Morningstar Quantitative Equity Ratings Methodology

Morningstar Quantitative Research
Dec. 2, 2024

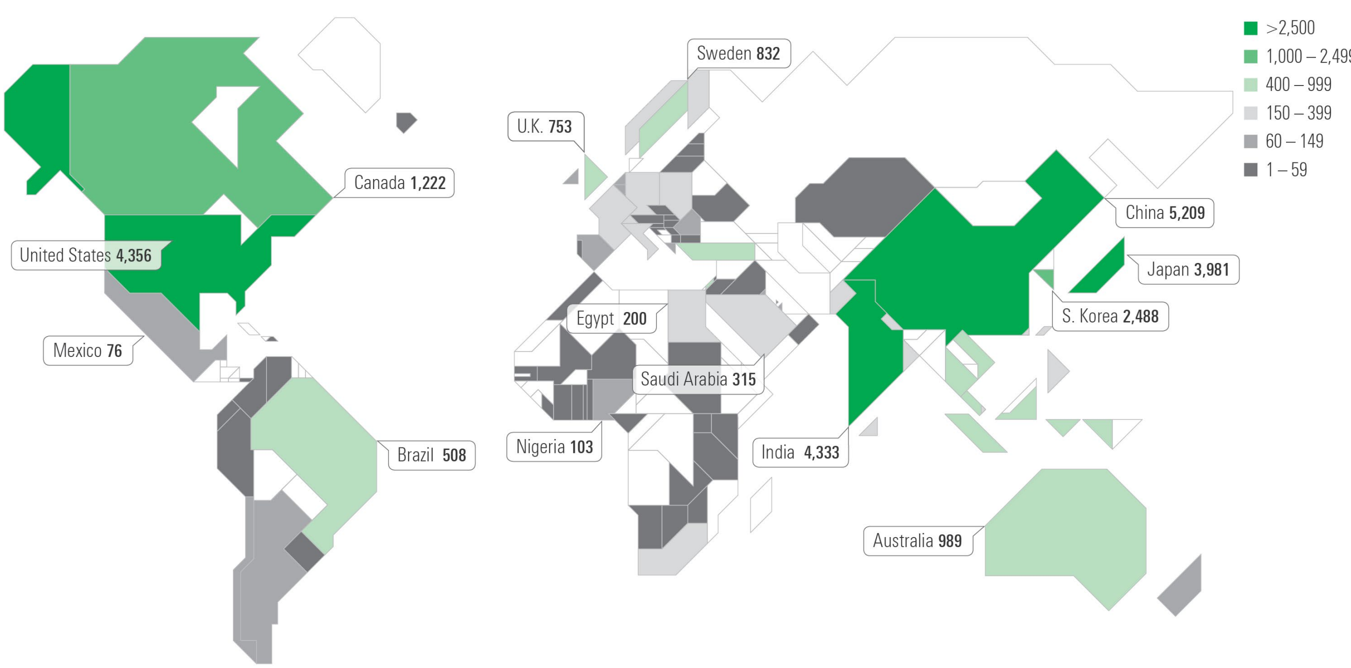
Contents

Quantitative Rating Philosophy

Established in 1984, Morningstar has evolved from managed product research to comprehensive investment analysis, including equities. While traditionally focused on analyst-driven, forward-looking insights, the company now combines analyst opinions with quantitative ratings to expand its coverage beyond human capabilities.

The quantitative equity ratings system, powered by proprietary analyst ratings, covers nearly 40,000 companies and continues to grow with new market entries and expanded data collection. This approach allows improvements in analyst-driven research to automatically enhance quantitative ratings, streamlining Morningstar's focus on core research advancement. This paper outlines the key assumptions and details behind our quantitative equity rating methodology.

Exhibit 1 Our Quantitative Coverage Touches Nearly Every Country in the World at Unrivaled Depth



Source: Morningstar Direct. Data as of Nov. 1, 2024. The coverage visualized above is incomplete but representative. Throughout 2024, coverage totaled nearly 40,000.

Mohit Mittal
Senior Quantitative Analyst
mohit.mittal@morningstar.com

Sandeep
Quantitative Research Manager
sandeep@morningstar.com

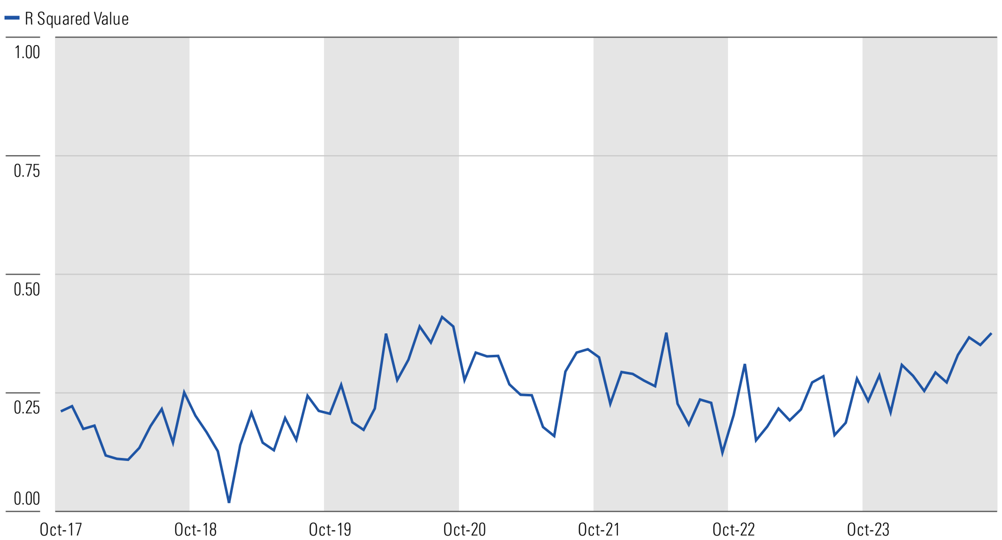
Charles Gross
Director of Quantitative Research
charles.gross@morningstar.com

