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Quant Lens

The Value of Investor Relations Quantified

Introducing the world's first Machine Learning algorithms that quantify the value of investor relations

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Cracking the IR Algorithm

Equity capital markets are a highly complex, dynamic and nuanced ecosystem that essentially seeks to synthesize vast arrays of data, analytics, and insights into risk and return metrics to derive a company's valuation.

Many organizations and leaders aspire to creating strong and sustainable returns for their share owners. This requires not only making intelligent management decisions on strategic, financial, and operational factors, but it also requires finesse in balancing trade-offs between risks and returns, earnings retention and dividend payouts, or the allocation of limited board and management time.

"Iridium advances the science and practice of investor relations to help organizations and leaders unlock their potential."

Oliver Schutzmann, CEO

Because boards and management teams often feel that the business value they generate is not well understood or adequately rewarded by the capital markets, they spend enormous effort to create business value - in the hope that this translates into market value - but only a tiny fraction of their resources on translating their achievements into tangible shareholder returns.

One underlying problem is a lack of quantitative research and evidence on how business value creation translates into shareholder value. In theory, this gap should be bridged through a professional investor relations function. After all, the core objective of investor relations is to ensure that:

- the market understands the value the business is creating, and
- the company management understands how the market views and values their business.

However, most companies have not yet invested sufficiently in investor relations because they do not have any real proof of the value it adds. For a number of professionals operating in the investor relations arena, it has been a career-long struggle to convince boards and management teams of the relevance of IR and the value that good IR adds (or poor IR subtracts) from a company's valuation.

In this context, Iridium sought to take a scientific and systematic approach, using the latest Machine Learning techniques, to crack the 'IR Algorithm' and quantify the value of investor relations.

Key Findings

The world's first Machine Learning algorithm that quantifies the value of investor relations

- **Iridium Quant Lens ML algorithms explain up to 98% of bank valuations**
- **Professional Investor Relations can add up to 24.2% to market valuations**
- **IR Quality was the 3rd most important factor impacting P/TBV of GCC banks**

Iridium Quant Lens ML algorithms sought to explain bank valuations

The Iridium Quant Lens Machine Learning platform was built on the foundations of classic finance theory that a company's stock price is derived through an evaluation of risk relative to return factors by market participants.

In order to identify the financial and non-financial drivers of bank valuations, four different Machine Learning algorithms were deployed to consider 30 risk and return features, compiled from over 9 million data points, and covering 673 banks globally. Models were run separately for all banks and for 65 GCC banks over different time horizons ranging from 1 to 10 years.

Iridium models are successful in explaining up to 98% of valuation

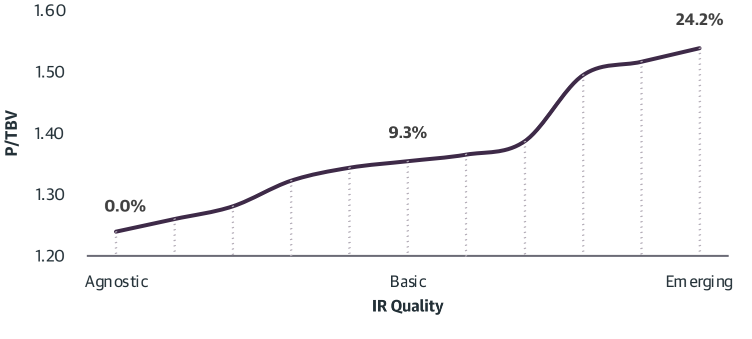
Iridium's algorithms proved highly successful in decomposing valuation drivers and, in aggregate, explained 86% of valuation variability for the test data set and 91% of the full data set. Furthermore, some individual models, such as the 3-year models for GCC banks, explained up 95% of the test data set and 98% of the full data set.

Investor Relations Really Matters

A significant finding of this study was that the quality of investor relations is a highly material factor consistently influencing valuations of GCC banks. In fact, for most GCC models it was the 3rd most important factor impacting price to tangible book value (P/TBV) and explained 6% of its variability on average.

Exhibit 1: Impact on P/TBV of three IR Quality Archetypes

IR Quality Archetypes
Impact on Valuation (%)



The impact of upgrading investor relations can be significant

In addition, the impact of upgrading investor relations is significant, with each upgrade step, for example from IR-Agnostic to IR-Basic, commanding an 12% valuation premium on average and a complete move along the investor relations upgrade path adding 24% to valuations.

