Morningstar's Quantitative Equity & Credit Ratings

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Morningstar Methodology Paper
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The Philosophy of Morningstar's Quantitative Ratings

Morningstar has been producing differentiated investment research since 1984. Although our roots are in the world of mutual funds, Morningstar research has expanded to Equity, Corporate Credit, Structured Credit, ETFs and more. Traditionally, our approach has been to provide analyst-driven, forward-looking, long-term insights alongside quantitative metrics for further understanding of the investment landscape. However, we have now developed a new way of combining our quantitative and analyst-driven output while expanding the coverage of our analysis beyond the capabilities of our analyst staff.

In general, there are two broad approaches that we could have chosen to expand our analyst-driven rating coverage in a quantitative way: either automate the analyst thought process without regard for output similarity, or, alternatively, replicate the analyst output as faithfully as possible without regard for the analyst thought process.

We find that attempting to mechanically automate a thought process introduces needless complexity without marginal benefit, so we have opted to build a model that replicates the output of an analyst as faithfully as possible.
To this end, our quantitative equity and credit ratings are empirically driven and based on the proprietary ratings our analysts are already assigning to stocks.

Utilizing the analyst-driven ratings in our quantitative rating system strengthens both systems. The quality of our quantitative recommendations is intertwined with the quality of our analyst-driven ratings. Accordingly, improvements to our analyst-driven research will immediately flow through our quantitative rating system and leaves the analyst-driven research as the internal focal point of our rating improvement efforts.

But perhaps the most obvious benefit of developing a quantitative set of ratings is the gains to breadth of coverage. Our quantitative coverage universe is many times the size of our analyst covered universe, and growing. It is limited only by our access to the necessary input data. Morningstar, and indeed the investment sector continue to grow their data collection efforts at a rapid pace.

Of course no rating system, quantitative or otherwise, is valuable without empirical evidence of its predictive ability. Just as we regularly test and diagnose problem areas in our analyst-driven research, we have rigorously tested the performance of our quantitative ratings. We have peppered some of these studies throughout this document and will continue to enhance our methodologies over time to improve performance.

Quantitative Valuation for Stocks

To an investor that thinks about stocks as a claim on the cash flows of a business, the true intrinsic value of those cash flows is a must-have piece of information for any investment decision. As part of our continuing effort 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 of stocks that most differentiate the overvalued stocks from the undervalued stocks as originally valued by our team of human 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 a random forest to fit a relationship between the variable we are trying to predict (an analyst's estimate of the over- or under-valuation of the stock) and our fundamental and market-based input variables. A sample representation of our data is shown in Figure 1.

Figure 1: Sample Data Representation for Random Forest Model

Identifiers	Input Variables												Variable to predict
UNIQUE COMPANY ID	EP	BP	SP	MV	EV	EVMV	REV	VOLUME	VOLATILITY	DRAWDOWN	ROA	SECTORID	FVP
0P000000OE	0.0347	0.081	0.0743	39199114198	36681008676	0.935761	18369517000	5674537	0.31351	-0.263773	0.400154	IG000BA008	0.086801732
0P000000OG	0.0923	0.8306	1.0667	19942746460	24182746460	1.212608	21246000000	6026459	0.277207	-0.241388	0.073901	IG000BA009	0.106692919
0P000000OM	0.0637	0.1796	1.256	6545107721	9884307721	1.510182	8649000000	1090576	0.146817	-0.220973	0.057214	IG000BA003	-0.013511769
0P0000A5RZ	0.0688	1.2264	0.7631	33389928000	1.23468E+11	3.697759	24110000000	66307334	0.349422	-0.336826	0.003652	IG000BA010	-0.052260517
0P000000OY	0.0853	0.514	0.4299	61122484587	36129282001	0.591096	55928324000	9071117	0.235078	-0.252752	0.014602	IG000BA010	0.096673345
0P000000OZ	0.0925	0.5383	0.5677	71107636254	1.1671E+11	1.641309	82538000000	13562853	0.277794	-0.254558	0.016547	IG000BA010	0.145448765
0P0000A5JA	0.0651	1.3175	0.7017	55893574928	2.86867E+11	5.132371	53736722000	97791713	0.340433	-0.358028	0.003851	IG000BA010	-0.032205931

Variable we're trying to predict (FVP) = log(.0001+Analyst-Driven Fair Value Estimate/ Most Recent Closing Price)

Input Variables:

- ► Trailing 12 Month (TTM) Return on Assets (ROA)
- ► TTM Earnings Yield (EP)
- ► TTM Sales Yield (SP)
- ► Most Recent (MR) Book Value Yield (BP)
- ► TTM Equity Volatility (VOLATILITY)
- ► TTM Maximum Drawdown (DRAWDOWN)
- ► TTM Total Revenue (REV)
- ► MR Market Capitalization (MV)
- ► MR Enterprise Value (EV)
- ► TTM Average Daily Volume (VOLUME)
- ► MR EV/MV (EVMV)

► Sector (SECTORID)

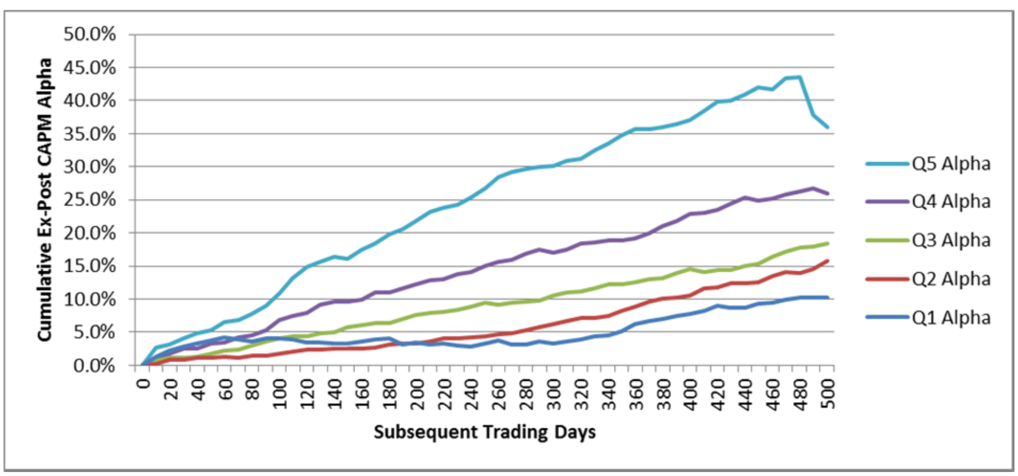
Our random forest model uses 500 individual regression trees to generate its predictions for the quantitative fair value estimates for stocks. See Appendix A for a description of a random forest model.

Of course this quantitative model is meaningless to an investor that does not understand the methodology used by a Morningstar equity analyst to value stocks in the first place. The methodology for our discounted cash flow approach to equity valuation can be found in Appendix B.

In production mode, we re-fit the random forest model each night using all of the most recent input data we can gather from Morningstar's Equity XML Output Interface (XOI) database. We refit each night because we believe the input variables have a dynamic impact on the valuations, which can change on a daily (if not more frequent) basis. Therefore a static model would not be appropriate. At the time of this update, we generate predictions for roughly 75,000 equities globally. Breakdowns of our coverage by country of domicile and exchange are available in Appendices D and E, respectively.

Naturally, all of the theoretical rigor in the world will not validate our quantitative model if it does not work in practice. Equity valuations are meant to predict future excess returns, and so we would hope that the stocks which appear undervalued in our quantitative system would generate positive excess returns and the stocks we designate as overvalued would generate negative excess returns. We have tested our quantitative valuations historically to examine how they would have performed. Figure 2 shows that the results of this test confirm the value of our quantitative valuations.

Figure 2: Out-of-Sample Quantitative Valuation Quintile Event Study
[Q5 is most undervalued quintile, Q1 is most overvalued quintile.]



Quantitative Valuation Uncertainty Ratings for Stocks

No valuation is a point estimate. There is always uncertainty embedded in any estimate of value. This uncertainty arises from two sources: model uncertainty and input uncertainty. Our quantitative valuation uncertainty rating is meant to be a proxy for the standard error in our valuation estimate or, if you will, the range of possible valuation outcomes for a particular company.

Unlike our quantitative valuations and quantitative moat ratings, we do not need to fit a separate model for valuation uncertainty. Our quantitative valuation model supplies all the data needed to calculate our quantitative uncertainty ratings.

