BARCLAYS

Special Report
Research
30 July 2019

Research Data Science

Modeling M&A Targets

Adam Kelleher**
+1 212 526 5697
adam.kelleher@barclays.com
BCI, US

Ryan Preclaw
+1 212 412 2249
ryan.preclaw@barclays.com
BCI, US

www.barclays.com

Using simple data variables/features, both linear and non-linear classification models improve the chances of finding companies that accept merger offers.

Companies accepting merger bids present an attractive place to look for investment opportunity because they predictably result in upside across the capital structure and occur frequently enough to produce a consistent stream of returns. That said, previous experience and the fact those returns have been persistently high for a long time tell us the identification problem is difficult. We evaluated the potential for a selection of classification models to predict which companies in the S&P 1500 are most likely to accept a merger offer in the near future.

This problem offers a number of challenges compared with standard classification tasks:

- There is a relatively small amount of data, with only about 1800 merger events affecting companies large enough to be interesting for large investors.
- The data suffer from class imbalance, with mergers very rare (at a given time) compared with non-mergers.
- There is a large number of possible drivers of mergers, with relatively little data to distinguish which are important.

Because of that, we use multiple steps to build and validate models, while mitigating the risk of overfitting. In the first step, we generate a large set of features to predict mergers. We walk through our feature selection process and then motivate our focus on simple models. We validate those models and tune parameters with a simple batch prediction where we fix training, quarantine, and testing sets in time. Then, we use a more elaborate point-in-time training/testing method to rank the surviving models.

In the end, we find that both linear and non-linear models outperform guessing, with forward-prediction AUROCs over 0.6 and collecting a higher share of deals in any given size group (over 70% of deals on average for the top 50% of companies).

The Investment Sciences team explored potential investment-related uses of this model in their report *Mergers Predictions Are High Risk, July 30, 2019*.

***This author is a member of Fixed Income, Currencies and Commodities Research department and not an equity or debt research analyst*

Barclays Capital Inc. and/or one of its affiliates does and seeks to do business with companies covered in its research reports.as a result, investors should be aware that the firm may have a conflict of interest that could affect the objectivity of this report. investors should consider this report as only a single factor in making their investment decision.

This is a Special Report that is not an equity or a debt research report under U.S. FINRA Rules 2241-2242.

FOR ANALYST CERTIFICATION(S) PLEASE SEE PAGE 14.

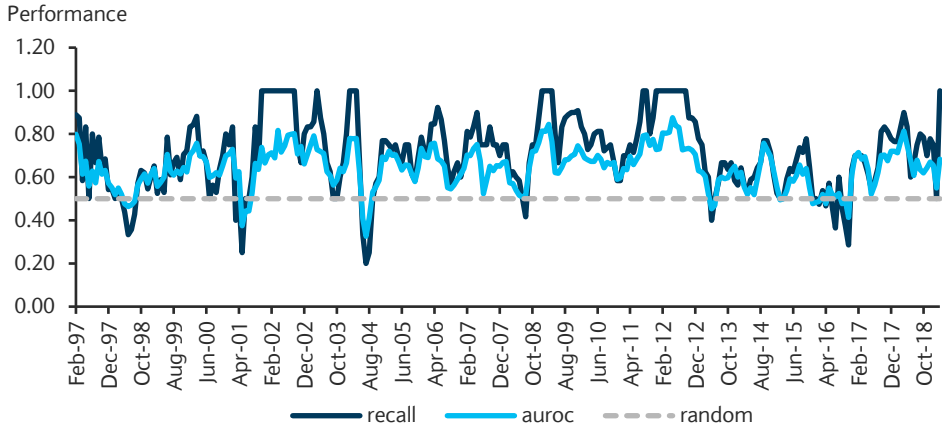
FOR IMPORTANT FIXED INCOME RESEARCH DISCLOSURES, PLEASE SEE PAGE 14.

FOR IMPORTANT EQUITY RESEARCH DISCLSOURES, PLEASE SEE PAGE 14.

Completed: 29-Jul-19, 20:18 GMT Released: 30-Jul-19, 04:10 GMT Restricted - External

FIGURE 1

Although the AUROC of Logistic Regression-Only Averages about 0.64, We Believe That Being Right 64% of the Time Is Enough to Be a Useful Investing Tool



Source: Barclays Research

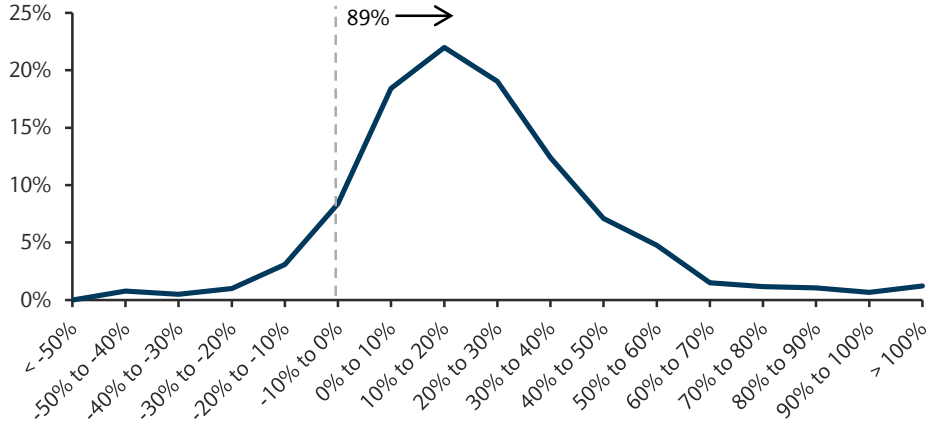
Predicting Mergers Is Difficult but Valuable

Mergers are the corporate event that most reliably results in outsized returns for securities across the capital structure. For example, among companies that announce they are accepting a merger offer (the "targets"), about 90% see their stocks post positive returns over the following month, with more than half generating returns greater than 20% (Figure 2). The story can be more complex for corporate credit, but the combination of acquirers typically being larger companies and the prevalence of change of control provisions means that bond holders of merger targets usually have upside in an announcement.

That makes identifying companies that are likely to accept a merger offer[1] a useful problem to solve for investors in any sort of corporate security. It is also difficult enough that we do not know of any solution that works well enough to be considered the gold standard. Given that, we are starting from the basics. We constructed a panel of merger data to train and test models, and we use it to evaluate whether simple features can classify companies into one of two types: those that are going to accept a merger bid, and those that are not.

FIGURE 2

Stocks That Accept M&A Bids Experience Positive Returns around 90% of Deal Announcements and >20% Returns Almost 50%



Source: Factset, Refinitiv, Barclays Research

[1] It is important to note that we are not attempting to design a model that will predict whether any accepted merger offer will ultimately lead to an M&A deal closing between the parties.