IR and Machine Learning

Iridium Quant Lens Machine Learnings algorithms seek to explain what investors really pay for

ML Algorithms build on classic finance theory of risk-and-return

Classic finance theory expounds that investors synthesize vast arrays of data, analytics and insights to derive a risk-return based valuation for a company. In other words, a company's valuation is a function of the reward it offers relative to its risk.

The Iridium Quant Lens Machine Learning algorithms were built on this foundation by searching for significant explanatory risk and return factors impacting valuation multiples (defined as Price to Book Value), thereby seeking to identify the financial and non-financial drivers of valuations at a particular point in time.

Models incorporated >9 million data points and considered >30 explanatory variables for 673 banks globally

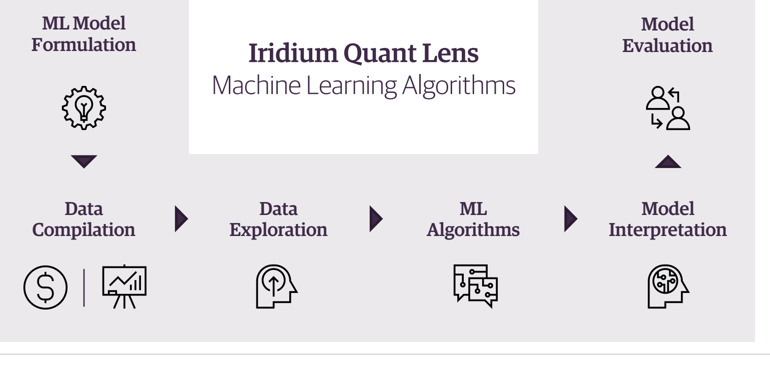
To achieve this, over 9 million data points were ingested and analyzed by Iridium Quant Lens' four different Machine Learning models (LASSO Linear Regression, LASSO Logarithmic Regression, Random Forest and XGBoost). They were deployed to consider over 30 risk and return factors, covering 673 banks globally. Each Machine Learning algorithm was deployed separately for all the banks, as well as a sample of 65 banks based in six GCC countries (Bahrain, Kuwait, Oman, Qatar, Saudi Arabia and United Arab Emirates), across different time horizons, ranging from 1 to 10 years.

Models considered the quality of IR as a potential factor impacting valuation

Aside from traditional risk-return factors such as net interest margins, cost-to-income ratios, cost of risk, and non-performing loan ratios, the models specifically incorporated the quality of investor relations (IR) as a potential explanatory factor. In this respect, the IR Quality of all 65 GCC banks was categorized into either *IR-Agnostic*, *IR-Basic* or *IR-Emerging* using Iridium's proprietary diagnostic methodology that classifies these archetypes of investor relations maturity level.

A summary of the methodology is illustrated in exhibit 2 below and is explained in more detail in the Methodology section.

Exhibit 2: Methodology Summary



Model Performance

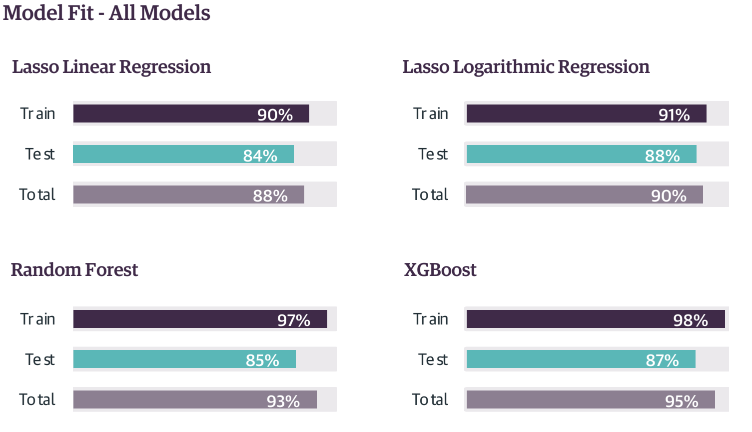
Iridium Quant Lens models are successful in explaining up to 95% of bank valuations

On average, the models explain 86% of valuation

The algorithms proved highly successful in decomposing valuation drivers across all models and, on average, explained 86% of valuation variability for the test data set and 91% of the full data set.

Additionally, as illustrated in Exhibit 3 below, the average explanatory performance of the models was strong for each of the four different Machine Learning algorithms used for all time periods.