Madison Sargis
Head of Quantitative Research
madison.sargis@morningstar.com

Quantitative Valuation

At the beginning of the model-building exercise, we considered a broad array of over 900 factors, a testament to Morningstar's comprehensive research. Although many factors enhance investor outcomes, the focus is on selecting the most pertinent and robust factors. This selection is based on good coverage, availability, and superior goodness-of-fit. The model employs fundamental, market-based, and Morningstar Risk Model inputs to replicate an analyst's output. An essential measure of the model's goodness-of-fit is its R-squared value. Exhibit 2 demonstrates that, from October 2017 to September 2024, the overall average R-squared value stands at approximately 24%, indicating an improvement over time. More recently, the average R-squared value has been around 35%.

Exhibit 2 Out-of-Sample Adjusted R-Squared Value of Quantitative Valuation



Source: Morningstar Direct. Data as of Sept. 30, 2024.
To calculate the R-squared value, we split the analyst coverage into 70% training data and 30% testing data. The model was trained on the 70% training sample and evaluated on the 30% testing sample. The R-squared was computed on the testing sample, measuring the correlation between predicted and analyst-assigned P/FVE.

To an investor who considers stocks a claim on a business' cash flows, the intrinsic value of those cash flows is a must-have piece of information for any investment decision. To provide investors with better estimates of intrinsic values for stocks, we have developed a Quantitative Valuation algorithm.

In essence, the Quantitative Valuation algorithm attempts to divine the characteristics that strongly differentiate overvalued stocks from undervalued stocks as valued initially by our equity analysts. Once these characteristics have been found and their impact on our analyst-driven valuations has been estimated, we can apply our model beyond the universe of analyst-covered stocks.

To be more precise, we use a machine-learning algorithm known as *gradient boosting* to fit a relationship between the variable we are trying to predict (an analyst's estimate of the stock's over- or undervaluation) and our fundamental and market-based input variables.

We exclude illiquid stocks and listed companies with a median daily traded value below 5,000 in their local currency over the last 60 days. This step ensures the inclusion of companies with adequate liquidity and trading activity, helping to mitigate potential inaccuracies and biases in the model. The variable we aim to predict is the natural logarithm of the ratio of the most recent closing price to the analyst-driven fair value estimate, denoted as log price to fair value, or log PFV. We use log transformation to limit the impact of outliers.

To generate the quantitative valuation, we use the inverse of the predicted price to fair value formula as follows:

Quantitative Valuation = 1 / EXP (log PFV).

The model employs 61 input variables, details of which are provided in Appendix A.

Our gradient boosting model uses 300 individual regression trees to generate Quantitative Fair Value Estimates. See Appendix C for a description of a gradient boosting model. As mentioned earlier, the efficacy is partly influenced by the approach and effectiveness of our equity analysts, and details of our methodology for equity valuation can be found here.

In production, we refit the gradient boosting model weekly using the most recent input data. We do this because we believe the input variables are dynamic enough to affect values weekly but insufficiently to affect valuations daily. At the time of this update, we generate predictions for roughly 40,000 listed companies globally.

Quantitative Uncertainty Score

No valuation is a point estimate. Any valuation estimate always contains uncertainty, which arises from two sources: model uncertainty and input uncertainty. Our Quantitative Valuation Uncertainty Score is a proxy for the standard error in our valuation estimate or the range of possible valuation outcomes for a particular company.

Unlike our Quantitative Economic Moat Ratings, we do not need to fit a separate model for valuation uncertainty. Our Quantitative Valuation model can inherently give us an estimate of Quantitative Valuation Uncertainty Scores.

As described in the Quantitative Valuation section of this document, we use a gradient boosting model to assign intrinsic valuations in the form of Quantitative Price/Fair Value Estimate ratios to stocks. However, our gradient boosting model generates 300 intermediate tree predictions before using them to arrive at the final prediction. The dispersion (or, more specifically, difference between 85th percentile and 15th percentile value) of these 300 tree predictions is our raw Quantitative Valuation Uncertainty Score. The higher the score, the higher the disagreement among the 300 tree models, and the more uncertainty is embedded in our Quantitative Valuation estimate. This is analogous to how an analyst-driven uncertainty estimate is derived.

Quantitative Star Rating

Morningstar Quantitative Ratings for stocks, or "quantitative star ratings," are assigned based on the combination of the Quantitative Valuation of the company dictated by our model, the current market price, the margin of safety determined by the Quantitative Uncertainty Score, the market capital, and momentum. Although our valuations are only estimated weekly, the star rating is estimated daily to account for day-to-day price movements.

