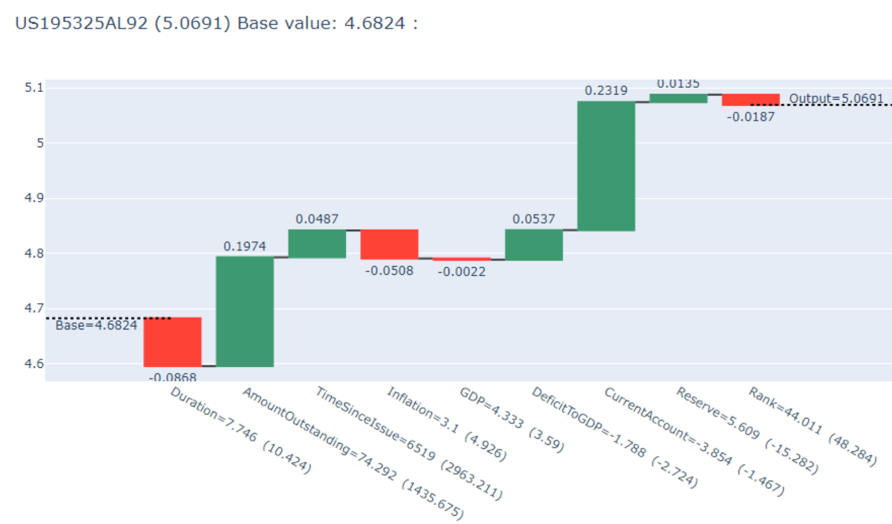
isin

US195325AL92

date

2014-12-31

Feature force plot



Results and Conclusion

Shap

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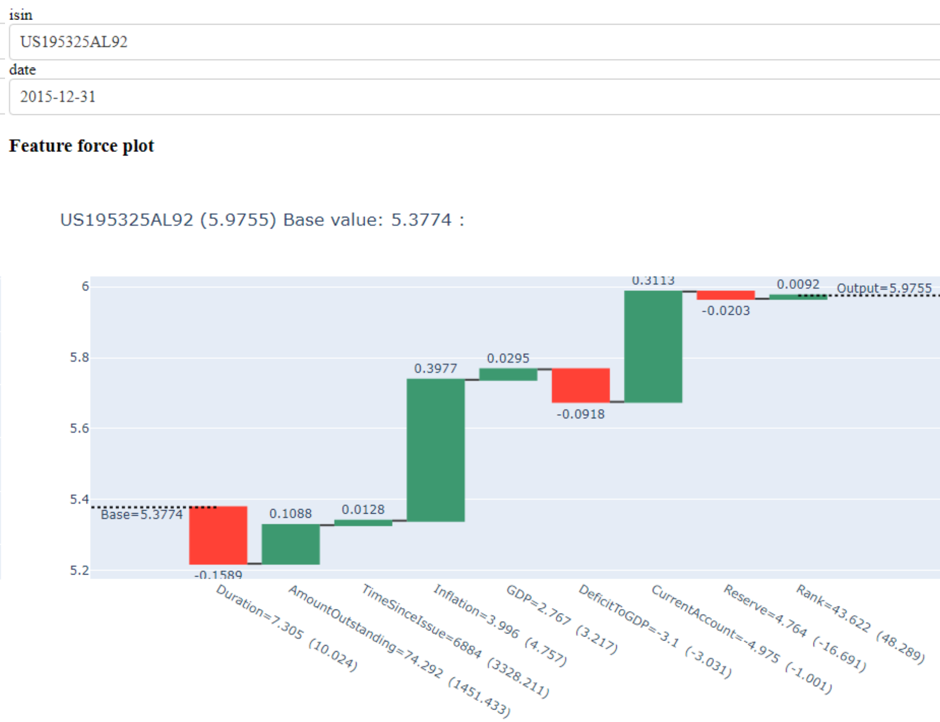
ISIN: US195325AL92, **Issuer**: Government of Colombia, **Currency**: U.S. Dollar, **Issue Date**: 1997-02-24, **Maturity Date**: 2027-02-15



Results and Conclusion

Shap

ISIN: US46513EJX13, **Issuer**: Government of Israel, **Currency**: U.S. Dollar, **Issue Date**: 2004-04-26, **Maturity Date**: 2024-04-26
ISIN: US195325AL92, **Issuer**: Government of Colombia, **Currency**: U.S. Dollar, **Issue Date**: 1997-02-24, **Maturity Date**: 2027-02-15

isin

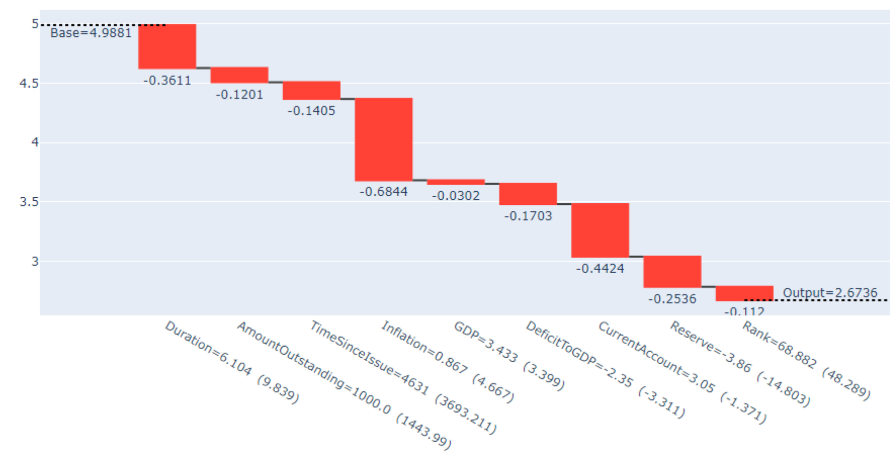
US46513EJX13

date

2016-12-30

Feature force plot

US46513EJX13 (2.6736) Base value: 4.9881 :



isin

US195325AL92

date

2016-12-30

Feature force plot

US195325AL92 (5.5138) Base value: 4.9881 :