Exhibit 3: Average model fit

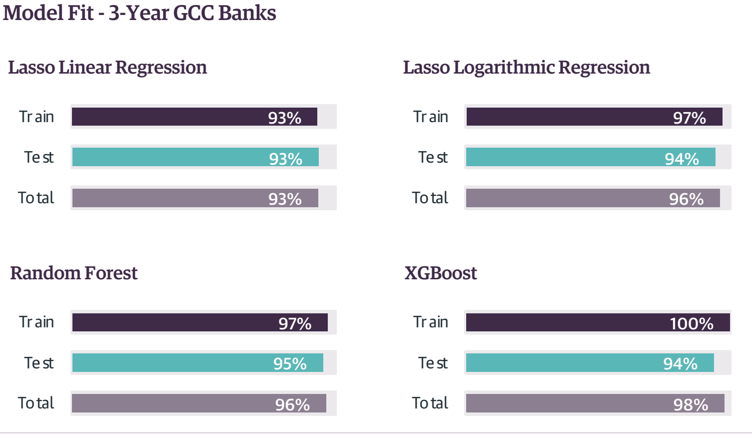


Standard Machine Learning techniques were used, whereby a random sample of the data set is used to "train" the models and the performance is then tested against the "test" set.

Some models explain up to 98% of valuation

While the average performance of the models was very good, some individual models were even more accurate in explaining valuation. In particular, the 3-year time horizon models for GCC banks were able to explain up to 95% of P/TBV for the test data set and up to 98% of the full data set.

Exhibit 4: Model fit for Gulf banks 3-year time horizon



Feature Importance

Investor Relations Quality Really Matters

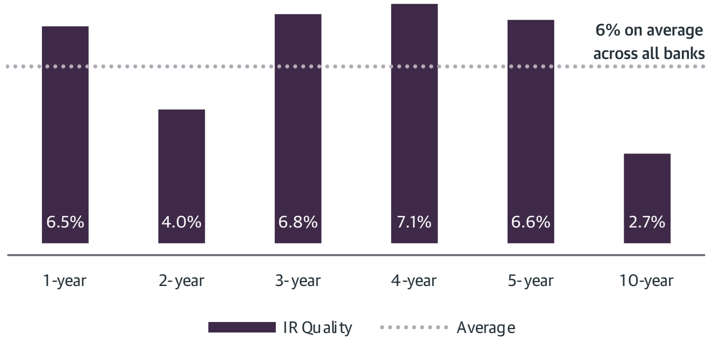
On average, IR Quality explains 6% of valuation

The algorithms calculated a measure called "feature importance" for each factor impacting valuation within each model. This measure assigns a percentage to explanatory variables based on how useful they are in predicting the target variable, with all explanatory variables for a given model summing to 100%.

Based on this measure, 'IR Quality' was consistently an important variable explaining bank value, with average feature importance of 6%, ranging from a low average of 2.7% for the 10-year models, to a high average of 7.1% for the 4-year model.

Exhibit 5: IR Quality is a key variable explaining 6% on average of all bank valuations

IR Quality
Feature Importance (%)



IR quality is on average the 3rd most important driver of valuation

Furthermore, as shown in Exhibit 6 below, the quality of IR was the 3rd most important valuation driver for the majority of model periods.

Exhibit 6: Feature importance of IR Quality by rank over time

IR Quality
Feature Importance Ranking

	1-year	2-year	3-year	4-year	5-year	10-year
1	Factor 1	Factor 5	Factor 2	Factor 1	Factor 2	Factor 1
2	Factor 2	Factor 2	Factor 1	Factor 5	Factor 1	Factor 4
3	IR Quality	Factor 6	IR Quality	IR Quality	IR Quality	Factor 6
4	Factor 6	IR Quality	Factor 4	Factor 4	Factor 7	Factor 7
5	Factor 4	Factor 1	Factor 7	Factor 6	Factor 4	Factor 9
6	Factor 15	Factor 11	Factor 5	Factor 7	Factor 6	IR Quality
7	Factor 17	Factor 4	Factor 8	Factor 13	Factor 8	Factor 2