Exhibit 3 Quantitative Star Rating Calculation Logic
Price to fair value is represented as "qv"; uncertainty score is represented as "qunc"

Quantitative Star Rating	Common Calculation	Micro-Cap Calculation
★	log(qv) < -1* qunc	log(qv) < -1.5* qunc
★★	log(qv) between (-1*qunc, -0.5* qunc)	log(qv) between (-1.5*qunc, -0.75* qunc)
★★★	log(qv) between (-0.5*qunc, 0.5* qunc)	log(qv) between (-0.75*qunc, 0.75* qunc)
★★★★	log(qv) between (0.5*qunc, 1* qunc)	log(qv) between (0.75*qunc, 1.5* qunc)
★★★★★	log(qv) > 1* qunc	log(qv) > 1.5* qunc

Source: Morningstar.

The quantitative star rating is our summary rating and is meant to indicate Morningstar's opinion on the future returns an investor can expect. More stars indicate a higher long-term expected return.

In addition to the aforementioned star ratings, two additional ratings, Not Rated and Under Review, are assigned under specific circumstances.

1. Not Rated: This rating is assigned if the closing price data is stale for at least 30 days. In such cases, the equity will be designated as Not Rated.
2. Under Review: An equity is rated as Under Review in the following scenarios:
    - Occurrence of a corporate event.
    - The closing price is stale at least seven days but remains within the 30-day time frame.
    - The quantitative fair value/price ratio does not fall within the range of 0.25 to 4.

To increase the rating stability for companies near star-rating breakpoints, we implement a buffering system. The buffer between all breakpoints is +/- 5%. A company near a rating breakpoint must move past the buffer before the rating changes. For example, a company below 0.5*qunc will need to move to (0.5*qunc+0.05) before the rating upgrades to 4 stars from 3 stars. Similarly, a company above 0.5*qunc will need to move below (0.5*qunc-0.05) before being downgraded to 3 stars from 4 stars. For companies that do not have a rating history, the initial quantitative star rating is based on the original breakpoints.

Because of the inherent risk associated with micro-caps, we increase the uncertainty thresholds for their quantitative star ratings, as shown in Exhibit 3. We define micro-caps based on regional thresholds calculated through the Morningstar Style Box methodology. Exhibit 4 shows an example of how these thresholds currently look across regions. For countries that do not have a region mapping, we use the simple average of thresholds across all regions. These values are recalculated monthly.

Exhibit 4 Micro-Cap Upper Thresholds Across Regions (Morningstar Style Box Methodology)

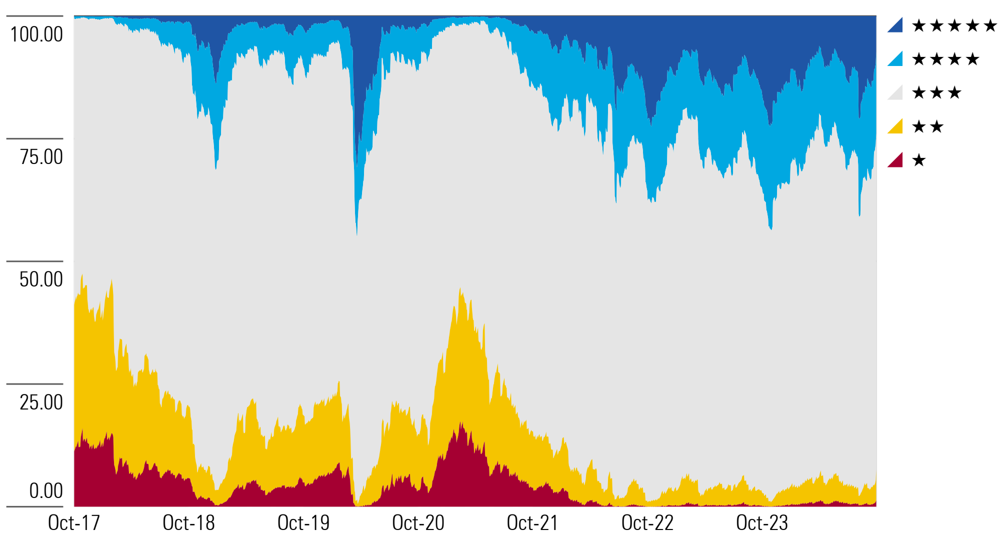
Region	USA	Canada	Latin America	Europe	Japan	Australia/ New Zealand	Asia ex-Japan
Market Cap Threshold (in USD mil)	2722	578	490	590	272	319	285

Source: Morningstar Direct. Data as of Sept. 30, 2024.

In instances where a stock price has experienced extreme negative returns relative to other stocks, it might appear cheap from a valuation perspective. However, it might be a "value trap." To screen for such stocks, we rank the companies based on their 12-1 month momentum, which is calculated using the cumulative returns of the stock over the past 12 months, ignoring the most recent month. Any stock below the 30th percentile of values is restricted to a 3-star maximum rating.

Exhibit 5 illustrates the quantitative star rating distribution plot. During the covid era, there was a rise in stocks rated 4 and 5 stars, pointing to a more undervalued coverage universe. Conversely, the covid recovery period saw an increase in 1- and 2-star-rated stocks, signifying the return of overvalued stocks.

Exhibit 5 Star Ratings Proportions Have and Will Vary Through Time
Star ratings as a proportion of the coverage universe through time, remeasured daily.