We know from experience and anecdote that predictive performance improvements due to model refinements are often small compared with those due to refining the input data. With that in mind, we kept our modelling scope small, while focusing on engineering many input features.

Input Features

We started by choosing a set of features we thought might predict mergers. Some we chose for fundamental reasons, others because they were convenient. Our intent was to select from this set based on their usefulness for prediction, without biasing our feature selection too much up front using our fundamental understanding. In short, we decided to stay open to surprises.

We left the detailed panel construction in appendix 1. We built one panel for the S&P 1500, and one for the S&P 500. Our intended investment universe was the S&P 500, but we found that the model benefits from the extra data in the S&P 1500. The panel was defined with monthly time steps, marked at the last business day of each month.

The features we used are summarized in Figure 3. We mean-centered and standardized them by industry.

FIGURE 3
Features Used in Our Models

Feature Name	Description	Source
Assets	Annual total assets	Compustat
Sales	Annual sales	Compustat
Total Liabilities	Most recent annual total liabilities	Compustat
Net Income	Most recent annual net income	Compustat
EBITDA	Most recent annual earnings before interest, taxation, depreciation, and amortization	Compustat
EBITDA to Assets	Total return index for common stock (IPO = 100) as of most recent day	Refinitiv QAD
Returns	Ratio of current total returns to the last month's end-of-month total returns	Refinitiv QAD
Market Value	Most recent common shares outstanding times closing price	Refinitiv QAD
Tobin's Q	Market value (QAD, daily) plus total liabilities (Compustat, annual) relative to total assets (Compustat, annual), engineered feature	Refinitiv QAD and Compustat
EBITDA to Capitalization	The ratio of EBITDA to market value plus total liabilities, engineered feature	Refinitiv QAD and Compustat
Total Returns Drawdown	The point-in-time total returns divided by the (past) maximum total returns	Refinitiv QAD
Market Value Drawdown	The point-in-time market value divided by the (past) maximum market value	Refinitiv QAD
Lagged Variables	One-, three-, and six-month lags of the above	Refinitiv QAD and Compustat
Ratio Variables	Ratios of each variable to its lags	Refinitiv QAD and Compustat

Source: Barclays Research

Including one-, six- and twelve-month lags of these, we ended up with well over 100 variables to build our model. This made it important to spend time doing variable selection.

Variable Selection

There are many different methods for doing variable selection. Some suggest doing tests for the statistical dependence of each variable with the outcome, but these tests miss whether our inputs are correlated with each other, so whether they really add information to our model.

Other approaches involve building models with the whole collection of variables except one, so seeing how additive each is to the full set. This is computationally expensive because it requires building lots of models: at least for each variable, but (if one wants to be thorough) combinations of variables as well.

Lasso Regression

We opted for a very simple approach: Lasso regression. This is commonly used for feature selection in machine learning and is very similar to ordinary least squares (OLS) regression. While OLS fits its coefficients by minimizing mean-squared error, lasso regression fits coefficients by minimizing the mean-squared error plus a weighted L1-norm. The L1-norm is just the sum of absolute values of the regression coefficients. The result is that the higher the weight on the L1-norm, the smaller the fit coefficients tend to be. This is called regularizing the coefficients, and the L1-norm's weight can also be called regularization strength.

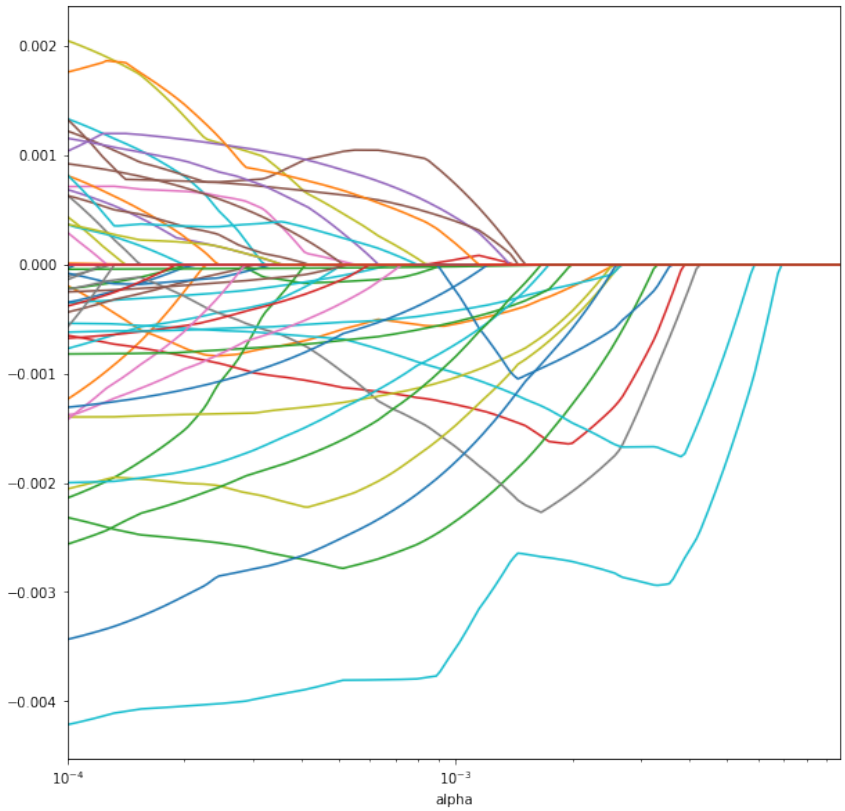
The L1-norm has the feature that it tends to force regression coefficients to zero. When the weight is zero, it has the same effect as not including that variable in the model. In that sense, lasso regression tells, for a given weight on the L1-norm, what is the best set of variables to use in the model. Since increasing weight tends to select fewer and fewer variables, this is like asking, "For a given model complexity, what is the best set of variables to use?"

Selection Results

Figure 4 shows the regression coefficients as a function of the regularization strength, alpha. The regularization is weakest for small alpha and gets stronger from left to right in the plot. There are too many coefficients to reasonably label them all, so we will select the most important and plot them later.