Results and Conclusion

Shap

ISIN: US46513EJX13, **Issuer**: Government of Israel, **Currency**: U.S. Dollar, **Issue Date**: 2004-04-26, **Maturity Date**: 2024-04-26
ISIN: US195325AL92, **Issuer**: Government of Colombia, **Currency**: U.S. Dollar, **Issue Date**: 1997-02-24, **Maturity Date**: 2027-02-15

isin

US46513EJX13

date

2017-12-29

Feature force plot

US46513EJX13 (2.5558) Base value: 4.3087 :

isin

US195325AL92

date

2017-12-29

Feature force plot

US195325AL92 (4.7713) Base value: 4.3087 :

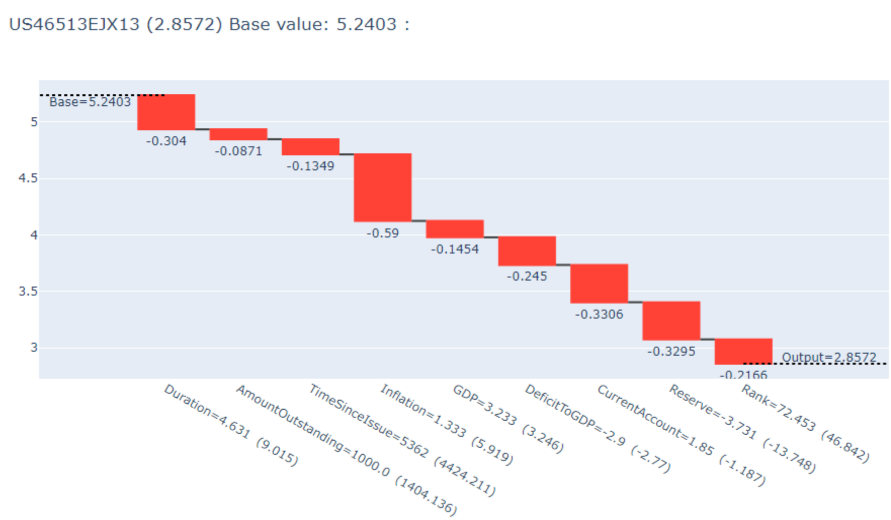
Results and Conclusion

Shap

ISIN: US46513EJX13, **Issuer**: Government of Israel, **Currency**: U.S. Dollar, **Issue Date**: 2004-04-26, **Maturity Date**: 2024-04-26
ISIN: US195325AL92, **Issuer**: Government of Colombia, **Currency**: U.S. Dollar, **Issue Date**: 1997-02-24, **Maturity Date**: 2027-02-15

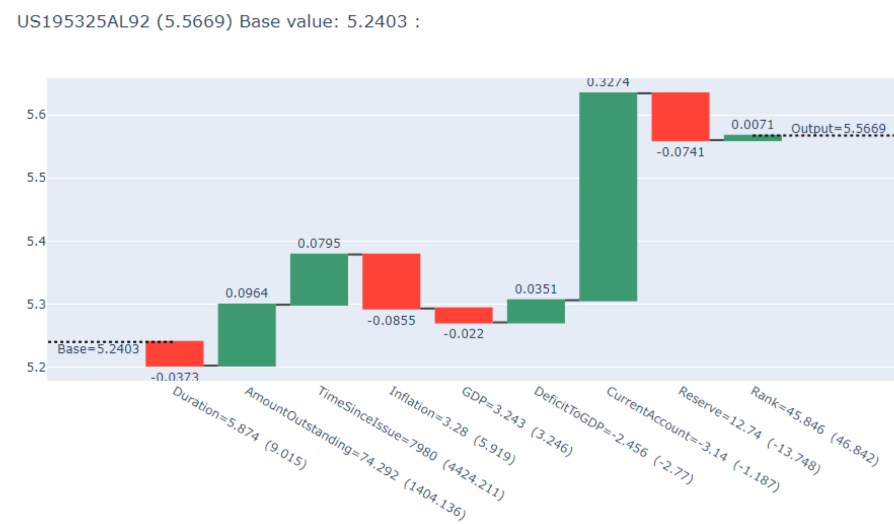
isin
US46513EJX13
date
2018-12-31

Feature force plot



isin
US195325AL92
date
2018-12-31

Feature force plot



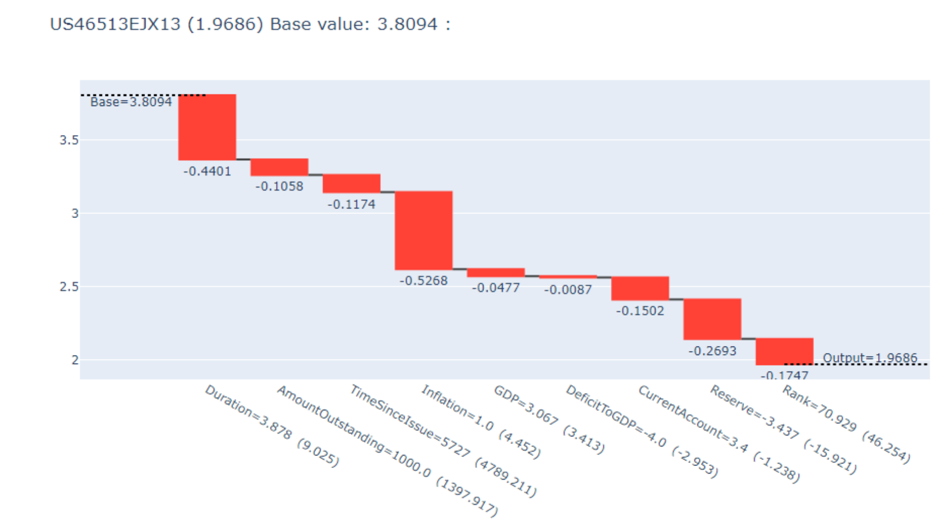
Results and Conclusion

Shap

ISIN: US46513EJX13, **Issuer**: Government of Israel, **Currency**: U.S. Dollar, **Issue Date**: 2004-04-26, **Maturity Date**: 2024-04-26
ISIN: US195325AL92, **Issuer**: Government of Colombia, **Currency**: U.S. Dollar, **Issue Date**: 1997-02-24, **Maturity Date**: 2027-02-15