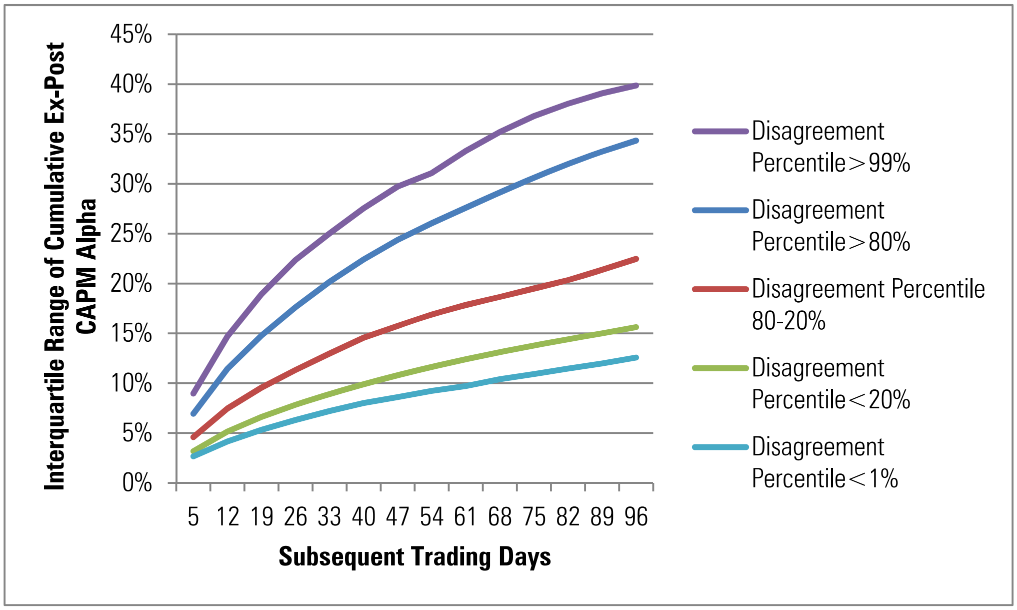
As described in the *Quantitative Valuation for Stocks* section of this document, we use a random forest model to assign intrinsic valuations, in the form of Quantitative Fair Value-to-Price ratios to stocks. However, our random forest model generates 500 intermediate tree predictions before averaging them to arrive at the final prediction. The dispersion (or more specifically, the interquartile range) of these 500 tree predictions is our raw Valuation Uncertainty Score. The higher the score, the higher the disagreement among the 500 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. The 10 companies with the lowest quantitative uncertainty and the 10 companies with the highest quantitative uncertainty as of the most recent update of this document are listed in Figure 3.

Figure 3: Ten Highest and Lowest Quantitative Uncertainty Rating Companies - 10/17/2012

10 Lowest Quantitative Uncertainty Companies	**10 Highest Quantitative Uncertainty Companies**
SCANA Corp (SCG)	Stem Cell Therapeutics Corp. (SSS)
CMS Energy Corp (CMS)	Loon Energy Inc. (LNE)
AGL Resources, Inc. (GAS)	Ventrus Biosciences, Inc. (VTUS)
OGE Energy Corp (OGE)	Geovic Mining Corporation (GMC)
Travelers Companies, Inc. (TRV)	Vanda Pharmaceuticals, Inc. (VNDA)
Alliant Energy Corporation (LNT)	SVC Group Ltd (SVC)
Chubb Corp (CB)	Vector Resources, Inc. (VCR.P)
DTE Energy Holding Company (DTE)	Syngas Limited (SYS)
Commerce Bancshares, Inc. (CBSH)	War Eagle Mining Company Inc. (WAR)
Fortis, Inc. (FTS)	St. Elias Mines Ltd. (SLI)

We tested our Quantitative Uncertainty metric to see if it were predictive of the future dispersion of excess returns. That is, stocks with low valuation uncertainty scores should have a relatively tight ex-post alpha distribution while stocks with very high uncertainty scores should have a very wide distribution of ex-post alpha. We see that empirically, these scores perform exactly as we would hope (Figure 4).

Figure 4: Quantitative Valuation Uncertainty Event Study



Quantitative Moat Ratings for Companies

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

In developing our quantitative moat algorithm, we took the same approach as we did with our quantitative valuation algorithm with a few small tweaks. 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 to be 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 as we do in our Quantitative Valuation.

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

Raw Quantitative Moat Score = Wide Moat Model Prediction + (1-No Moat Model Prediction)

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

Since 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 probabilities that our company does have a wide moat and the probability that it is not a no moat. Figure 5 shows the 10 highest and lowest Quantitative Moat rating companies globally.