FIGURE 4

Regression Coefficients vs. Lasso Regularization Strength



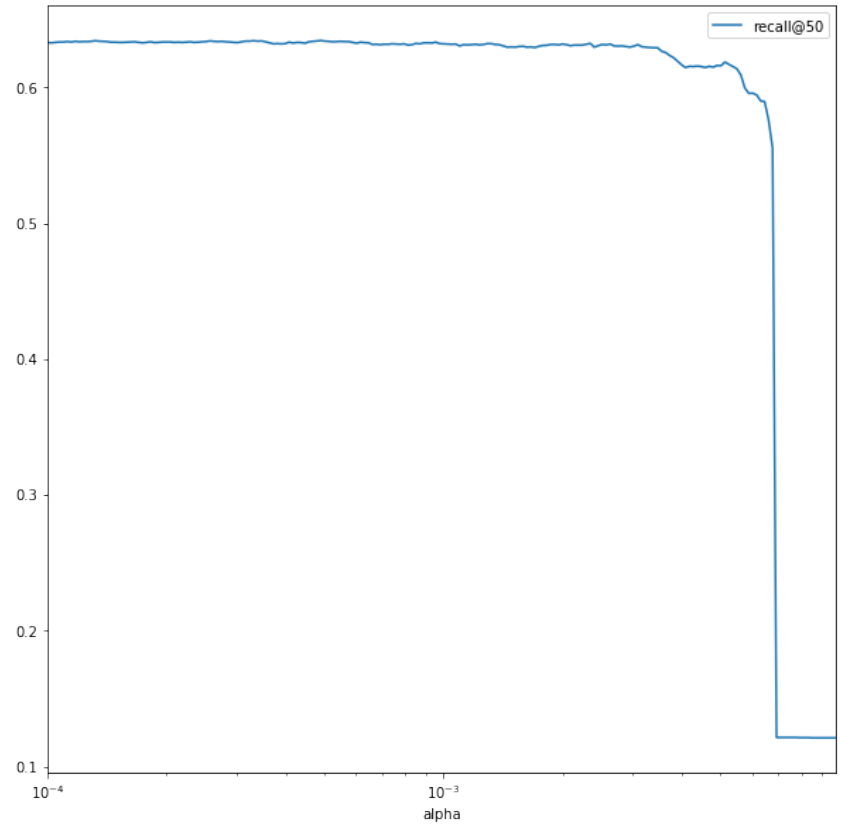
Source: Barclays Research

The regression coefficients start out mostly unconstrained in the left-hand side of the plot and are close to their OLS values. As we move left to the right, they get smaller as they are regularized, and some of them "turn off" as the regularization forces them to zero. Again, when the regression coefficient is zero, it has the same effect as not including that variable in the model.

Figure 5 shows how the model's recall changes as the regularization makes us turn on and off different variables. The recall achieves most of its value (moving right to left) around 5.4e-3, at the first "hump" in the recall curve. The active variables are shown in Figure 6, and the variable selection plot for the smaller model is in Figure 7. This smaller plot lets one see which variables "turn on" when.

FIGURE 5

Recall vs. Lasso Regularization Strength, prior to variable selection



Source: Barclays Research

The first big gain in recall (in Figure 5, again going right to left) is from including just market value and Q (higher Q means lower propensity to sell; note the x-axes in Figures 5 and 8 are aligned and the performance plot for the smaller model looks almost the same). That means the simplest model with comparable performance to our best model contains just those two variables. That suggests it is reasonable to analyze a company's merger propensity by thinking only about its market value (cheaper means higher propensity to sell) and its Q.

FIGURE 6

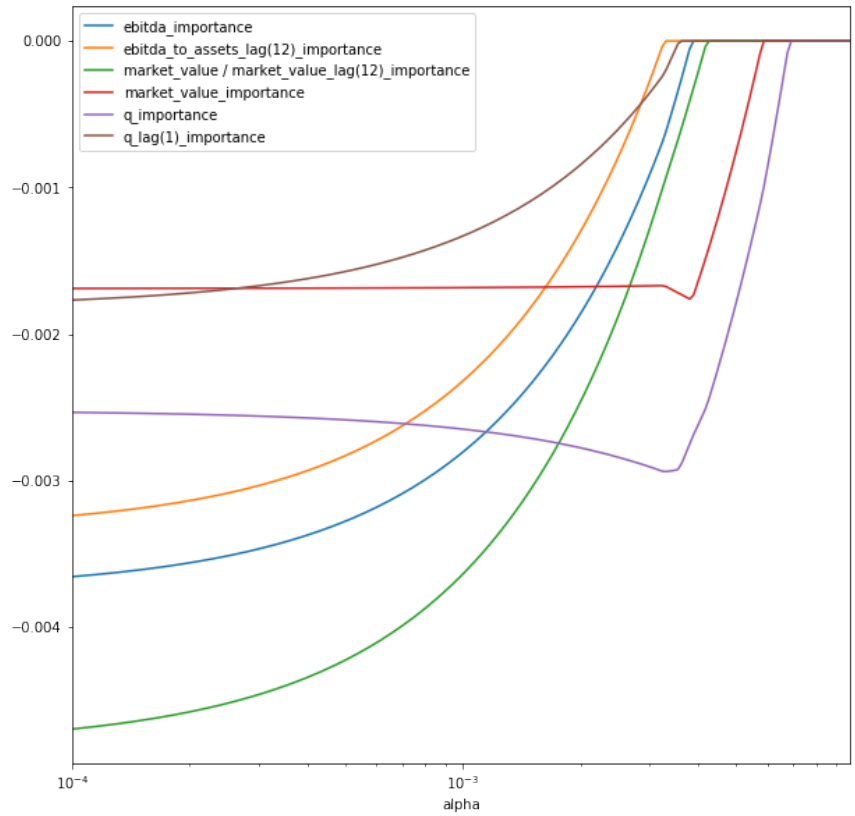
Lasso Selected Variables (all industry normalized)

Variable	Coefficient Sign
Ebitda	Negative
Ebitda to Assets (twelve months lagged)	Negative
Year-Over-Year Market Value	Negative
Last Reported Market Value	Negative
Tobin's Q	Negative
Tobin's Q (one month lagged)	Negative

Source: Barclays Research

Moving beyond the first big gain in recall to the second hump as we decrease alpha in Figure 5, our model adds a few more variables. Year-over-year market value activates next, followed by EBITDA, one-month lagged Q, and EBITDA relative to assets. These variables alone generate almost all of our largest model's performance.

FIGURE 7
Lasso Plot after Variable Selection



Source: Barclays Research

Having looked at which variables drive the linear model performance, next we wanted to see how much changing our model affected performance. Occam's Razor would say to choose the simplest model that gets the best performance. With that in mind, we tested our models with all of the variables, and again with this small subset from Figure 6.

Modeling

Predicting mergers is a classification problem: either a company will or will not sell themselves in a merger deal during a given holding period (more precisely, the event "they announce a deal" will or will not occur). With that in mind, we focused on building a classification model to distinguish more likely from less likely candidates. This is a standard machine learning problem, so this section focuses primarily on the machine learning considerations we made.

Model Selection

There is an ROI question to answer. Many models are available to us, and each has many parameters. We could spend a long time testing models and tuning parameters, but this can represent a significant time investment. This is especially true with non-linear models, with neural networks as an extreme example. The random forest classifier in scikit-learn, for example, has twelve parameters that might affect performance. If we simplified to just high and low settings for each parameter, that would make 2^{12} = 4,906 parameter combinations. With a two-minute run time for a medium-sized (100 estimator) model, it would take over five days just to tune our random forest. This exponential growth in modeling complexity is a good reason to constrain its scope.