Valuation Impact

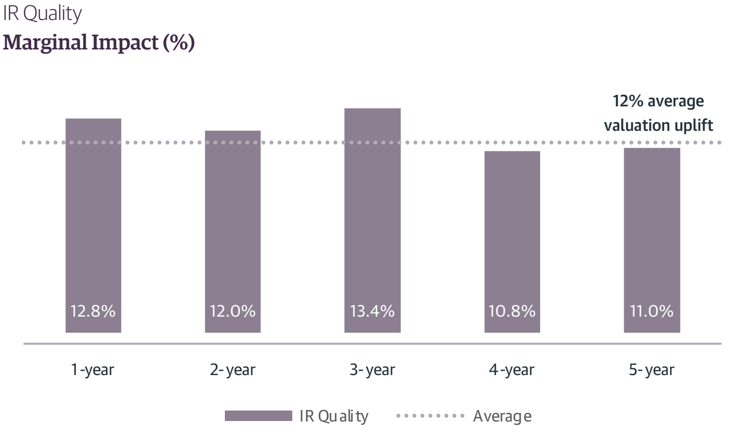
The impact of upgrading investor relations quality can be material

Each upgrade step in IR quality commands a 12% valuation premium on average

The algorithms further computed the marginal impact on valuation of upgrading from one level of IR quality to the next, for example from IR-Agnostic to IR-Basic.

On average each such upgrade commands an 12% valuation uplift. Further, as illustrated in Exhibit 7, this impact was consistent over time, ranging from 10.8% to 13.4% on average for the one- to five-year models.

Exhibit 7: Marginal impact of upgrading Investor Relations

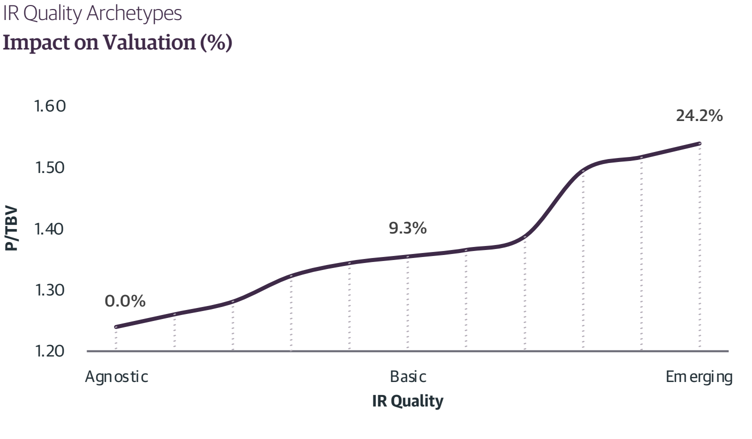


The full upgrade path adds 24% on average to P/TBV

Exhibit 8 below plots the full investor relations upgrade path, showing how P/TBV increases as IR quality is upgraded from Agnostic to Basic, and then to Emerging levels.

On average, P/TBV rises from 1.24x to 1.35x (+9.3%) to 1.54x (+24.2%) at each step-change on this upgrade path, representing a material valuation uplift along the full curve to IR-Emerging.

Exhibit 8: Impact on P/TBV of IR Quality



Impact Examples

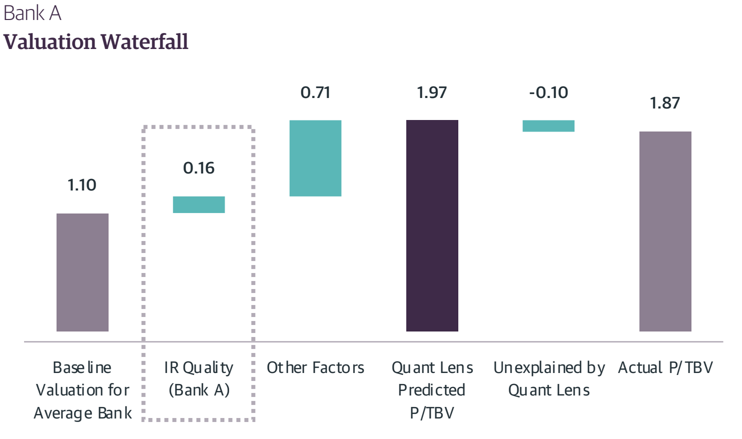
Valuation Waterfalls

USD 3 billion in incremental value and USD 220 million net profit equivalent for an IR-Emerging bank

To illustrate the impact of IR Quality with real-world examples, Exhibits 9 and 10 show two unnamed banks.