Source: Morningstar Direct. Data as of Sept. 30, 2024.

Quantitative Economic Moat Rating

A company that has an economic moat can be expected to earn economic profits for decades or longer. Many investors look for the presence of an economic moat as a quality litmus test when considering investing in a company. The stability of a firm's expected economic profits yields some insight into the safety net that investors have if they choose to invest. Companies with economic moats tend to experience smaller drawdowns, fewer dividend cuts, smaller dividend cuts, and lower odds of financial distress. This information can be very valuable when considering the risk exposure of a portfolio.

In developing our Quantitative Economic Moat Rating algorithm, we use the random forest regression model. We built two random forest models—one to predict whether a company has a wide moat or not, and one to predict whether a company has no moat or not. At first glance, these models may appear redundant, but they are not. The characteristics that separate a wide-moat company from the rest of the universe are not identical to the characteristics that separate a no-moat company from the rest of the universe. For example, while wide-moat stocks tend to have larger market caps than the rest of the universe, market cap is much less significant in differentiating no-moat companies. We use the same input variables for these two models, which are listed in Appendix A.

Once we have fit the two models, we need to aggregate their two predictions into a single metric describing the moatworthiness of the company in question. To do so, we use the following equation:

$$\text{Raw Quantitative Moat Score} = \frac{Wide\ Moat\ Model\ Prediction + (1 - No\ Moat\ Model\ Prediction)}{2}$$

Because both the wide-moat model and no-moat model predictions range from 0 to 1, they can be interpreted as probability estimates. So, in essence, our raw quantitative moat score is equivalent to the average of the probability that the company does have a wide moat and the probability that it is not a no moat. Exhibit 6 shows the 10 highest and lowest Quantitative Economic Moat Rating companies globally.

Exhibit 6 10 Highest and Lowest Quantitative Economic Moat Rating Companies

10 Lowest Quantitative Economic Moat Companies	10 Highest Quantitative Economic Moat Companies
Fastly Inc	Mastercard Inc
Bohai Automotive Systems Co Ltd	Merck & Co Inc
Kingsoft Cloud Holdings Ltd	Procter & Gamble Co
OPKO Health Inc	McDonald's Corp
Tabcorp Holdings Ltd	Accenture PLC
The Star Entertainment Group Ltd	Texas Instruments Inc
Evotec SE	Union Pacific Corp
China Vanke Co Ltd	Zoetis Inc
Teladoc Health Inc	Novo Nordisk AS
Patterson-UTI Energy Inc	The Home Depot Inc

Source: Morningstar Direct. Data as of Sept. 30, 2024.

Because moat ratings are not meant to predict excess returns, a cumulative alpha event study would not be appropriate to measure the performance of our Quantitative Economic Moat Rating model. Instead, we decided to see how closely it replicated our analyst-assigned Morningstar Economic Moat Ratings. Exhibit 7 shows that there is significant agreement between the analyst-given ratings and the Quantitative Economic Moat Ratings.

Exhibit 7 Agreement Table Comparing Analyst Economic Moat Ratings With Quantitative Economic Moat Ratings
Quantitative moat ratings are displayed at the top (x-axis), and analyst moat ratings are displayed at the left (y-axis).

Rating (Top - Quant)	Wide	Narrow	None
Wide	97.4%	0.0%	0.2%
Narrow	2.6%	99.8%	0.0%
None	0.0%	0.2%	99.8%

Source: Morningstar Direct. Data as of Sept. 30, 2024.

The economic moat of a company generally demonstrates significant durability, reflecting long-term competitive advantages. To improve the stability of our Quantitative Economic Moat Rating, we have implemented a buffering mechanism designed to reduce rating volatility. This requires a company to receive the same moat rating in three consecutive assessments before any changes to its Quantitative Economic Moat Rating are applied. This approach ensures that temporary fluctuations do not result in premature rating adjustments, thereby providing a more stable and consistent measure of a company’s competitive position.

Quantitative Financial Health

Morningstar's market-implied Quantitative Financial Health measure ranks companies on the likelihood that they will tumble into financial distress. The measure is a linear model of the percentile of a firm's leverage (ratio of enterprise value/market value), the percentile of a firm's equity volatility relative to the rest of the universe, and the interaction of these two percentiles. This is a proxy methodology for the common definition of Distance to Default, which relies on an option-based pricing model. The proxy has the benefit of increased breadth of coverage, greater simplicity of calculation, and more predictive power while maintaining the timeliness of a market-driven metric.

- Step 1: Calculate annualized trailing 300-day equity total return volatility (EQVOL)
- Step 2: Calculate current enterprise value/market-cap ratio (EVMV)
- Step 3: Transform EQVOL into a percentile [0,1] by ranking it relative to all other stocks in the calculable universe (EQVOLP). 1 represents high-equity volatility, while 0 represents low-equity volatility.
- Step 4: Transform EVMV into a percentile [0,1] by ranking it relative to all other stocks in the calculable universe (EVMVP). 1 represents high-leverage companies, while 0 represents low-leverage companies.
- Step 5: Calculate new raw DTD = 1-(EQVOLP + EVMVP + EQVOLP*EVMVP)/3
- Step 6: Transform new raw DTD into a decile [1,10] by ranking it relative to all calculable US-domiciled stocks. 10 represents poor financial health, while 1 represents strong financial health.