If more sophisticated modeling does not result in commensurate performance improvements, then we get lower ROI for having explored more sophisticated models when we end up using the linear model with which we started.

In addition to being a smaller time investment, linear models have the benefit of interpretability. With these points in mind, we opted to focus on simple linear models and to do a quick (low investment) sanity check to make sure there was no surprisingly large benefit to using more sophisticated non-linear ones.

We decided to focus our effort on logistic regression, but test two other non-linear models.

- **Non-linear Models**: We focused on ensembles of decision trees, with different refinements to their fitting process. The relative rarity of M&A creates a problem of imbalanced classes, which can lead to problems with sub-sampling in ensemble models: it is easy to bootstrap a small sample of data with positive cases. We opted to use two methods that leverage different statistical techniques to improve over simple batch training models.
  - A **gradient-boosting classifier** (GBC): GBCs use decision trees, but combine them using a more sophisticated algorithm called "boosting".[2] Boosting works one stage at a time. At each stage, these relatively inexpressive smaller models (the decision trees) are fit to the residuals of the previous collection of decision trees. That tree's predictions are subtracted from the original predictions, and the process is repeated, minimizing the total model's residuals. One can look at the addition of each decision tree as taking a small step in function space in the direction that minimizes the model's residuals.
  - **Random forest classifier** (RF) with class re-weighting. Random forests use "bagging," or bootstrap-aggregating, to prevent overfitting. Bagging generates bootstrap samples of the data to train each decision tree, then averages their predictions. Random forest additionally samples features (at each split), as well as the data points. Class re-weighting balances the classes during sub-sampling and makes it less likely that we end up with no positive cases in a sub-sample.

We think the recent focus on neural network models justifies a little further explanation for why we did not choose them. Neural networks typically have more parameters to tune than classic models because there are many more components used to construct them. The analyst has to define architectures, link functions, objective functions, regularization methods, and gradient descent methods. Each of these components has many parameters.

Aside from the cost, many of the newsworthy performances or neural networks have come from representation learning: learning to represent hard-to-quantify data, such as images and text, in a way that reduces the complexity of a fuller non-linear specification through parameter sharing[3] (through convolutions on pixel data with convolutional neural networks (CNNs), or through re-using layers with recurrence in recurrent neural networks (RNNs)). Our data were already represented well as a vector of floats, so we saw no advantage from representation learning here. The only real advantage we saw would be efficient use of lag terms by using an RNN (worth looking into, but too complicated for a starting place), or incorporating additional non-linearity (which could be better achieved

[2] Gradient-boosting models fit a sequence of trees in a forward stage-wise fashion, see Friedman, Jerome. "Greedy Function Approximation: A Gradient Boosting Machine". IMS 1999 Reitz Lecture (1999)
[3] Goodfellow, Bengio, and Courville. Deep Learning (2016), sec 7.9 for parameter sharing. Introduction pp 4-7 for context of representation learning.

with polynomial regression than DNNs[4]). We decided the value was not worth the cost and opted for the simple approach for now.

Model Evaluation

To evaluate these models, we use two validation methods.

The first method is a temporal train/quarantine/test split for cross-validation. We split the data into three fixed groups by time, we train our model on the oldest group and evaluate the results by its predictions in the newest. We drop to middle group to limit test set contamination due to autocorrelation. This has the advantage of being much faster than our other validation method, but the disadvantage of being somewhat different from how we would use our models in practice. We use primarily this to tune model parameters.

The second method is a point-in-time predictive performance approach for cross-validating. We validate using a rolling group of training data and evaluate based on predictions made for the next time step. We explain these choices in detail in the next section.

We looked at two key model performance criteria. The first was "Area under the receiver operator characteristic" (AUROC), which is a measure of classification correctness that captures both positive (will merge) and negative (will not merge) outcomes. A model with an AUROC of 0.5 corresponds to a model that can correctly distinguish a company that will announce a merger from one that will not 50% of the time: this is equal to random guessing, meaning the model has learned nothing. An AUROC of 1 corresponds to a model that can correctly tell a company that will merge from one that will not 100% of the time, a perfect model (at least on our test data).

The second performance criterion was recall, which is a measure that at a certain score cut-off tells us what fraction of companies above the cut-off will merge. If we set the cut-off to include the top half of companies, the recall in excess of 50% indicates how well the model is outperforming guessing.

Temporal Train/Quarantine/Test Split Cross-Validation Results

First, we tested the effect of the quarantine period on model performance. It turned out not to affect model performance, so we proceeded with just a train/test split. We made this split at January 1, 2005, excluding the 2008 recession from our training data. We used lasso regression for feature selection and found our models improved when using a subset of features, rather than the full collection. The recall and AUROC of our best models after parameter tuning (by recall at 50% cut-off) are given in Figure 8.

FIGURE 8

Best Model Performances by Recall

Model	AUROC	Recall (at 50%)	Parameter
Random Forest Classifier	0.551	0.547	n_estimators = 150
Gradient Boosting Classifier	0.599	0.633	n_estimators = 130
Lasso Regression	0.598	0.633	alpha = 0.0027
Logistic Regression	0.599	0.630	C = 0.17

Source: Barclays Research

The best model, the gradient boosting classifier, included some non-linearity. It did not outperform the simpler models enough to justify the computational (and time) cost, suggesting it probably was not worth focusing too much more on non-linear models. At

[4] Polynomial Regression As an Alternative to Neural Nets *https://arxiv.org/abs/1806.06850*

this stage, we stopped examining the random forest classifier and focused on the Logistic Regression (LR) and Gradient Boosting Classifier (GBC) more deeply.

Point-in-Time Predictive Performance Results

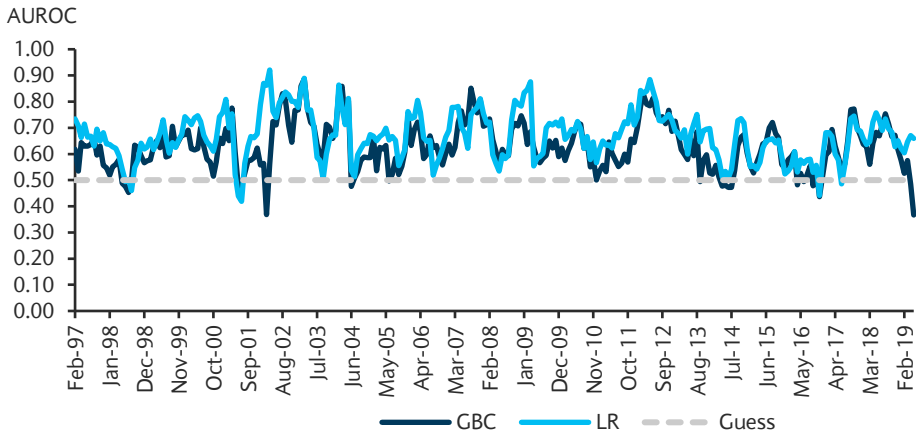
At each point in time, t, for our S&P 1500 panel, we trained a model based on the knowledge we would have hypothetically had at that time. We removed all training data whose six-month-ahead window overlapped with the prediction time and used the remaining data to train our model. We then took the panel for the same point in time from the S&P 500 (the actual investment universe on which we were focusing) and predicted the propensity for each asset's issuer to merge in the next six months. We validated these predictions on the actual outcomes.