One bank (Bank A) currently operates at an 'IR-Emerging' level which adds 0.16x to its P/TBV valuation. Given the bank's current market capitalization of USD 33 billion, this translates to almost USD 3 billion of its market value, or the equivalent of USD 220 million in net profits. Considering the valuation uplift achieved by the 'IR-Emerging" level this is a compelling return on investment, being typically achievable with a USD 1.0 million annual IR budget.

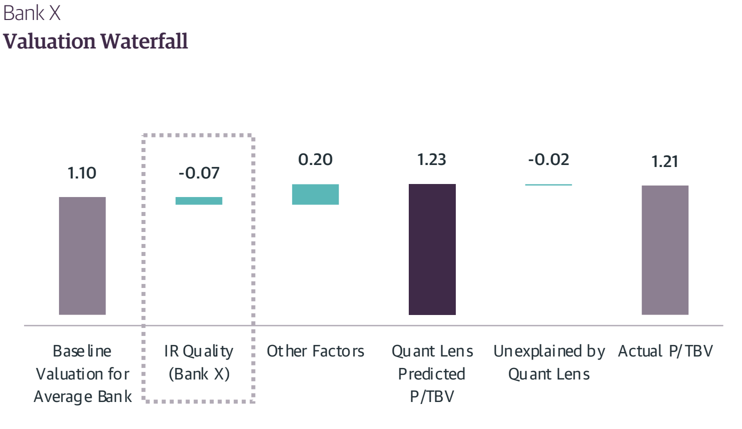
Exhibit 9: Impact of 'IR-Emerging' on valuation of Bank A



Conversely, IR-Agnostic detracts from market value

The converse is true for low IR quality. Exhibit 10 shows another unnamed bank that currently operates at an 'IR-Agnostic' level, which in fact subtracts -0.07x from its P/TBV valuation.

Exhibit 10: Impact of 'IR-Agnostic' on valuation of Bank X



Methodology

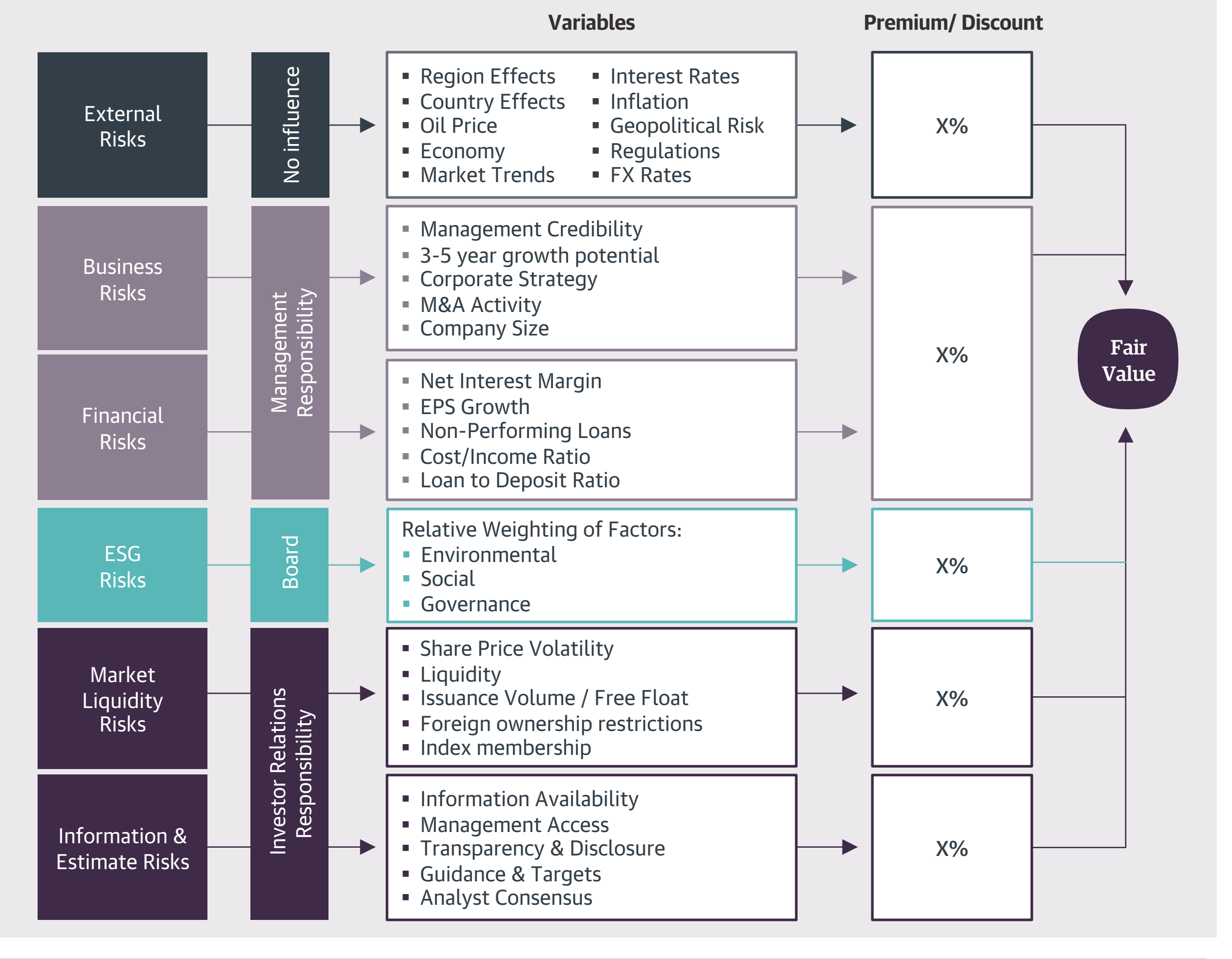
Iridium Quant Lens Machine Learning Algorithms