Concluding Remarks

Morningstar Quantitative Equity Ratings are intended to expand coverage of ratings beyond our analyst staff. This paper explains different approaches taken to achieve that. For additional details on these, feel free to contact us.

We expect that, over time, we will develop enhancements to our quantitative models to improve their performance. We will document methodological changes in this document as they are made.

Appendix A: Input Variables

Exhibit 8 Variables Breakdown Used in Quantitative Valuation and Quantitative Economic Moat

Variables	Quantitative Valuation and Uncertainty	Quantitative Economic Moat
Sales Yield	Yes	Yes
Book Value Yield	Yes	Yes
Earnings Yield	Yes	Yes
Enterprise Value to Market Value	Yes	Yes
Maximum Drawdown	Yes	Yes
Volatility	Yes	Yes
Median Volume (of past 60 days)	Yes	Yes
Enterprise Value		Yes
Market Capitalization		Yes
Return on Assets		Yes
Total Revenue		Yes
SectorId		Yes
Quality*	Yes	
Value-Growth*	Yes	
Liquidity*	Yes	
Momentum*	Yes	
Developed Asia Pacific*	Yes	
Developed Europe*	Yes	
Developed Americas*	Yes	
Emerging Asia Pacific*	Yes	
Emerging Europe*	Yes	
Emerging Latin Americas*	Yes	
Emerging Middle East & Africa*	Yes	
Basic Materials*	Yes	
Telecommunications*	Yes	
Consumer Cyclical*	Yes	
Consumer Defensive*	Yes	
Healthcare*	Yes	
Industrials*	Yes	
Real Estate*	Yes	
Technology*	Yes	
Energy*	Yes	
Financial Services*	Yes	
Utilities*	Yes	
Volatility*	Yes	
Yield*	Yes	
Size*	Yes	
Enterprise Value to Free Cash Flow	Yes	

Enterprise Value to EBITDA	Yes
Enterprise Value to Revenue	Yes
Cash Ratio	Yes
Cash Flow Yield	Yes
Free Cash Flow Yield	Yes
Forward Dividend Yield	Yes
Dividend Per Share Growth (Rolling Annual Growth)	Yes
Cash Flow Per Share Growth (Rolling Annual Growth)	Yes
Diluted EPS 3 Year Growth	Yes
EBITDA 3 Year Growth	Yes
EBITDA Per Share (Rolling Annual Growth)	Yes
EBIT 3 Year Growth	Yes
Diluted EPS 5 Year Growth	Yes
Revenue 5 Year Growth	Yes
Revenue 3 Year Growth	Yes
Expected Dividend Growth Rate	Yes
Free Cash Flow/Assets Ratio	Yes
Free Cash Flow/Sales Ratio	Yes
EBITDA Margin	Yes
Return on Invested Capital	Yes
Gross Margin	Yes
EBIT Margin	Yes
Debt/EBITDA Ratio	Yes
EBITDA Interest Coverage Ratio	Yes
Current Ratio	Yes
Long-Term Debt/Assets Ratio	Yes
Dividend Payout Ratio	Yes
Assets Turnover Ratio	Yes

* From Morningstar Risk Model: Morningstar Standard Factor Model.
Source: Morningstar Inc.

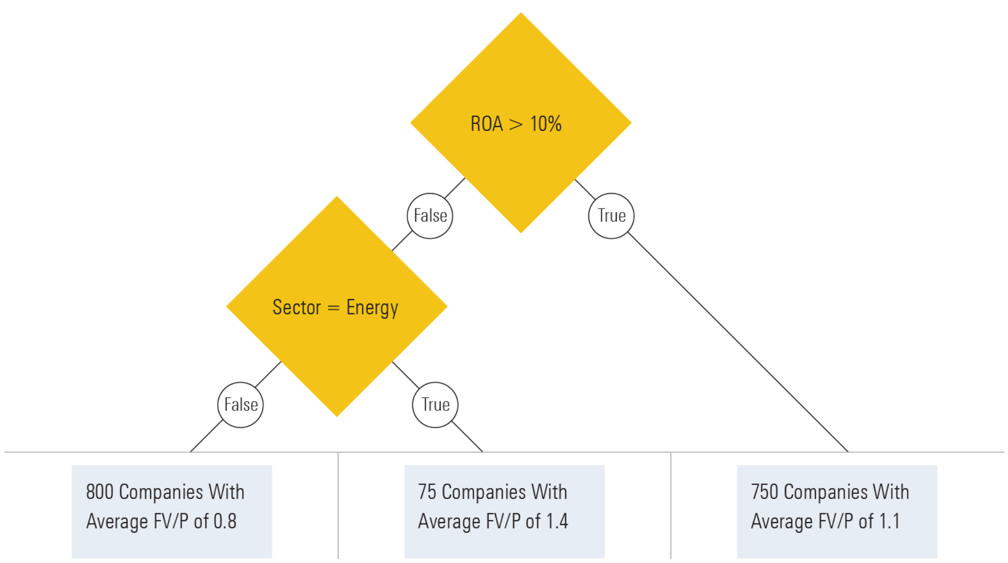
Appendix B: Random Forest

A random forest is an ensemble model, meaning its end prediction is formed based on the combination of the predictions of several submodels. In the case of a random forest, these submodels are typically regression or classification trees (hence, the *forest* part of the name *random forest*). To understand the random forest model, we must first understand how these trees are fit.