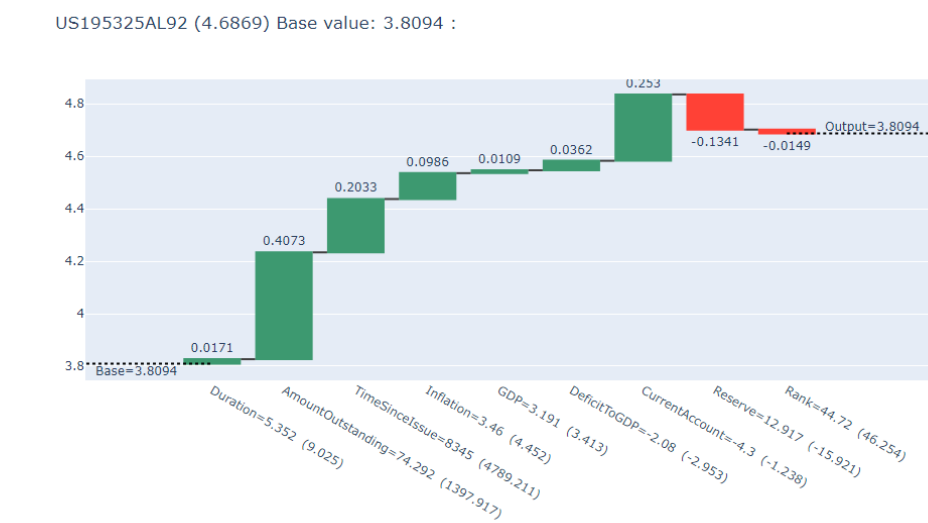
isin
US46513EJX13
date
2019-12-31

Feature force plot



isin
US195325AL92
date
2019-12-31

Feature force plot

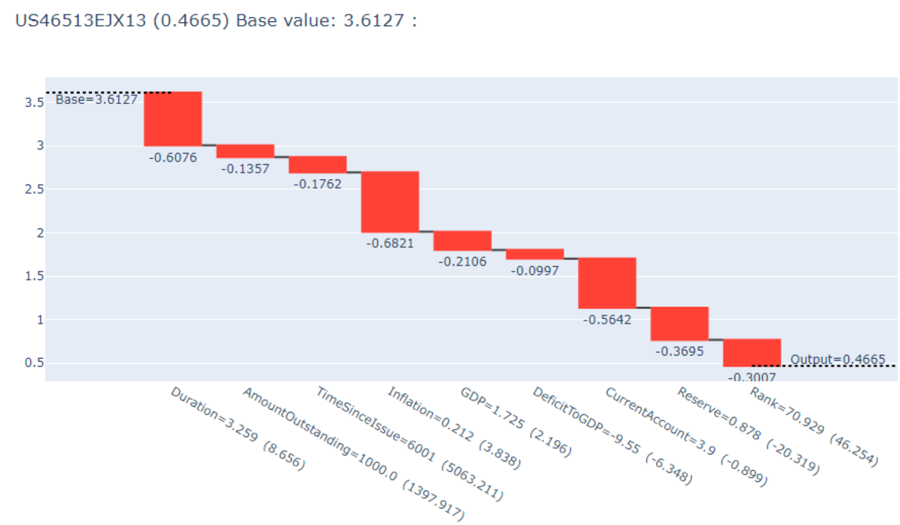


Results and Conclusion

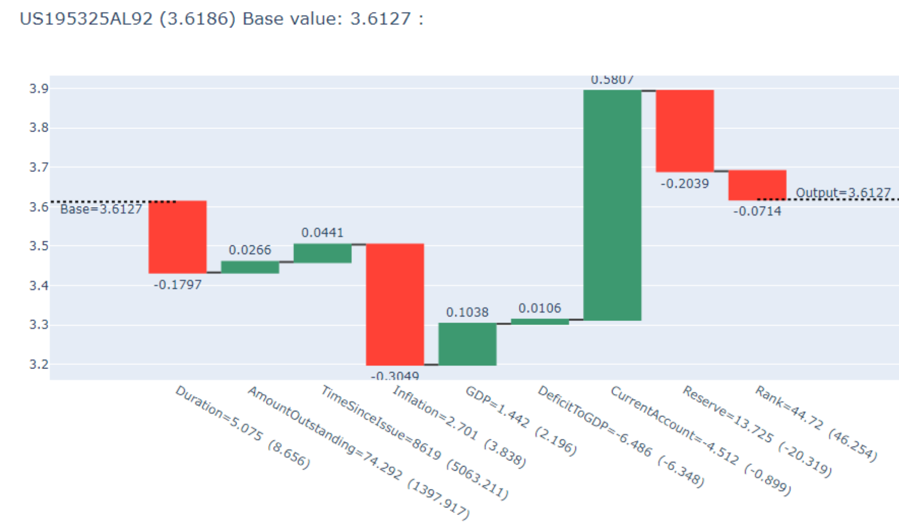
Shap

ISIN: US46513EJX13, **Issuer**: Government of Israel, **Currency**: U.S. Dollar, **Issue Date**: 2004-04-26, **Maturity Date**: 2024-04-26
ISIN: US195325AL92, **Issuer**: Government of Colombia, **Currency**: U.S. Dollar, **Issue Date**: 1997-02-24, **Maturity Date**: 2027-02-15