Figure 5: Ten Highest and Lowest Quantitative Moat Rating Companies - Data as of 10/17/2012

10 Lowest Quantitative Moat Companies	**10 Highest Quantitative Moat Companies**
Trina Solar Limited (TSL)	Altria Group Inc. (MO)
JA Solar Holdings Co., ADR (JASO)	Abbott Laboratories (ABT)
Yingli Green Energy Holding Company, Ltd. (YGE)	Coca-Cola Co (KO)
Energy Solutions, Inc. (ES)	Roche Holding AG (ROG)
SunPower Corporation (SPWR)	British American Tobacco PLC (BATS)
Finmeccanica SpA (FNC)	Colgate-Palmolive Company (CL)
Century Aluminum Company (CENX)	Merck & Co Inc (MRK)
Barnes & Noble, Inc. (BKS)	GlaxoSmithKline PLC (GSK)
MEMC Electronic Materials Inc (WFR)	Oracle Corporation (ORCL)
Suntech Power Holdings Co., Ltd. (STP)	Philip Morris International, Inc. (PM)

Since 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 Moat model. Instead, we decided to see how closely it replicated our analyst ratings. Figure 6 shows that there is significant agreement between the analyst ratings and the Quantitative Moat ratings.

Figure 6: Agreement Table Comparing Analyst Moat Ratings with Quantitative Moat Ratings – Data as of 9/28/2012

	Quant Moat Score Percentile Rank			
	[1,.9)	**[.9,.5)**	**[.5,0)**	**Total**
Wide	152	2	0	154
Narrow	3	738	0	741
None	0	20	505	525
Null	100	11,634	12,241	23,976
Total	255	12,394	12,746	25,396

Market Implied Financial Health for Companies

Morningstar's Market Implied 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 to 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, 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, 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.

For more information about the performance of Morningstar's Market Implied Financial Health metric, please refer to the following white paper:

http://corporate.morningstar.com/us/documents/MethodologyDocuments/MethodologyPapers/CompareModelsCorpBankruptcyPrediction.pdf

Solvency Score for Companies

We consider several ratios to assess a firm's financial strength, including the size of a company's obligations relative to its assets, and comparing the firm's debt load with its cash flow. In addition to examining these ratios in past years, our analysts explicitly forecast the cash flows we think a company is likely to earn in the future, as well as consider how these balance sheet ratios will change over time. In addition to industry-standard measures of profitability (such as profit margins and returns on equity), we focus on return on invested capital as a key metric in determining whether a company's profits will benefit debt and equity holders. At Morningstar, we have been focusing on returns on invested capital to evaluate companies for more than a decade, and we think it is particularly important to understand a firm's ability to generate adequate returns on capital in order to accurately assess its prospects for meeting debt obligations.

Any credit scoring system would be remiss to ignore a company's current financial health as described by key financial ratios. In our effort to create a ratio-based metric, we used binary logistic regression analysis to evaluate the predictive ability of several financial ratios commonly believed to be indicative of a company's financial health. This extensive testing yielded a calculation that has shown to be more predictive of corporate bankruptcy. We refer to it as the Morningstar Solvency Score™.

Financial ratios can describe four main facets of a company's financial health: liquidity (a company's ability to meet short-term cash outflows), profitability (a company's ability to generate profit per unit of input), capital structure (how does the company finance its operations), and interest coverage (how much of profit is used up by interest payments). The Morningstar Solvency Score includes one ratio from each of these four categories.

Although our extensive testing was based on previously reported accounting values, Morningstar's equity analysts continually forecast the very same accounting values for future time periods. No testing of our analysts' forecasts has been possible due to data limitations, but it is reasonable to assume that using analyst estimates of future accounting values will yield more predictive results than previously reported ratios. As a result, the Morningstar Solvency Score uses some analyst estimates of future ratios.