The LR and GBC models perform similarly well over time (Figures 9 and 10). The LR model seems to have particularly good performance around recessions. Both models occasionally perform worse than guessing. We should expect this with repeated use of any model with imperfect performance. Here especially, the number of mergers to predict can be small in any given year, so the recall is especially noisy to measure (there just are not that many mergers to recall!).

The time-averaged AUROC for the LR model is 0.669, and the recall is 0.735. The GBC model's time-averaged AUROC is 0.63, and the recall is 0.67. These are not very big differences and might not be statistically significant. They suggest we should prefer (everything else equal) the logistic regression model over the gradient boosting classifier. The LR model is also simpler, so should be preferred by Occam's Razor, everything else held equal.

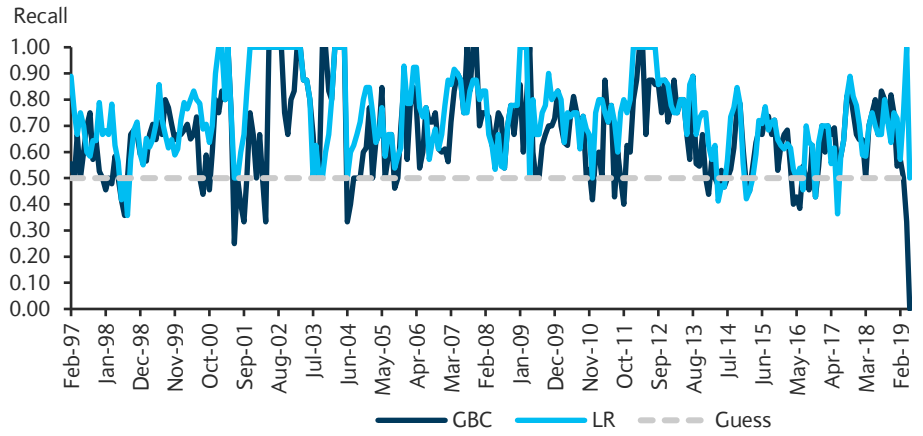
FIGURE 9

GBC and LR model AUROC



Source: Barclays Research

FIGURE 10
Recall at 50% cutoff for GBC and LR



Source: Barclays Research

Takeaways

In this case, our best model was the logistic regression one. Not only did non-linear models not perform better, they actually performed worse than the linear model (LR). This can be for a number of reasons, including the tree-based models not being very good when the underlying function is a simple linear model, and while these models of techniques mitigate class imbalance, they do not do it perfectly (sub-samples can still have only negative classes).

We started with a very large set of features and relied on machine learning techniques, along with Occam's Razor, to narrow them down. We selected not only a small set of features in the end, but a set that is consistent with our fundamental understanding of how M&A works, as Ryan Preclaw details in his companion piece, [TODO: link to M&A basket report goes here].

Our final model performed at the level of a "D+ to C- student". It achieved a 0.669 AUROC and a 0.735 recall, averaged over point-in-time predictions. It is a passable baseline and one that we expect to be improved by including alternative data sources.

Appendix 1: Panel construction

To construct a panel of merger data for model training and validation, we took the following steps:

- We started with the S&P 1500 constituents from Compustat, from 1995 to the present. This gave point-in-time sales, common shares, total liabilities, total assets, preferred stock, and index membership dates for 3708 and 1142 unique Cusips for each index, respectively, which we kept in two separate panels.
- We joined these on gkvey with point-in-time GIC classifications and on Cusip with total returns from QAD.
- We included an indicator variable in our N x T (Cusips by time steps) panels to indicate whether the company was in the index at that time step.
- We joined these on Cusip with FactSet's M&A database to get announcement dates for deals, restricting to include only merger targets. These will become the outcome data for our prediction problem.
- We computed our outcome metric as an indicator variable for whether a Cusip would be the target of a merger in the next six months. We add a variable t_180 to indicate the six-month look-ahead time. This is useful when choosing a slice of data on which to train, so we do not accidentally train on future outcomes.
- We subtracted the GIC-level means of all independent variables and standardized to unit variance, where the means and variances were computed for each GIC and date over assets that were in the index on that date.
- A summary of our features and their statistics (pre-normalization) is given for the S&P 1500 panel in Figure 9.

FIGURE 11

Panel Features and Key Statistics for S&P 1500 Super Composite Panel

Feature	Descrption, Source	mean	std	25%	50%	75%
Assets	Annual total assets, Compustat	16724	91813	706	2143	7618
Common Shares Outstanding	Total outstanding common shares, QAD	214	635	31	63	162
Total Liabilities	Most recent annual total liabilities, Compustat	13192	82525	304	1170	4964
Net Income	Most recent annual net income, Compustat	433	2052	22	80	283
EBITDA	Most recent annual earnings before interest, taxation, depreciation, and amortization, Compustat	1160	3916	75	222	735
Total Return Index	Total return index for common stock (IPO = 100) as of most recent day, IDC	16367	149659	314	1271	6240
Total Return	Returns over end of last business month; engineered feature	1.01	0.12	0.95	1.01	1.07
Market Value	Most recent common shares outstanding times closing price, QAD	9423	29691	738	1958	6171
Tobin's Q	Market value (QAD, daily) plus total liabilities (compustat, annual) relative to total assets (compustat, annual), engineered feature.	2.01	1.89	1.14	1.51	2.23
EBITDA to Capitalization	The ratio of EBITDA to market value plus total liabilities, engineered feature	0.071	0.052	0.043	0.072	0.097