isin
US46513EJX13
date
2020-09-30
Feature force plot

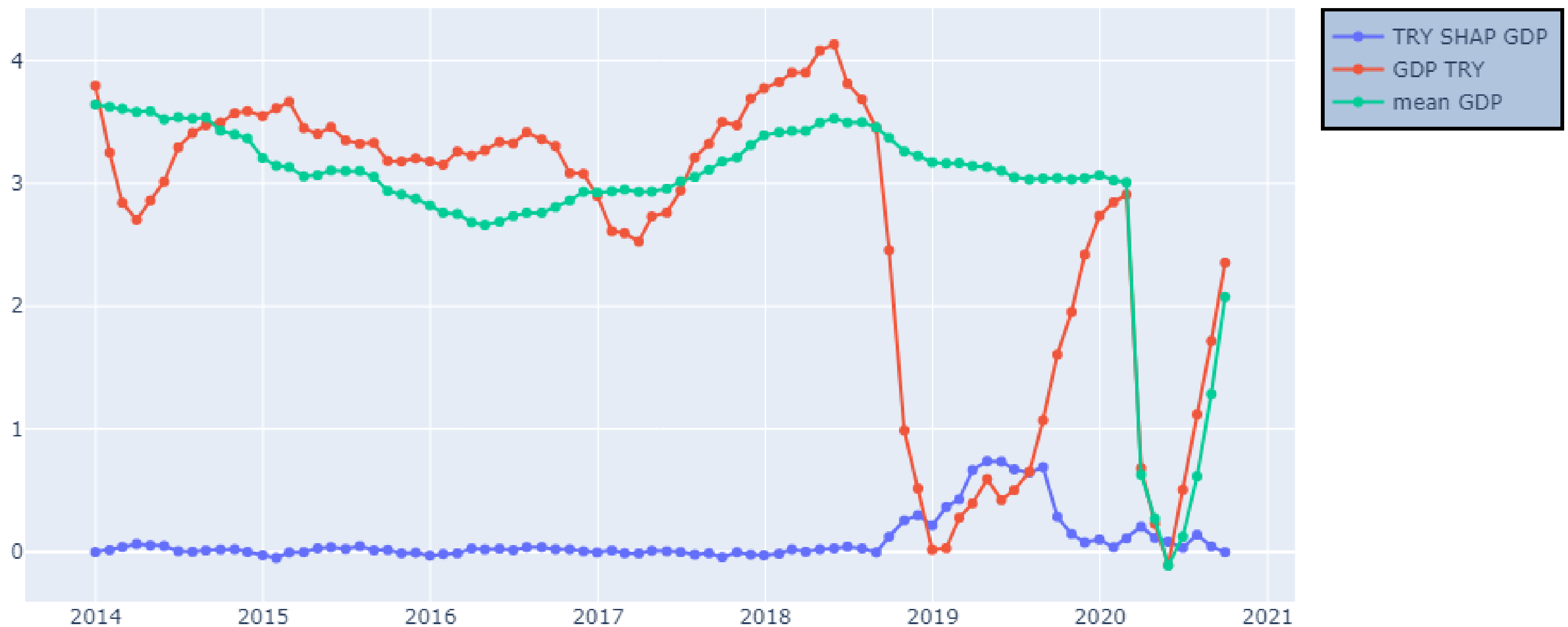


isin
US195325AL92
date
2020-09-30
Feature force plot



Results and Conclusion

Example with Turkey GDP contribution to the yield prediction



Results and Conclusion

Extracting a Measure Value in EM Sovereign Debt

What is **value**?

The value effect can be described simply as the tendency of assets with lower valuation ratios (cheap) to earn more than the average return over the long-run.

We use duration-adjusted residuals as a value proxy rather than just the residuals.

- The machine-learning (ML) **random-forest** framework is the core methodology here.
- The key outputs from the random-forest framework are the YTM residuals that are deviations of actual YTM yields from model-implied yields.
- These residuals can therefore be regarded as ***expected yield changes,*** i.e., they show by how much the current yield needs to change in order to converge to “fair value” yield over time.
- On the other hand, it is also worth noting that securities with different sensitivities to yield changes realize different returns on investment for the same change in yields.
    - Image that Bond A has a residual YTM yield of 1bps and an effective duration of 10 years while Bond B has a residual YTM yield of 10bps and an effective duration of 1 year. From a value point of view, these two bonds should be expected to realize the same return on investment over time and therefore should be given the same weight.

Based on these considerations, our proxy for Value factor is therefore = ML-based YTM residual x bond duration .