Morningstar Solvency Score

$$5 \times \sqrt{\frac{TL_0 + CLO_0}{TA_0 + CLO_0} \times \frac{IE_1 + RE_1}{EBITDAR_1}} - (4 \times ROIC_1) - (1.5 \times QR_0)$$

Where:

TL_0 = Total Liabilities
CLO_0 = Capital Lease Obligations
TA_O = Total Assets
IE_1 = Interest Expense
RE_1 = Rent Expense
$EBITDAR_1$ = Earnings before Interest, Taxes, Depreciation, Amortization and Rent
$ROIC_1$ = Return on Invested Capital
QR_0 = Quick Ratio

$$ROIC_1 = \frac{EBITDAR_1}{IC_0}$$

$$IC_0 =$$
$$CA + NetPPE + NetGW + IA + LTOA + CLO - ExcessCash - AP - OtherCL - LTOL$$

Where:

CA = Current Assets
$NetPPE$ = Net Property, Plant and Equipment
$NetGW$ = Net Goodwill
IA = Intangible Assets
$LTOA$ = Long Term Operating Assets
CLO = Capital Lease Obligations
$ExcessCash$ = Excess Cash
AP = Accounts Payable
$OtherCL$ = Other Current Liabilities
$LTOL$ = Long Term Operating Liabilities

Part of the attractiveness of the Solvency Score is in its appeal to intuition. A practitioner of financial analysis will recognize that each of the ratios included has its own ability to explain default risk. In addition, the weighting scheme and ratio interaction appeal to common sense. For instance, it is logical to assume that an interest coverage ratio would be highly predictive of default.

Even healthy companies, however, can have odd years in which profits may suffer and interest coverage is poor. For this reason, a multiplicative combination of the interest coverage ratio with a capital structure ratio is more explanatory than either ratio individually, or even a linear combination of the two. This is because interest coverage is not highly important for companies with healthy balance sheets (perhaps they have cash on hand to weather even the most severe of downturns), but interest coverage becomes more important as liabilities increase as a percentage of a company's total capital structure.

For more information about the performance of the Morningstar Solvency Score, please refer to the following white paper:

http://corporate.morningstar.com/us/documents/MethodologyDocuments/MethodologyPapers/IntroMorningstarSolvencyScore.pdf

Concluding Remarks

Morningstar's Quantitative ratings are intended to be predictive of future return distributions, and extensive performance studies (beyond those described in this document) have affirmed that they are, in fact, performing as intended. For additional details on these performance studies, please 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.

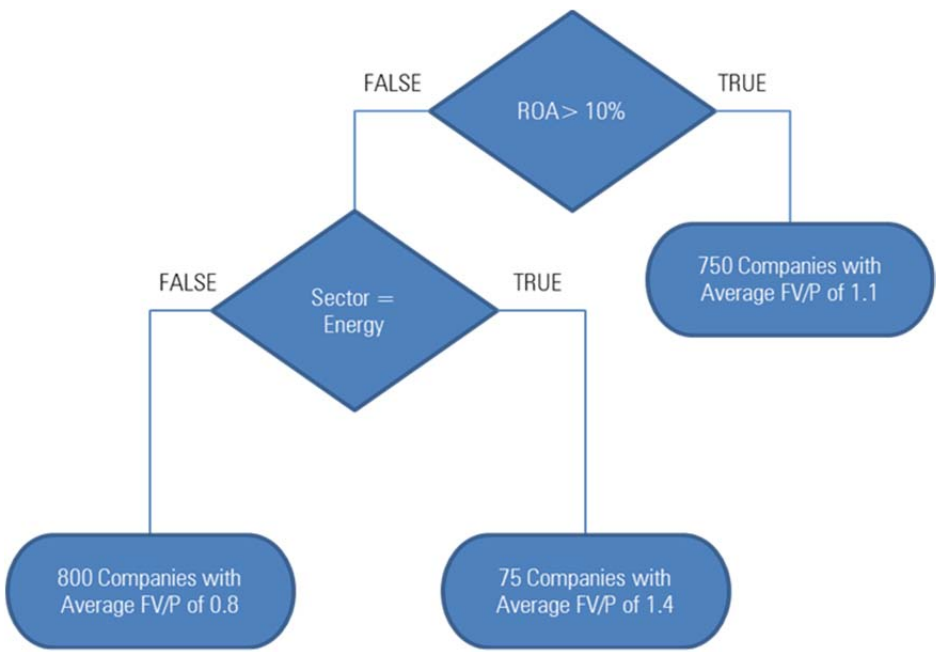
Appendix A: How Does a Random Forest Work?

A random forest is an ensemble model, meaning its end prediction is formed based on the combination of the predictions of several sub-models. In the case of a random forest, these sub-models 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 Figure 7. 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.

Figure 7: Sample Representation of a Regression Tree with Dummy Data



How are splits determined?
As you can see, the tree is comprised of nodes which then are split 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 ROA or Sector in Figure 7. The algorithm determines where to make these splits by attempting to split our data using all possible splitpoints for all of the input variables and 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.