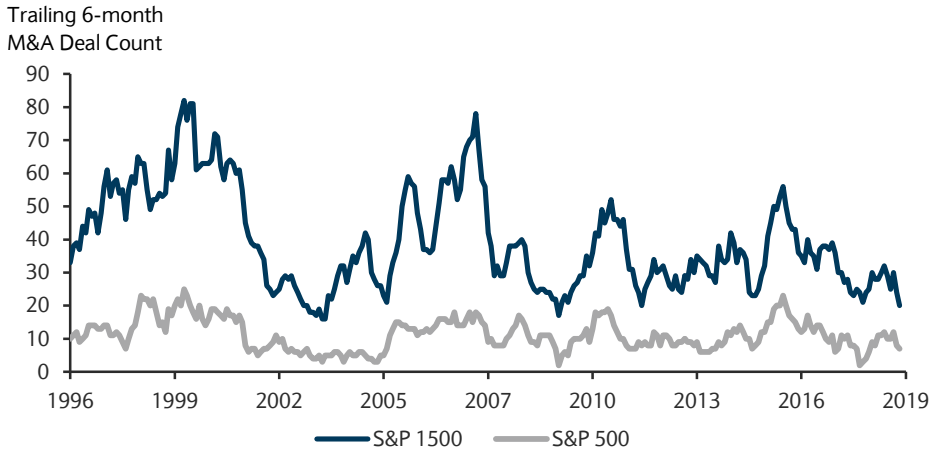
Source: Factset, Compustat, Refinitiv, Barclays Research

Appendix 2: Outcome Statistics

Our final training panel consisted of 3,687 Cusips across 276 monthly observations periods from January 31, 1996, to December 31, 2018. Among those companies, we observed 1,835 events where a company announced that it had accepted a takeover offer. The number of deals varies significantly over time, with as few as about 20 deals, and as many as 80, in a six-month period (Figure 12).

FIGURE 12

The Number of Merger Offers Accepted by Large Companies Fluctuates over Time



Source: Factset, Barclays Research

Analyst Certification
We, Adam Kelleher and Ryan Preclaw, hereby certify (1) that the views expressed in this research report accurately reflect our personal views about any or all of the subject securities or issuers referred to in this research report and (2) no part of our compensation was, is or will be directly or indirectly related to the specific recommendations or views expressed in this research report.

Important Disclosures (FICC RESEARCH):
Barclays Research is produced by the Investment Bank of Barclays Bank PLC and its affiliates (collectively and each individually, "Barclays").
All authors contributing to this research report are Research Analysts unless otherwise indicated. The publication date at the top of the report reflects the local time where the report was produced and may differ from the release date provided in GMT.

Availability of Disclosures:
For current important disclosures regarding any issuers which are the subject of this research report please refer to https://publicresearch.barclays.com or alternatively send a written request to: Barclays Research Compliance, 745 Seventh Avenue, 13th Floor, New York, NY 10019 or call +1-212-526-1072.

Barclays Capital Inc. and/or one of its affiliates does and seeks to do business with companies covered in its research reports. As a result, investors should be aware that Barclays may have a conflict of interest that could affect the objectivity of this report. Barclays Capital Inc. and/or one of its affiliates regularly trades, generally deals as principal and generally provides liquidity (as market maker or otherwise) in the debt securities that are the subject of this research report (and related derivatives thereof). Barclays trading desks may have either a long and / or short position in such securities, other financial instruments and / or derivatives, which may pose a conflict with the interests of investing customers. Where permitted and subject to appropriate information barrier restrictions, Barclays fixed income research analysts regularly interact with its trading desk personnel regarding current market conditions and prices. Barclays fixed income research analysts receive compensation based on various factors including, but not limited to, the quality of their work, the overall performance of the firm (including the profitability of the Investment Banking Department), the profitability and revenues of the Markets business and the potential interest of the firm's investing clients in research with respect to the asset class covered by the analyst. To the extent that any historical pricing information was obtained from Barclays trading desks, the firm makes no representation that it is accurate or complete. All levels, prices and spreads are historical and do not necessarily represent current market levels, prices or spreads, some or all of which may have changed since the publication of this document. Barclays Research Department produces various types of research including, but not limited to, fundamental analysis, equity-linked analysis, quantitative analysis, and trade ideas. Recommendations and trade ideas contained in one type of Barclays Research may differ from those contained in other types of Barclays Research, whether as a result of differing time horizons, methodologies, or otherwise.
In order to access Barclays Statement regarding Research Dissemination Policies and Procedures, please refer to *https://publicresearch.barcap.com/S/RD.htm*. In order to access Barclays Research Conflict Management Policy Statement, please refer to: *https://publicresearch.barcap.com/S/CM.htm*.

All pricing information is indicative only. Prices are sourced from Refinitiv as of the last available closing price at the time of production of the research report, unless another time and source is indicated.

Types of investment recommendations produced by Barclays FICC Research:
In addition to any ratings assigned under Barclays' formal rating systems, this publication may contain investment recommendations in the form of trade ideas, thematic screens, scorecards or portfolio recommendations that have been produced by analysts in FICC Research. Any such investment recommendations produced by non-Credit Research teams shall remain open until they are subsequently amended, rebalanced or closed in a future research report. Any such investment recommendations produced by the Credit Research teams are valid at current market conditions and may not be otherwise relied upon.

Disclosure of other investment recommendations produced by Barclays FICC Research:
Barclays FICC Research may have published other investment recommendations in respect of the same securities/instruments recommended in this research report during the preceding 12 months. To view all investment recommendations published by Barclays FICC Research in the preceding 12 months please refer to *https://live.barcap.com/go/research/Recommendations*.

Important Disclosures (EQUITY RESEARCH):
Barclays Research is produced by the Investment Bank of Barclays Bank PLC and its affiliates (collectively and each individually, "Barclays").
All authors contributing to this research report are Research Analysts unless otherwise indicated. The publication date at the top of the report reflects the local time where the report was produced and may differ from the release date provided in GMT.

Availability of Disclosures:
Where any companies are the subject of this research report, for current important disclosures regarding those companies please refer to https://publicresearch.barclays.com or alternatively send a written request to: Barclays Research Compliance, 745 Seventh Avenue, 13th Floor, New York, NY 10019 or call +1-212-526-1072.
The analysts responsible for preparing this research report have received compensation based upon various factors including the firm's total revenues, a portion of which is generated by investment banking activities, the profitability and revenues of the Markets business and the potential interest of the firm's investing clients in research with respect to the asset class covered by the analyst.
Research analysts employed outside the US by affiliates of Barclays Capital Inc. are not registered/qualified as research analysts with FINRA. Such non-US research analysts may not be associated persons of Barclays Capital Inc., which is a FINRA member, and therefore may not be subject to FINRA Rule 2241 restrictions on communications with a subject company, public appearances and trading securities held by a research analyst's account.
Analysts regularly conduct site visits to view the material operations of covered companies, but Barclays policy prohibits them from accepting payment or reimbursement by any covered company of their travel expenses for such visits.