Regression Trees

A regression tree is a model based on the idea of splitting data into separate buckets based on your input variables. A visualization of a typical regression tree is shown in Exhibit 9. The tree is fit from the top down, splitting the data further, into a more complex structure as you go. The end nodes contain groupings of records from your input data. Each grouping contains records that are similar to each other based on the splits that have been made in the tree.

Exhibit 9 Sample Representation of a Regression Tree With Dummy Data



Source: Morningstar Inc.

How Are Splits Determined?

As you can see, the tree is composed of split nodes until they reach terminal nodes that no longer split. Each split represents a division of our data based on a particular input variable, such as return on assets or sector in Exhibit 9. The algorithm determines where to make these splits by attempting to split our data using all possible split points for all of the input variables. It chooses the split variable and split point to maximize the difference between the variance of the unsplit data and the sum of the variances of the two groups of split data as shown in the following function.

$$VarDiff = \sum(y - \bar{y}_{presplit})^2/N_{presplit} - \left[\sum(y - \bar{y}_{left})^2/N_{left} + \sum(y - \bar{y}_{left})^2/N_{right}\right]$$

Intuitively, we want the split that maximizes the function because the maximizing split reduces the heterogeneity of our output variable the most. That is, the companies grouped on each side of the split are more similar to each other than the presplit grouping.

A regression or classification tree will generally continue splitting until a set of user-defined conditions has been met. One of these conditions is the significance of the split. That is, if the split does not reduce heterogeneity beyond a user-defined threshold, then it will not be made. Another condition commonly used is to place a floor on the number of records in each end node. These conditions can be made more or less restrictive to tailor the bias-variance trade-off of the model.

How Are the End-Node Values Assigned?

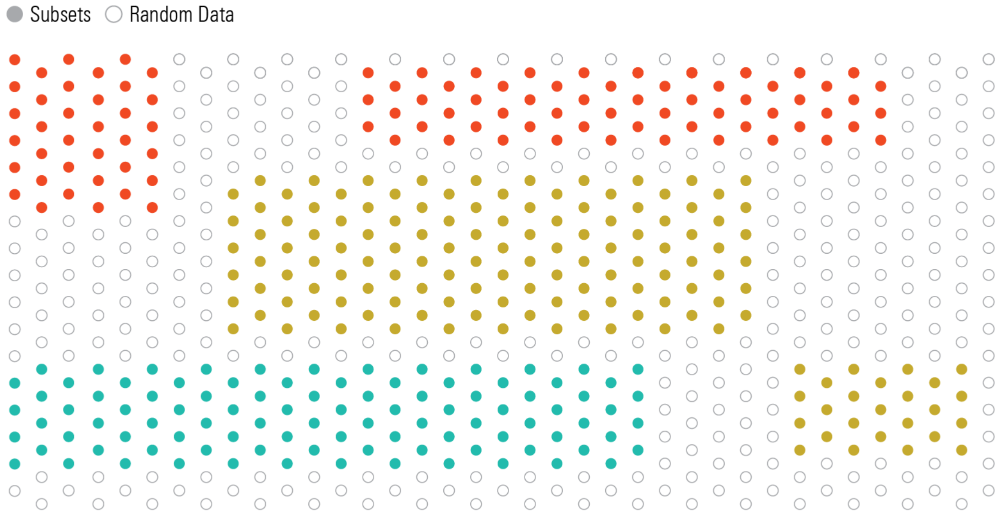
Each tree, once fully split, can be used to generate predictions on new data. If a new record is run through the tree, it will inevitably fall into one of the terminal nodes. The prediction for this record then becomes the arithmetic mean of the output variable for all training set records that fell into that terminal node.

Aggregating the Trees

Now that we understand how trees are fit and how they can generate predictions, we can move further in our understanding of random forests. To arrive at an end prediction from a random forest, we first fit N trees (where N can be whatever number is desired—in practice, 100 to 500 are common values), and we run our input variables through each of the N trees to arrive at N individual predictions. From there, we take the simple arithmetic mean of the N predictions to arrive at the random forest's prediction.

A logical question at this point is: Why would the N trees we fit generate different predictions if we give them the same data? The answer is: They wouldn't. That's why we give each tree a different and random subset of our data for fitting purposes. (This is the *random* part of the name *random forest.*) Think of your data as represented in Exhibit 10.

Exhibit 10 Sample Random Forest Data Representation



Source: Morningstar Inc.

A random forest will choose random chunks of your data including random cross-sectional records as well as random input variables as represented by the highlighted sections in Exhibit 10 each time it attempts to make a new split. While Exhibit 9 shows three random subsets, the actual random forest model would choose N random subsets of your data, which may overlap, and variables selected may not be adjacent. The purpose of this is to provide each of your trees with a differentiated dataset and, thus, a differentiated view of the world.

Ensemble models are a "wisdom of crowds" type of approach to prediction. The theory behind this approach is that many "weak learners," which are only slightly better than random at predicting your output variable, can be aggregated to form a "strong learner" so long as the "weak learners" are not perfectly correlated. Mathematically, combining differentiated, better-than-random "weak learners" will always result in a "strong learner," or a better overall prediction than any of your weak learners individually.

The archetypal example of this technique is when a group of individuals is asked to estimate the amount of jelly beans in a large jar. Typically, the average of a large group of guesses is more accurate than a large percentage of the individual guesses.