Results and Conclusion

Extracting a Measure Value in EM Sovereign Debt

	('EGP', 'US038461AF62')	('BRL', 'US105756AL40')	('BRL', 'US105756AR10')	('BRL', 'US105756AZ36')	('BRL', 'US105756BF62')	('CLP', 'US168863BP27')	('COP', 'US195325AL92')	('COP', 'US195325BB02')	('COP', 'US195325BQ67')	('COP', 'US195325BK01')	('HUF', 'US445545AF36')	('IDR', 'US455780AT33')	('IDR', 'US455780AK45')	('IDR', 'US455780AZ92')	('IDR', 'US455780BJ42')	('ILS', 'US4651387N91')	('ILS', 'US4651382R91')	('ILS', 'US465138FG26')	('ILS', 'US46513JEX13')	('ILS', 'US46513EKL55')	('KRW', 'US50064FAE43')	('MXN', 'US593048AX90')	('PEN', 'US715638AP79')	('PEN', 'US715638AS19')	('PEN', 'US715638BM30')
2020-09-30	220.3	271.75	-93.01	-59.03	70.57	71.47	201.97	281.59	-92.7	165.73	-269.21	30.08	35.8	11.06	-34.27	437.34	61.41	-274.33	-72.95	-0.79	-104.01	-6.03	79.83	-144.44	-244.61
2020-08-31	255.41	298.79	-77.19	-95.1	69.13	35.15	144.29	273.05	-112.89	162.21	-209.73	-7.09	12.69	7.81	-0.87	530.78	137.12	-166.97	-67.14	-26.03	-119.54	-148.21	70.93	-129.36	-291.54
2020-07-31	327.77	392.09	-95.33	-101.5	157.01	-507.31	151.88	240.96	-112.58	105.92	-789.65	-6.6	-1.47	-59.61	-126.45	391.87	138.95	-186.19	-44.74	-38.42	-179.32	-103.29	149.51	-110.28	-348.13
2020-06-30	328.18	301.36	-113.24	-155.09	111.93	-214.91	147.16	378.63	-112.38	186.56	-692.27	-3.31	-13.14	10.05	-6.49	680.33	182.96	-210.3	-63.81	-61.07	-128.01	-166.65	111.57	-112.75	-110.89
2020-05-29	313.58	333.34	-166.76	-136.03	80.79	-186.56	300.88	269.1	-135.07	206.18	-344.19	-2.66	15.38	10.26	-22.64	855.21	227.91	-174.46	-92.35	-38.11	-149.54	-153.06	-20.21	-153.56	-248.19
2020-04-30	260.3	305.81	-166.98	-132.99	85.84	-362.43	383.56	161.62	-97.82	196.26	-28.56	30.41	-21.57	4.54	38.99	1019.03	291.28	-303.06	-143.52	-27.98	-193.41	-33.37	153.01	-168.5	-131.26
2020-03-31	243.67	325.62	-116.57	-91.55	-9.93	-314.16	336.48	425.01	-113.74	184.45	111.27	49.24	-19.7	16.78	-49.05	1195.04	148.4	-334.23	-58.38	-39.24	-136.82	-13.04	151.38	-256.13	-220.36
2020-02-28	220.76	218.18	-91.59	-110.29	-29.27	167.83	462.83	313.41	-147.9	142.11	-103.72	16.14	-4.01	6.71	10.91	348.66	227.38	-333.26	-54.55	-21.99	-141.9	-51.95	66.93	-75.47	107.13
2020-01-31	178.24	222.76	-68.09	-85.39	-5.53	62.66	378.11	226.24	-123.2	-59.94	-85.58	-2.48	-0.62	5.04	9.39	317.17	160.87	-231.08	-65.09	-3.68	-121.99	22.05	38.12	-88.01	65.49
2019-12-31	289.32	168.45	-80.42	-132.25	41.37	-112.08	416.88	130.78	-108.31	144.34	-133.74	2.5	-0.34	3.8	2.77	269.18	-97.32	-196.65	-60.78	13.16	-126.23	-78.77	9.6	-67.93	-14.1
2019-11-29	333.33	209.56	-103.94	-116.72	33.36	-183.35	393.11	65.47	-122.41	100.92	141.92	-6.85	1.86	6.29	18.97	307.76	70.78	-251.27	-59.85	-1.72	-118.45	-77.91	4.63	-77.59	-10.01
2019-10-31	360.31	175.25	-90.72	-113.04	36.28	-177.33	413.62	223.11	-143.66	39.03	-37.48	-0.55	0.38	4.69	-1.44	109.72	155.77	-263.78	-62.18	-52.8	-163.4	3.61	62.54	-86.56	-20.82
2019-09-30	298.78	199.92	-87.4	-93.76	-1.75	-186.97	380.03	184.31	-122.36	64.87	-146.53	-17.73	-8.14	7.33	-0.93	274.34	154.38	-223.36	-63.2	-24.18	-94.88	49.32	61.98	-56.73	55.27
2019-08-30	295.96	207.03	-80.25	-117.15	-1.48	-351.75	398.38	203.43	-101.75	181.16	-417.21	16.33	-15.02	12.35	28.97	151.23	59.44	-341.63	-43.3	-49.84	-139.77	40.67	-87.17	-115.66	12.92
2019-07-31	357.97	262.64	-101.57	-72.4	20.76	-271.44	413.01	166.88	-124.67	57.99	46.38	33.17	8.13	0.51	20.79	283.2	52.93	-167.29	-40.94	-0.59	-151.78	-70.86	-58.85	-136.43	78.44
2019-06-28	437.28	254.51	-87.54	-64.39	31.64	-294.94	402.21	106.78	-109.15	45.42	-63.4	41.16	7.78	2.53	17.54	318.96	151.41	-173.38	-52.96	-14.1	-166.58	-24.14	17.72	-120.5	49.93
2019-05-31	312.33	265.49	-69.13	-82.71	34.71	-249.47	445.76	108.77	-92.25	143.67	-650.41	19.6	7.41	-2.19	19.17	365.93	204.49	-327.62	-54.6	-53.83	-196.6	-18.59	-57.05	-111.67	44.61
2019-04-30	244.04	282.21	-99.51	-106.02	29.35	-410.11	443.22	79.44	-101.68	146.11	-57.19	36.56	-6.98	3.57	27.08	411.31	124.17	-211.12	-68.01	-37.34	-123.42	4.96	9.99	-138.33	86.65
2019-03-29	277.9	311.45	-81.21	-79.79	33.72	-383.22	246.78	140.32	-90.99	97.41	135.35	21.02	-2.4	7.32	-4.99	333.7	214.45	-268.04	-64.94	-46.85	-125.56	37.75	-22.34	-147.41	103.66
2019-02-28	398.91	267.52	-92.26	-84.31	41.71	-461.24	246.72	96.65	-106.67	123.01	71.23	4.36	-10.95	9.03	-24.24	302.34	159.35	-264.29	-49.68	-46.11	-84.92	-5.12	-0.67	-134.58	13.01
2019-01-31	410.31	281.22	-87.5	-105.72	26.32	-318.96	152.13	59.91	-71.73	136.37	161.9	11.27	12.82	-1.71	10.78	426.56	346.93	-357.68	-50.54	-46.65	-123.01	8.48	54.06	-116.11	133.96
2018-12-31	391.07	257.49	-78.06	-82.12	49.72	-562.61	225.41	44.66	-65.08	89.59	87.46	29.08	-11.95	7.32	-22.63	476.69	461.87	-342.58	-68.75	-53.18	-184.93	-62.84	122.9	-84.54	226.25