Barclays Research Department produces various types of research including, but not limited to, fundamental analysis, equity-linked analysis, quantitative analysis, and trade ideas. Recommendations contained in one type of Barclays Research may differ from those contained in other types of Barclays Research, whether as a result of differing time horizons, methodologies, or otherwise.
In order to access Barclays Statement regarding Research Dissemination Policies and Procedures, please refer to https://publicresearch.barcap.com/S/RD.htm. In order to access Barclays Research Conflict Management Policy Statement, please refer to: https://publicresearch.barcap.com/S/CM.htm.

Legal entities involved in producing Barclays Research:
Barclays Bank PLC (Barclays, UK)
Barclays Capital Inc. (BCI, US)
Barclays Bank Ireland PLC, Frankfurt Branch (BBI, Frankfurt)
Barclays Bank Ireland PLC, Paris Branch (BBI, Paris)
Barclays Bank Ireland PLC, Milan Branch (BBI, Milan)
Barclays Securities Japan Limited (BSJL, Japan)
Barclays Bank PLC, Hong Kong branch (Barclays Bank, Hong Kong)
Barclays Capital Canada Inc. (BCCI, Canada)
Barclays Bank Mexico, S.A. (BBMX, Mexico)
Barclays Securities (India) Private Limited (BSIPL, India)
Barclays Bank PLC, India branch (Barclays Bank, India)
Barclays Bank PLC, Singapore branch (Barclays Bank, Singapore)

Disclaimer:
This publication has been produced by Barclays Research Department in the Investment Bank of Barclays Bank PLC and/or one or more of its affiliates (collectively and each individually, "Barclays"). It has been prepared for institutional investors only and not for retail investors. It has been distributed by one or more Barclays affiliated legal entities listed below. It is provided to our clients for information purposes only, and Barclays makes no express or implied warranties, and expressly disclaims all warranties of merchantability or fitness for a particular purpose or use with respect to any data included in this publication. To the extent that this publication states on the front page that it is intended for institutional investors and is not subject to all of the independence and disclosure standards applicable to debt research reports prepared for retail investors under U.S. FINRA Rule 2242, it is an "institutional debt research report" and distribution to retail investors is strictly prohibited. Barclays also distributes such institutional debt research reports to various issuers, media, regulatory and academic organisations for their own internal informational news gathering, regulatory or academic purposes and not for the purpose of making investment decisions regarding any debt securities. Media organisations are prohibited from re-publishing any opinion or recommendation concerning a debt issuer or debt security contained in any Barclays institutional debt research report. Any such recipients that do not want to continue receiving Barclays institutional debt research reports should contact debtresearch@barclays.com. Barclays will not treat unauthorized recipients of this report as its clients and accepts no liability for use by them of the contents which may not be suitable for their personal use. Prices shown are indicative and Barclays is not offering to buy or sell or soliciting offers to buy or sell any financial instrument.
Without limiting any of the foregoing and to the extent permitted by law, in no event shall Barclays, nor any affiliate, nor any of their respective officers, directors, partners, or employees have any liability for (a) any special, punitive, indirect, or consequential damages; or (b) any lost profits, lost revenue, loss of anticipated savings or loss of opportunity or other financial loss, even if notified of the possibility of such damages, arising from any use of this publication or its contents.
Other than disclosures relating to Barclays, the information contained in this publication has been obtained from sources that Barclays Research believes to be reliable, but Barclays does not represent or warrant that it is accurate or complete. Barclays is not responsible for, and makes no warranties whatsoever as to, the information or opinions contained in any written, electronic, audio or video presentations of third parties that are accessible via a direct hyperlink in this publication or via a hyperlink to a third-party web site ('Third-Party Content'). Any such Third-Party Content has not been adopted or endorsed by Barclays, does not represent the views or opinions of Barclays, and is not incorporated by reference into this publication. Third-Party Content is provided for information purposes only and Barclays has not independently verified its accuracy or completeness.
The views in this publication are solely and exclusively those of the authoring analyst(s) and are subject to change, and Barclays Research has no obligation to update its opinions or the information in this publication. Unless otherwise disclosed herein, the analysts who authored this report have not received any compensation from the subject companies in the past 12 months. If this publication contains recommendations, they are general recommendations that were prepared independently of any other interests, including those of Barclays and/or its affiliates, and/or the subject companies. This publication does not contain personal investment recommendations or investment advice or take into account the individual financial circumstances or investment objectives of the clients who receive it. The securities and other investments discussed herein may not be suitable for all investors. Barclays is not a fiduciary to any recipient of this publication. Investors must independently evaluate the merits and risks of the investments discussed herein, consult any independent advisors they believe necessary, and exercise independent judgment with regard to any investment decision. The value of and income from any investment may fluctuate from day to day as a result of changes in relevant economic markets (including changes in market liquidity). The information herein is not intended to predict actual results, which may differ substantially from those reflected. Past performance is not necessarily indicative of future results. The information provided does not constitute a financial benchmark and should not be used as a submission or contribution of input data for the purposes of determining a financial benchmark.
United Kingdom: This document is being distributed (1) only by or with the approval of an authorised person (Barclays Bank PLC) or (2) to, and is directed at (a) persons in the United Kingdom having professional experience in matters relating to investments and who fall within the definition of "investment professionals" in Article 19(5) of the Financial Services and Markets Act 2000 (Financial Promotion) Order 2005 (the "Order"); or (b) high net worth companies, unincorporated associations and partnerships and trustees of high value trusts as described in Article 49(2) of the Order; or (c) other persons to whom it may otherwise lawfully be communicated (all such persons being "Relevant Persons"). Any investment or investment activity to which this communication relates is only available to and will only be engaged in with Relevant Persons. Any other persons who receive this communication should not rely on or act upon it. Barclays Bank PLC is authorised by the Prudential Regulation Authority and regulated by the Financial Conduct Authority and the Prudential Regulation Authority and is a member of the London Stock Exchange.

European Economic Area ("EEA"): This material is being distributed in the EEA by Barclays Bank PLC. Barclays Bank PLC is not registered in France with the Autorité des marchés financiers or the Autorité de contrôle prudentiel.

Americas: The Investment Bank of Barclays Bank PLC undertakes U.S. securities business in the name of its wholly owned subsidiary Barclays Capital Inc., a FINRA and SIPC member. Barclays Capital Inc., a U.S. registered broker/dealer, is distributing this material in the United States and, in connection therewith accepts responsibility for its contents. Any U.S. person wishing to effect a transaction in any security discussed herein should do so only by contacting a representative of Barclays Capital Inc. in the U.S. at 745 Seventh Avenue, New York, New York 10019.

Non-U.S. persons should contact and execute transactions through a Barclays Bank PLC branch or affiliate in their home jurisdiction unless local regulations permit otherwise.

This material is distributed in Canada by Barclays Capital Canada Inc., a registered investment dealer, a Dealer Member of IIROC (www.iiroc.ca), and a Member of the Canadian Investor Protection Fund (CIPF).