Random forests can also be used for classification tasks. They are largely the same as described in this appendix except for the following changes: Slightly different rules are used for the splitting of nodes in the individual tree models (gini coefficient or information gain), and the predictor variable is a binary 0 or 1 rather than a continuous variable. This means that the end predictions of a random forest for classification purposes can be interpreted as a probability of being a member of the class designated as "1" in your data.

Appendix C: Gradient Boosting

Gradient boosting is also a tree-based ensemble method that applies the boosting principle by focusing on problematic observations that were difficult to predict in previous iterations. It constructs an ensemble of weak learners, typically decision trees, in an iterative manner, with each new model relying on the previous one.

The gradient boosting algorithm consists of three main components:

Loss Function: The loss function represents the objective that the algorithm aims to minimize during training. It quantifies the difference between the predicted values and the actual values.

Weak Learner: A weak learner refers to an individual decision tree with limited depth, also known as a *base learner.* These trees are considered "weak" because they have limited predictive power on their own and are prone to overfitting. However, when combined in an ensemble, they can collectively build a strong predictive model.

Additive Model: In each iteration of gradient boosting, a new decision tree is fitted to the residuals (the difference between the predicted and actual values) of the previous iteration. This process gradually reduces the error and improves the model's predictive performance.

$$\hat{y}_i^{(0)} = 0$$

$$\hat{y}_i^{(1)} = f_1(x_i) = \hat{y}_i^{(0)} + f_1(x_i)$$

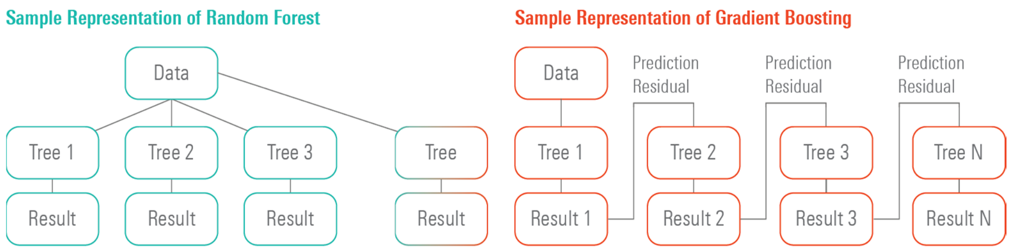
$$\hat{y}_i^{(2)} = f_1(x_i) + f_2(x_i) = \hat{y}_i^{(1)} + f_2(x_i)$$

$$\hat{y}_i^{(t)} = \sum_{k=1}^{t} f_k(x_i) = \hat{y}_i^{(t-1)} + f_t(x_i)$$

Difference Between Random Forest and Gradient Boosting

Both random forest and gradient boosting are tree-based models that excel in capturing complex patterns in data. Random forest employs a bagging technique, training multiple trees in parallel, with the final output determined by the majority of tree decisions. In contrast, the gradient boosting algorithm creates a sequential ensemble of tree models, each improving on the errors of the previous ones to determine the final output. This sequential nature allows gradient boosting to better fit the data. It often leads to higher predictive accuracy compared with random forests, especially in situations where there are complex interactions or nonlinear relationships in the data.

Exhibit 11 Sample Representation of Random Forest and Gradient Boosting



Source: Morningstar Inc.

Appendix D: Coverage by Domicile

Exhibit 12 Variables Breakdown Used in Quantitative Valuation and Quantitative Economic Moat

Country of Domicile	Companies Covered	Country of Domicile	Companies Covered	Country of Domicile	Companies Covered	Country of Domicile	Companies Covered
CHN	5215	EGY	200	MUS	28	BFA	3
USA	4379	PHL	198	BGR	26	FRO	3
IND	4339	ZAF	169	ISL	26	GIB	3
JPN	3987	HKG	164	JOR	26	PNG	3
KOR	2490	FIN	157	ZWE	25	PSE	3
TWN	2054	DNK	143	COL	22	SEN	3
CYM	1370	NLD	125	OMN	22	BWA	2
CAN	1221	ESP	119	PRT	20	CUW	2
AUS	998	NGA	103	GGY	19	LIE	2
VNM	973	KWT	99	KAZ	18	LVA	2
IDN	844	ARE	97	PER	18	NAM	2
MYS	842	VGB	92	PAN	17	TGO	2
SWE	839	BEL	87	TUN	17	BEN	1
THA	792	NZL	84	CYP	16	BHS	1
GBR	758	CHL	82	HRV	15	GAB	1
TUR	562	GRC	79	IMN	14	GHA	1
BRA	509	MEX	76	CZE	13	LBN	1
ISR	457	IRL	66	MLT	12	LBR	1
FRA	377	ROU	64	EST	11	MCO	1
PAK	374	ARG	60	TZA	10	MLI	1
BGD	347	JAM	60	BHR	9	NER	1
POL	338	MAR	54	MKD	8	RWA	1
BMU	317	QAT	52	MWI	8	SDN	1
SAU	315	LUX	49	SVN	8	SVK	1
DEU	310	AUT	47	ECU	7	UGA	1
ITA	273	JEY	44	LTU	7	UKR	1
SGP	254	HUN	40	VEN	7	URY	1
NOR	247	KEN	37	TTO	6	VIR	1
NPL	233	MHL	33	ZMB	5		
LKA	230	CIV	31	PRI	4		
CHE	205	IRQ	28	SRB	4		

Source: Morningstar Direct. Data as of Sept. 30, 2024.