Results and Conclusion

Extracting a Measure Value in EM Sovereign Debt

country

ILS

Value Factor Heatmap

	US4651387N91	US465138ZR91	US46513EFG26	US46513EJX13	US46513EKL55
2020-09-30	437.34	61.41	-274.33	-72.95	-0.79
2020-08-31	530.78	137.12	-166.97	-67.14	-26.03
2020-07-31	391.87	138.95	-186.19	-44.74	-38.42
2020-06-30	680.33	182.96	-210.3	-63.81	-61.07
2020-05-29	855.21	227.91	-174.46	-92.35	-38.11
2020-04-30	1019.03	291.28	-303.06	-143.52	-27.98
2020-03-31	1195.04	148.4	-334.23	-58.38	-39.24
2020-02-28	348.66	227.38	-333.26	-54.55	-21.99
2020-01-31	317.17	160.87	-231.08	-65.09	-3.68
2019-12-31	269.18	-97.32	-196.65	-60.78	13.16
2019-11-29	307.76	70.78	-251.27	-59.85	-1.72
2019-10-31	109.72	155.77	-263.78	-62.18	-52.8
2019-09-30	274.34	154.38	-223.36	-63.2	-24.18
2019-08-30	151.23	59.44	-341.63	-43.3	-49.84
2019-07-31	283.2	52.93	-167.29	-40.94	-0.59
2019-06-28	318.96	151.41	-173.38	-52.96	-14.1
2019-05-31	365.93	204.49	-327.62	-54.6	-53.83
2019-04-30	411.31	124.17	-211.12	-68.01	-37.34
2019-03-29	333.7	214.45	-268.04	-64.94	-46.85
2019-02-28	302.34	159.35	-264.29	-49.68	-46.11
2019-01-31	426.56	346.93	-357.68	-50.54	-46.65
2018-12-31	476.69	461.87	-342.58	-68.75	-53.18
2018-11-30	297.33	294.03	-277.71	-43.49	-66.03
2018-10-31	242.57	92.08	-184.04	-54.37	-51.3
2018-09-28	380.05	44.65	-141.77	-42.76	-48.02
2018-08-31	287.44	51.22	-165.83	-64.07	-49.9
2018-07-31	344.37	148.67	-140.92	-31.5	-56.83
2018-06-29	297.74	75.8	-254.75	-61.42	-54.95
2018-05-31	330.22	281.77	-292.03	-50.23	-64.44
2018-04-30	192.43	225.81	-310.66	-60.47	-65.99
2018-03-30	352.84	236.37	-382.73	-40.31	-82.19
2018-02-28	311.16	167.73	-276.47	-34.83	-43.03

country

COP

Value Factor Heatmap

	US195325AL92	US195325BB02	US195325BD67	US195325BK01
2020-09-30	201.97	281.59	-92.7	165.73
2020-08-31	144.29	273.05	-112.89	162.21
2020-07-31	151.88	240.96	-112.58	105.92
2020-06-30	147.16	378.63	-112.38	186.56
2020-05-29	300.88	269.1	-135.07	206.18
2020-04-30	383.56	161.62	-97.82	196.26
2020-03-31	336.48	425.01	-113.74	184.45
2020-02-28	462.83	313.41	-147.9	142.11
2020-01-31	378.11	226.24	-123.2	-59.94
2019-12-31	416.88	130.78	-108.31	144.34
2019-11-29	393.11	65.47	-122.41	100.92
2019-10-31	413.62	223.11	-143.66	39.03
2019-09-30	380.03	184.31	-122.36	64.87
2019-08-30	398.38	203.43	-101.75	181.16
2019-07-31	413.01	166.88	-124.67	57.99
2019-06-28	402.21	106.78	-109.15	45.42
2019-05-31	445.76	108.77	-92.25	143.67
2019-04-30	443.22	79.44	-101.68	146.11
2019-03-29	246.78	140.32	-90.99	97.41
2019-02-28	246.72	96.65	-106.67	123.01
2019-01-31	152.13	59.91	-71.73	136.37
2018-12-31	225.41	44.66	-65.08	89.59
2018-11-30	282.19	58.03	-97.32	56.1
2018-10-31	297.56	-39.33	-106.17	220.83
2018-09-28	342.63	82.3	-172.11	68.64
2018-08-31	385.2	146.53	-123.16	83.4
2018-07-31	350.72	-8.23	-95.82	144.8
2018-06-29	325.17	75.15	-136.62	87.12
2018-05-31	403.42	64.02	-102.39	171.08
2018-04-30	332.43	16.28	-100.76	83.25
2018-03-30	91.91	136.92	-55.41	234.14
2018-02-28	118.86	122.28	-64.1	265.21

country

RUB

Value Factor Heatmap

	US78307ADE01	US78307ADH32	XS0767473852	XS0971721963
2020-09-30	-53.23	2.22	-53.23	2.22
2020-08-31	-48.77	2.72	-48.77	2.72
2020-07-31	-42.88	-2.5	-42.88	-2.5
2020-06-30	-47.44	-25.84	-47.44	-25.84
2020-05-29	-54.09	-20.68	-54.09	-20.68
2020-04-30	19.05	6.53	19.05	6.53
2020-03-31	-14.8	15.74	-14.8	15.74
2020-02-28	-42.99	13.67	-42.99	13.67
2020-01-31	-43.97	13.18	-43.97	13.18
2019-12-31	-46.67	17.96	-46.67	17.96
2019-11-29	-46.42	9.56	-46.42	9.56
2019-10-31	-37.01	18.26	-37.01	18.26
2019-09-30	-36.13	14.74	-36.13	14.74
2019-08-30	11.48	14.39	11.48	14.39
2019-07-31	11.75	1.83	11.75	1.83
2019-06-28	11.6	-33.66	11.6	-33.66
2019-05-31	13.73	26.33	13.73	26.33
2019-04-30	-1.95	41.23	-1.95	41.23
2019-03-29	6.44	10.0	6.44	10.0
2019-02-28	1.32	2.45	1.32	2.45
2019-01-31	1.91	-0.25	1.91	-0.25
2018-12-31	0.74	10.7	0.74	10.7
2018-11-30	-1.3	22.95	-1.3	22.95
2018-10-31	-0.84	0.62	-0.84	0.62
2018-09-28	-29.17	7.59	-29.17	7.59
2018-08-31	-42.46	13.89	-42.46	13.89
2018-07-31	-30.9	-4.71	-30.9	-4.71
2018-06-29	-23.97	7.03	-23.97	7.03
2018-05-31	-11.38	12.17	-11.38	12.17
2018-04-30	4.4	15.94	4.4	15.94
2018-03-30	-12.37	20.08	-12.37	20.08
2018-02-28	-0.34	14.2	-0.34	14.2

Results and Conclusion

Extracting a Measure of Sovereign Quality /Defensiveness/ in EM Sovereign Debt

What is **defensive**?
The defensive effect can be described simply as the economic stability or the relative immunity to economic fluctialtions. Defensive countries have better fundamentals with higher probability for debt payments and remain relatively unaffected in an event of economic boom or recession.

We use the same machine-learning (ML) **random-forest** framework as the core methodology here and SHAP local model explanations.

- The key outputs from the random-forest framework are the YTM residuals that are deviations of actual YTM yields from model-implied yields.
- The key outputs from the SHAP are the feature contributions for each predicted value. (Explaining the difference between the base (average) value and the predicted one).