Valuation is a function of risk and return

As mentioned previously, the Machine Learnings algorithms are based on the classical understanding that risk and return factors drive valuation.

The large number of characteristics and inter-relationships between these risks and rewards, both from a company and investor perspective, makes it very difficult to assess their impact on shareholder value creation as illustrated in Exhibit 11 below.

Exhibit 11: Illustrative risk and return factors to derive company "Fair Value" the traditional way



From Model to Insights

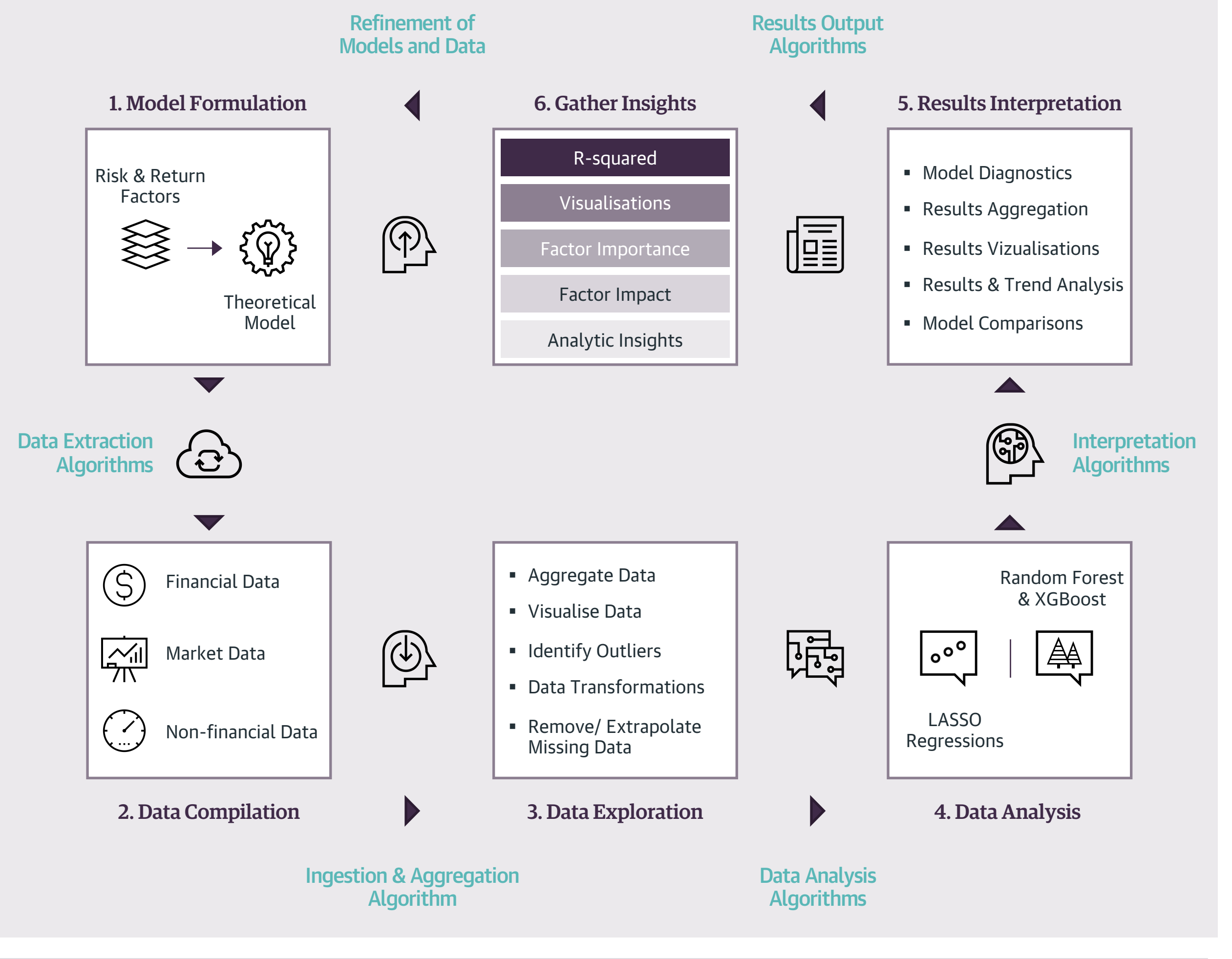
Iridium Quant Lens ML algorithms explained