Appendix E: Coverage by Exchange

Exhibit 13 Variables Breakdown Used in Quantitative Valuation and Quantitative Economic Moat

Exchange	Equities Covered	Exchange	Equities Covered	Exchange	Equities Covered	Exchange	Equities Covered
EX$$$$XFRA	10534	EX$$$$XMIL	657	EX$$$$XNSA	105	EX$$$$XNAM	19
EX$$$$XSTU	8371	EX$$$$HSTC	603	EX$$$$XSAT	105	EX$$$$XTUN	17
EX$$$$XMUN	6705	EX$$$$XIST	567	EX$$$$XKUW	102	EX$$$$XZAG	16
EX$$$$XDUS	6668	EX$$$$SHSC	539	EX$$$$XLUX	98	EX$$$$XPTY	12
EX$$$$XBER	6448	EX$$$$SZSC	539	EX$$$$XAMS	97	EX$$$$XTAL	12
EX$$$$PINX	5984	EX$$$$XTSX	442	EX$$$$XBRU	92	EX$$$$XBAH	10
EX$$$$XTKS	3893	EX$$$$XPAR	402	EX$$$$NEOE	84	EX$$$$XDAR	10
EX$$$$XBOM	3844	EX$$$$XTAE	400	EX$$$$XATH	84	EX$$$$XMSW	10
EX$$$$XNAS	3205	EX$$$$XWAR	388	EX$$$$XBSE	83	EX$$$$BVCA	9
EX$$$$XSHE	2851	EX$$$$XKAR	376	EX$$$$XNZE	82	EX$$$$XMAE	9
EX$$$$XKRX	2588	EX$$$$XSTC	372	EX$$$$XJAM	62	EX$$$$XTRN	9
EX$$$$XNSE	2398	EX$$$$XDHA	347	EX$$$$XKAZ	62	EX$$$$XLJU	8
EX$$$$XSHG	2303	EX$$$$XSAU	316	EX$$$$XNGM	62	EX$$$$XLIT	7
EX$$$$XNYS	1957	EX$$$$XBUE	315	EX$$$$XBUD	60	EX$$$$XQUI	7
EX$$$$XSEC	1631	EX$$$$XOSL	299	EX$$$$XADS	55	EX$$$$XBOT	6
EX$$$$XHKG	1571	EX$$$$XSES	288	EX$$$$XCAS	55	EX$$$$XLUS	6
EX$$$$CHIX	1562	EX$$$$XBUL	258	EX$$$$DSMD	52	EX$$$$UKEX	5
EX$$$$XMEX	1407	EX$$$$XCOL	248	EX$$$$XDFM	51	EX$$$$XBEL	4
EX$$$$XHAN	1377	EX$$$$XSWX	236	EX$$$$XPRA	48	EX$$$$XGHA	4
EX$$$$XSSC	1372	EX$$$$XNEP	234	EX$$$$XBOG	45	EX$$$$XGUA	4
EX$$$$BVMF	1338	EX$$$$XASE	227	EX$$$$XBRV	42	EX$$$$XPAE	4
EX$$$$XBKK	1187	EX$$$$XJSE	213	EX$$$$PFTS	41	EX$$$$ARCX	3
EX$$$$ROCO	1136	EX$$$$XPHS	207	EX$$$$XNAI	39	EX$$$$XBDA	3
EX$$$$XASX	1080	EX$$$$XCAI	201	EX$$$$XFKA	35	EX$$$$XCYS	3
EX$$$$XHAM	1042	EX$$$$XHEL	168	EX$$$$XICE	30	EX$$$$XMAL	3
EX$$$$XTAI	1036	EX$$$$XSGO	165	EX$$$$XSAP	29	EX$$$$XRIS	3
EX$$$$XLON	969	EX$$$$AQSE	154	EX$$$$XIQS	28	EX$$$$XBEY	2
EX$$$$XSTO	918	EX$$$$XNGO	152	EX$$$$XAMM	26	EX$$$$BATS	1
EX$$$$XKLS	846	EX$$$$GREY	151	EX$$$$XZIM	25	EX$$$$DIFX	1
EX$$$$XIDX	844	EX$$$$XMAD	144	EX$$$$XMUS	24	EX$$$$XBRA	1
EX$$$$XWBO	802	EX$$$$XCSE	140	EX$$$$XLIS	23	EX$$$$XMNT	1
EX$$$$XETR	710	EX$$$$XCNQ	122	EX$$$$XDUB	22		
EX$$$$XTSE	673	EX$$$$XLIM	122	EX$$$$XMAU	21		

Source: Morningstar Direct. Data as of Sept. 30, 2024.

About Morningstar® Quantitative Research™

Morningstar's Data and Analytics group creates one of the world's broadest and highest quality financial data assets in the world. The team is committed to the meticulous collection, organization, and dissemination of investment information that powers financial decisions globally.

Our data and analytics capabilities span millions of securities and entities across a diverse range of asset classes, including funds, equities, fixed income, and a variety of other financial products. Our unwavering commitment to high-quality data and analytics is the foundation for empowering investor success.

For More Information

madison.sargis@morningstar.com

MORNINGSTAR®

22 West Washington Street
Chicago, IL 60602 USA