We take an average of the country-specific contributions for the bonds on a country level and extract the quality/defensive measure for this country.

Results and Conclusion

Extracting a Measure of Sovereign Quality /Defensiveness/ in EM Sovereign Debt

	ILS	KRW	PHP	PLN	PEN	CLP	MXN	HUF	BRL	RUB	IDR	COP	ZAR	TRY	EGP
2020-09-30	1.83	1.73	1.55	1.53	1.11	0.86	0.54	0.85	0.49	0.69	0.31	-0.06	-1.27	-3.14	-3.07
2020-08-31	1.82	1.8	1.43	1.46	1.12	1.0	0.58	0.67	0.3	0.65	0.28	-0.09	-1.18	-3.06	-2.91
2020-07-31	1.83	1.58	1.52	1.42	1.36	0.84	0.51	-0.02	0.4	0.69	0.24	-0.01	-1.3	-3.36	-3.12
2020-06-30	1.94	1.76	1.33	1.35	1.25	0.7	0.26	0.02	0.22	0.74	0.14	-0.14	-1.16	-2.68	-3.21
2020-05-29	1.91	1.78	1.41	0.93	1.22	0.53	0.35	0.42	0.26	0.93	0.21	-0.15	-1.29	-2.93	-3.15
2020-04-30	2.25	2.34	1.68	1.06	1.36	0.64	0.11	0.8	0.33	0.97	0.19	-0.64	-1.75	-2.91	-3.34
2020-03-31	2.13	2.03	1.23	1.18	1.42	0.89	0.95	0.66	0.82	0.81	0.34	-0.31	-2.5	-3.01	-3.78
2020-02-28	1.3	1.36	1.07	0.97	0.99	0.82	0.85	0.38	0.43	0.51	0.24	0.06	-0.66	-2.62	-2.82
2020-01-31	1.07	1.04	0.92	0.84	0.84	0.72	0.58	0.35	0.33	0.4	0.07	-0.18	-0.79	-1.75	-2.45
2019-12-31	1.1	0.97	0.97	0.94	0.81	0.63	0.52	0.42	0.34	0.47	0.12	-0.07	-0.57	-2.17	-2.21
2019-11-29	1.21	1.1	1.22	1.04	0.97	0.7	0.43	0.68	0.41	0.32	0.21	-0.13	-0.54	-2.44	-2.53
2019-10-31	1.2	1.0	1.25	1.02	1.01	0.83	0.37	0.59	0.37	0.24	0.23	0.01	-0.47	-2.49	-2.49
2019-09-30	1.32	1.19	1.32	1.03	0.98	0.8	0.24	0.52	0.41	0.17	0.26	0.02	-0.45	-2.62	-2.46
2019-08-30	1.39	1.22	1.35	1.11	1.09	0.88	0.28	0.33	0.45	0.12	0.37	0.24	-0.28	-3.13	-2.5
2019-07-31	1.21	1.03	1.27	0.95	0.96	0.6	0.17	0.57	0.57	0.14	0.28	-0.0	-0.36	-2.62	-2.05
2019-06-28	1.36	1.2	1.28	1.07	0.97	0.71	0.26	0.6	0.44	0.14	0.29	0.03	-0.12	-2.74	-2.11
2019-05-31	1.46	1.25	1.37	1.06	1.06	0.8	0.28	0.16	0.57	0.14	0.35	0.08	-0.23	-3.04	-2.48
2019-04-30	1.39	1.21	1.26	1.1	1.03	0.68	0.25	0.65	0.49	0.14	0.34	0.15	-0.25	-2.89	-2.21
2019-03-29	1.36	1.15	1.29	1.11	1.07	0.74	0.21	0.67	0.49	0.0	0.19	0.19	-0.29	-2.8	-2.14
2019-02-28	1.18	1.02	1.18	0.88	0.87	0.54	0.17	0.57	0.39	0.09	0.07	-0.04	-0.32	-2.1	-2.05
2019-01-31	1.22	0.98	1.11	0.9	0.91	0.63	0.09	0.56	0.41	0.02	0.1	0.05	-0.25	-1.99	-2.38
2018-12-31	1.55	1.09	1.2	0.99	1.06	0.53	0.16	0.66	0.31	0.01	0.04	-0.07	-0.56	-2.04	-2.86

Example TRY 2020-09-30: Due to the country-specific factors, on average the yields of the turkish bonds are 3.14bp higher than the universe average yield for the date. This is our model-implied measure of the compensation the market requires for assuming country-specific risk.