Quantitative Research

In order to better understand and assess the impact of risk and reward factors on company valuation, Iridium conducted an extensive quantitative research project using Machine Learning techniques, focused on the banking sector. This sector was chosen as banks tend to be more difficult to understand and value, and because Iridium has extensive experience and expertise in this sector.

Our systematic approach and the methodology employed in this research project is illustrated in Exhibit 12 and explained further below.

Exhibit 12: Methodology employed for Machine Learning algorithms



Step 1: Theoretical formulation of model

The theoretical formulation of the model was based on a risk and return-based approach highlighted previously and the classical understanding that a bank's valuation, as measured by the commonly employed Price to Tangible Book Value (P/TBV) metric, is a function of multiple fundamental company, industry, market and economic risk and return factors, how well these are understood by the market, and their future outlook. From this model formulation, 30+ banking industry specific metrics were defined to capture risk and return factors as follows:

Return Profile

The primary measure used for quantifying a bank's return profile was return on equity (ROE), which was decomposed using an extended Du Pont methodology into its key constituent determinants being the net interest margin, net fee income, cost to income ratio, cost of risk and capital ratios.

Risk Profile & Credit Ratings

Bank risk profiles were measured using non-performing loan (NPL) ratios, NPL coverage ratios, capital ratios (T1) and loan to deposit ratios (LDR), as well as credit ratings and credit rating outlook/watch.

Growth Expectations

Future growth expectations were covered using consensus earnings per share (EPS) growth for 1- and 3-year periods.

Investor Relations Quality

The investor relations quality archetype was assessed for each individual GCC bank in the sample and classified as either 'IR-Agnostic', 'IR-Basic' or 'IR-Emerging' using the proprietary Iridium IR diagnostic methodology.

Other company-specific factors

Other bank-specific factors included company size, whether banks were pure Islamic institutions, and environmental, social and governance scores. The model further incorporated company fixed effects to capture the aggregate impact of other factors such as management credibility, experience, track record, and franchise strength.

Stock market factors

Technical stock market factors were also considered using metrics such as stock liquidity, free float, foreign ownership limits and levels, share price momentum and volatility.

External factors

Finally, industry, market and economic risk and return factors were not individually modelled but rather quantified in aggregate through inclusion of fixed country and time effects in the model.

Step 2: Data gathering and compilation

The next step in the process involved gathering and compiling the data points required by the model.

Data Source S&P Capital IQ

The underlying financial and stock market measures were in the first instance extracted from Standard & Poor's Capital IQ data platform. This raw data was then used to calculate the various risk and return metrics using custom code.

For example, daily share price data was used to compute share price momentum and volatility measures, while bank-specific metrics, such as cost of risk, net interest margin and capital ratios, were computed from underlying financial data.

Supplemented by manual data compilation

The compilation of non-financial and certain technical market data was mostly performed manually, requiring reviews of company and stock market websites, reports and disclosures, particularly the quantification of foreign ownership limits and levels and the classification of IR quality into IR-Agnostic, IR-Basic and IR-Emerging archetypes.