This material is distributed in Mexico by Barclays Bank Mexico, S.A.

Japan: This material is being distributed to institutional investors in Japan by Barclays Securities Japan Limited. Barclays Securities Japan Limited is a joint-stock company incorporated in Japan with registered office of 6-10-1 Roppongi, Minato-ku, Tokyo 106-6131, Japan. It is a subsidiary of Barclays Bank PLC and a registered financial instruments firm regulated by the Financial Services Agency of Japan. Registered Number: Kanto Zaimukyokucho (kinsho) No. 143.

Asia Pacific (excluding Japan): Barclays Bank PLC, Hong Kong Branch is distributing this material in Hong Kong as an authorised institution regulated by the Hong Kong Monetary Authority. Registered Office: 41/F, Cheung Kong Center, 2 Queen's Road Central, Hong Kong.

All Indian securities-related research and other equity research produced by Barclays' Investment Bank are distributed in India by Barclays Securities (India) Private Limited (BSIPL). BSIPL is a company incorporated under the Companies Act, 1956 having CIN U67120MH2006PTC161063. BSIPL is registered and regulated by the Securities and Exchange Board of India (SEBI) as a Research Analyst: INH000001519; Portfolio Manager INP000002585; Stock Broker/Trading and Clearing Member: National Stock Exchange of India Limited (NSE) Capital Market INB231292732, NSE Futures & Options INF231292732, NSE Currency derivatives INE231450334, Bombay Stock Exchange Limited (BSE) Capital Market INB011292738, BSE Futures & Options INF011292738; Depository Participant (DP) with the National Securities & Depositories Limited (NSDL): DP ID: IN-DP-NSDL-299-2008; Investment Adviser: INA000000391. The registered office of BSIPL is at 208, Ceejay House, Shivsagar Estate, Dr. A. Besant Road, Worli, Mumbai – 400 018, India. Telephone No: +91 2267196000. Fax number: +91 22 67196100. Any other reports produced by Barclays' Investment Bank are distributed in India by Barclays Bank PLC, India Branch, an associate of BSIPL in India that is registered with Reserve Bank of India (RBI) as a Banking Company under the provisions of The Banking Regulation Act, 1949 (Regn No BOM43) and registered with SEBI as Merchant Banker (Regn No INM000002129) and also as Banker to the Issue (Regn No INBI00000950). Barclays Investments and Loans (India) Limited, registered with RBI as Non Banking Financial Company (Regn No RBI CoR-07-00258), and Barclays Wealth Trustees (India) Private Limited, registered with Registrar of Companies (CIN U93000MH2008PTC188438), are associates of BSIPL in India that are not authorised to distribute any reports produced by Barclays' Investment Bank.

This material is distributed in Singapore by the Singapore branch of Barclays Bank PLC, a bank licensed in Singapore by the Monetary Authority of Singapore. For matters in connection with this material, recipients in Singapore may contact the Singapore branch of Barclays Bank PLC, whose registered address is 10 Marina Boulevard, #23-01 Marina Bay Financial Centre Tower 2, Singapore 018983.

This material is distributed to persons in Australia by Barclays Bank PLC. None of Barclays Bank PLC, nor any other Barclays group entity, holds an Australian financial services licence and instead relies on an exemption from the requirement to hold such a licence. This material is intended to only be distributed to "wholesale clients" as defined by the Australian Corporations Act 2001.

Middle East: Nothing herein should be considered investment advice as defined in the Israeli Regulation of Investment Advisory, Investment Marketing and Portfolio Management Law, 1995 ("Advisory Law"). This document is being made to eligible clients (as defined under the Advisory Law) only. Barclays Israeli branch previously held an investment marketing license with the Israel Securities Authority but it cancelled such license on 30/11/2014 as it solely provides its services to eligible clients pursuant to available exemptions under the Advisory Law, therefore a license with the Israel Securities Authority is not required. Accordingly, Barclays does not maintain an insurance coverage pursuant to the Advisory Law.

This material is distributed in the United Arab Emirates (including the Dubai International Financial Centre) and Qatar by Barclays Bank PLC. Barclays Bank PLC in the Dubai International Financial Centre (Registered No. 0060) is regulated by the Dubai Financial Services Authority (DFSA). Principal place of business in the Dubai International Financial Centre: The Gate Village, Building 4, Level 4, PO Box 506504, Dubai, United Arab Emirates. Barclays Bank PLC-DIFC Branch, may only undertake the financial services activities that fall within the scope of its existing DFSA licence. Related financial products or services are only available to Professional Clients, as defined by the Dubai Financial Services Authority. Barclays Bank PLC in the UAE is regulated by the Central Bank of the UAE and is licensed to conduct business activities as a branch of a commercial bank incorporated outside the UAE in Dubai (Licence No.: 13/1844/2008, Registered Office: Building No. 6, Burj Dubai Business Hub, Sheikh Zayed Road, Dubai City) and Abu Dhabi (Licence No.: 13/952/2008, Registered Office: Al Jazira Towers, Hamdan Street, PO Box 2734, Abu Dhabi). Barclays Bank PLC in the Qatar Financial Centre (Registered No. 00018) is authorised by the Qatar Financial Centre Regulatory Authority (QFCRA). Barclays Bank PLC-QFC Branch may only undertake the regulated activities that fall within the scope of its existing QFCRA licence. Principal place of business in Qatar: Qatar Financial Centre, Office 1002, 10th Floor, QFC Tower, Diplomatic Area, West Bay, PO Box 15891, Doha, Qatar. Related financial products or services are only available to Business Customers as defined by the Qatar Financial Centre Regulatory Authority.

Russia: This material is not intended for investors who are not Qualified Investors according to the laws of the Russian Federation as it might contain information about or description of the features of financial instruments not admitted for public offering and/or circulation in the Russian Federation and thus not eligible for non-Qualified Investors. If you are not a Qualified Investor according to the laws of the Russian Federation, please dispose of any copy of this material in your possession.

IRS Circular 230 Prepared Materials Disclaimer: Barclays does not provide tax advice and nothing contained herein should be construed to be tax advice. Please be advised that any discussion of U.S. tax matters contained herein (including any attachments) (i) is not intended or written to be used, and cannot be used, by you for the purpose of avoiding U.S. tax-related penalties; and (ii) was written to support the promotion or marketing of the transactions or other matters addressed herein. Accordingly, you should seek advice based on your particular circumstances from an independent tax advisor.

© Copyright Barclays Bank PLC (2019). All rights reserved. No part of this publication may be reproduced or redistributed in any manner without the prior written permission of Barclays. Barclays Bank PLC is registered in England No. 1026167. Registered office 1 Churchill Place, London, E14 5HP. Additional information regarding this publication will be furnished upon request.