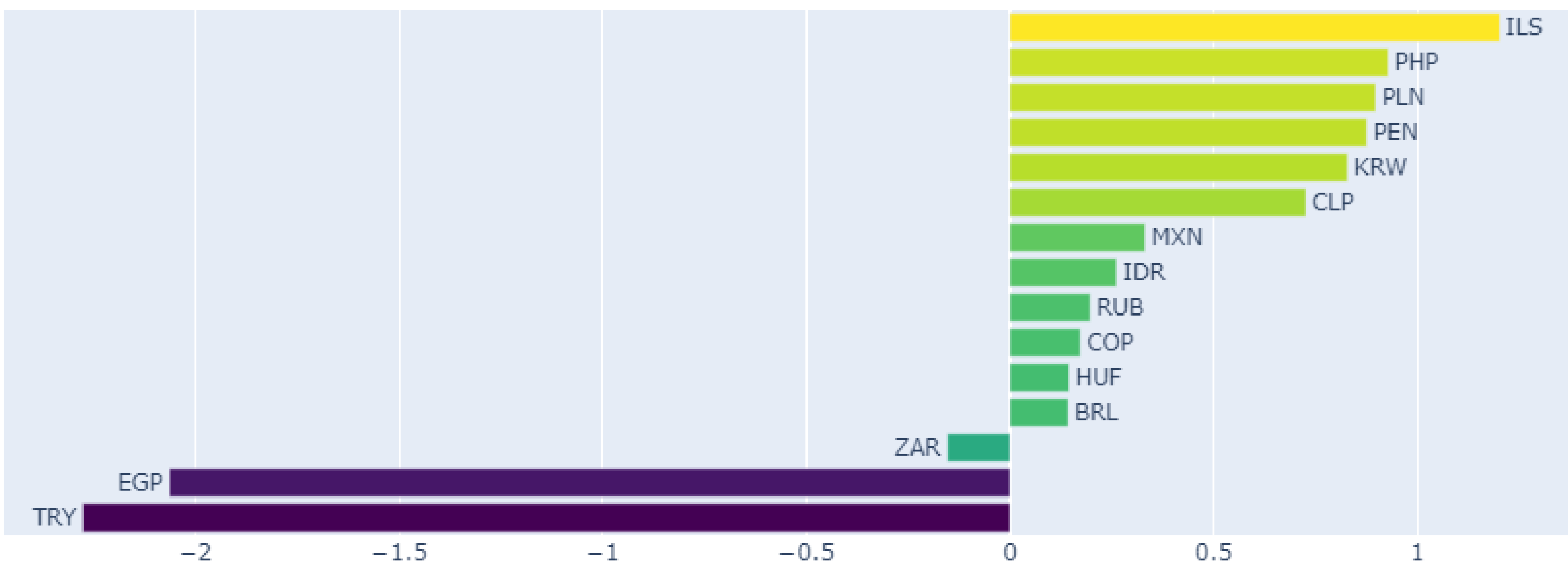
Results and Conclusion

Extracting a Measure of Sovereign Quality /Defensiveness/ in EM Sovereign Debt

This EM Sovereign Risk Index uses data from six categories that each count toward a country's final score: **GDP Growth, Inflation, Fiscal Deficit, Short-term Debt to FX Reserves, Current Account, Institutional Strength (Rank)**.

Example TRY: Inflation: -0.681636 (11.035088 (4.859)), GDP: -0.026047 (3.683680 (3.837)), DeficitToGDP: -0.017480 (-2.487500 (-2.852)), CurrentAccount: -0.952339 (-5.764881 (-1.49)), Reserve: -0.598108 (-70.206278 (-13.243)), Rank: -0.085087 (49.689237 (48.289))

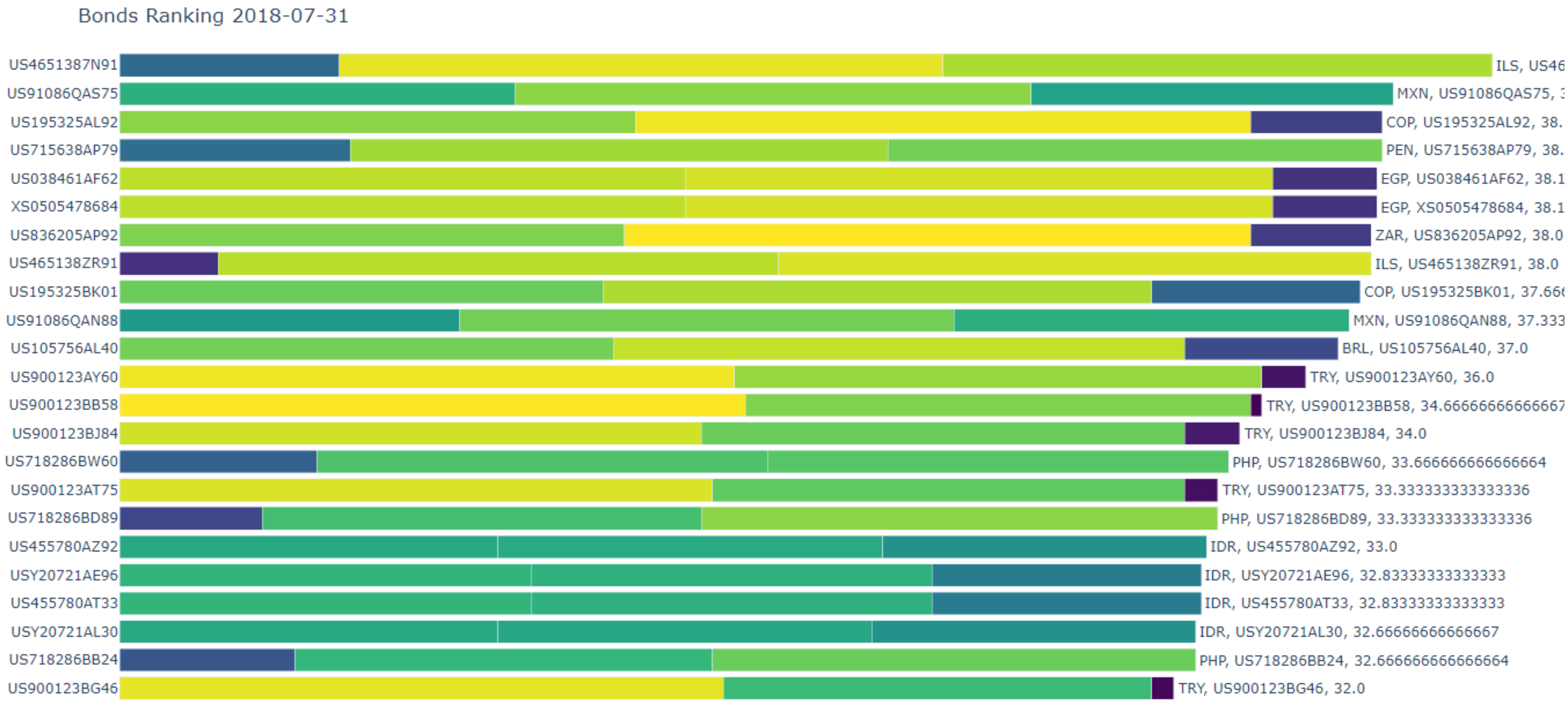
Emerging Markets Sovereign Risk Index Country Ranking 2018-07-31



Results and Conclusion

Scanning for the Optimal Portfolio:Achieving High Income, Good Value and Strong Sovereign Quality in EM Sovereign Debt

ISIN: US4651387N91 (Rank: 41.67), Country: Israel (ILS)
Yield Rank: 6.67 (YTM: 4.319) (Higher yield -> higher rank)
Value Rank: 18.33 (Value: 344.37) (Higher Value-> higher rank)
Defensive Rank: 16.67 (Defensive: 0.939) (Higher quality -> higher rank)



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Thank You