9+ million data points for 673 banks globally covering 10 years

During this process, over 9 million data points were compiled covering 673 banks worldwide for each quarter during the last 10 years.

Step 3: Data aggregation, exploration and refinement

Having compiled and computed the required model metrics, custom code was employed to aggregate the data for data exploration and refinement.

Data visualization, validation and refinement

This involved visualizing and validating the data to identify, investigate and, if appropriate, remove outliers, as well as to investigate and statistically quantify the nature and extent of the partial dependencies between the various factors and company valuation (i.e. partial r-squared for linear, logarithmic or quadratic relationships).

An illustrative sample of some of these explanatory data visualizations are shown in Exhibit 13 below.

Exhibit 13:
Sample exploratory visualizations

Step 4: Data analysis utilizing Machine Learning techniques

4x Machine Learning algorithms

Four analytical techniques or Machine Learning algorithms were employed to identify significant drivers of company valuation. In each of these models, 2/3rds of sample observations were randomly selected to train the model (i.e. "train" sample) and the remaining 1/3rd was used to test the accuracy of the models (i.e. "test" sample). These four approaches are explained below in turn.

1. LASSO Linear Regression

The LASSO (least absolute shrinkage and selection operator) algorithm improves upon the prediction accuracy and interpretability of traditional least squares linear regression. With LASSO, the model fitting process is altered to include both variable selection and regularization, by introducing a penalty to coefficient sensitivity. In doing so, it forces certain coefficients to be set to zero, effectively choosing a simpler and more robust model that does not include those coefficients.

2. LASSO Logarithmic Regression

This model is identical to the LASSO linear regression model, with the exception that target and/or regressor variables are log-transformed prior to model construction, to allow for logarithmic or exponential relationships (as opposed to pure linear relationships). In the Iridium Quant Lens model, both target and regressor variables were log-transformed, which effectively models a multiplicative regression function (i.e. $Y = a \times bX_1 \times \ bX_2$), as opposed to the additive function (i.e. $Y = a + bX_1 + bX_2$) used in the standard linear regression.

3. Random Forest

A Random Forest consists of a large number of individual decision trees that operate as an ensemble. Each individual decision tree in the random forest gives a prediction of outcome based on decisions made relative to regressor variable value through each node in the tree. Similar to a committee, the class with the most votes becomes the model's prediction. Unlike linear regression models, random forest algorithms can model irregular and non-linear relationships operates by constructing a multitude of these decision trees at training time and outputting the average prediction of the individual trees.

4. XGBoost

XGBoost (Extreme Gradient Boosting) is an optimized and more sophisticated algorithm for creating decision trees, whereby models are "boosted" by iteratively learning from the results of the previous iterations, errors are minimized by a more efficient gradient descent algorithm, and other software and hardware optimization techniques are utilized to yield superior results using less computing resources in the shortest amount of time.

Algorithms run for Gulf and All Banks separately, and over different time horizons

Each of the above algorithms was deployed separately for all the banks as well as just for the Gulf-based banks, across different time horizons, ranging from 1 to 10 years.

Step 5: Interpretation and analysis of results

Iterative process requiring finetuning of data and models

The final step of the process involved aggregating, interpreting and analyzing the results of the various models to derive insights, for which several custom scripts and visualizations were created.

This analysis process required further fine-tuning of the data and models at various stages to avoid data overfitting and to ensure model robustness.

As such, the above process was iterative in nature as models and data were fine-tuned over Iridium's development period of twelve months.

About Iridium

Iridium is a management consulting firm and the Middle East's leading advisor on investor relations.

Iridium was founded in 2015 on the belief that first-hand capital markets and senior management experience are central to the process of converting business value into shareholder returns.

Our results-oriented experts design, build and operate professional investor relations programs that help organizations and leaders engage, transact and grow - whether they are healthy, challenged or distressed.

Iridium specializes in:

- Delivering a clear picture of what drives company valuations with quantitative and qualitative insights,
- Helping boards and management teams see their companies through the eyes of analysts and investors,
- Identifying and closing maturity and capability gaps
- Creating institutional-grade information content and presentation materials that enable meaningful financial analysis and attract investment.
- Protecting downside and unlocking potential.

Feel free to reach out to us with any questions. We are here to help.

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