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

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

A regression or classification tree will generally continue splitting until a set of user-defined conditions have 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 constrictive in order to tailor the bias-variance tradeoff of the model.

How are 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 of the 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 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 Figure 6.

Figure 6: Sample Random Forest Data Representation

	InputVar1	InputVar2	InputVar3	InputVar4	InputVar5	InputVar6	InputVar7	InputVar8	InputVar9	InputVar10	Variable To Predict
Record1	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record2	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record3	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record4	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record5	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record6	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record7	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record8	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record9	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record10	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record11	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record12	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record13	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record14	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record15	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record16	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record17	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record18	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record19	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record20	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record21	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record22	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record23	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record24	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record25	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record26	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record27	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record28	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record29	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record30	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record31	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record32	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX
Record33	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX	X.XX

Random Subset1
Random Subset2
Random Subset3

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 Figure 6 each time it attempts to make a new split. While Figure 6 shows 3 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 data set, 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 are asked to estimate the number of jelly beans in a large jar. Typically the average of a large group of guesses in 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 B: The Morningstar Analyst-Driven Valuation Methodology

Discounted Cash Flow Valuation—Stage I

We value companies using a three-stage discounted cash flow (DCF) model. The first stage includes our explicit forecasts. Analysts make specific predictions about a company's future financial performance to arrive at annual estimates of free cash flow to the firm (FCFF). Our Stage I forecasts can be seen on the Inputs tab in the section entitled "Discounted Cash Flows" starting on row 254. Free cash flow to the firm has two components: earnings before interest (EBI) and net new investment (NNI). EBI is calculated as follows:

	Operating Income (excluding charges)
+	Amortization
+	Other Non-Cash Charges[1]
−	Restructuring & Other Cash Charges
+	After-tax Operating Adjustments[2]
−	Cash Taxes[3]
+	Pension Adjustment[4]
=	Earnings Before Interest

Net new investment is added to EBI to arrive at free cash flow to the firm. NNI is calculated as follows:

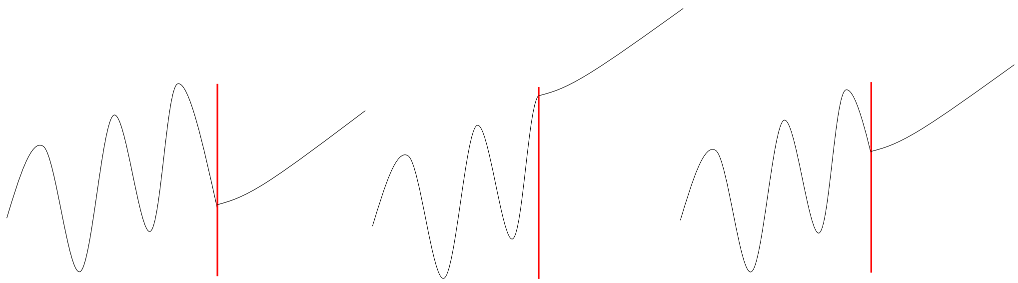
	Depreciation
−	Capital Expenditures
−	Net Investment in Working Capital[5]
−	Net Change in Other Operating Assets / Liabilities
−	Net Acquisitions / Asset Sales
=	Net New Investment

[1] Impairment of goodwill and other intangibles, and other noncash charges, included in SG&A or other operating expense accounts.
[2] Minority interest and other after-tax operating gains.
[3] Cash taxes are calculated as taxes from the income statement, plus the net interest tax shield, plus net changes in deferred taxes.
[4] This adjustment is needed to prevent double-counting of non-service components of pension cost (i.e. components of pension cost related to existing assets and liabilities).
[5] Excludes changes in cash.

The most important element of Stage I is earnings before interest in the last year of the explicit forecast horizon, since this is used as the jumping-off point for Stages II and III. *It is critical that the last year's EBI be representative of a normalized, sustainable, midcycle level of earnings.* Analysts have the ability to choose either five or 10 years as the length of Stage I. For most companies, five years is appropriate, as estimates become increasingly unreliable as the forecast horizon is extended. However, if a normalized level of EBI cannot be attained within five years, a 10-year Stage I should be used.

Figure 1 shows the importance of the EBI forecast in the last year of Stage I. Stage II and III assume a steady growth rate off of this base. If Stage I ends with a company's trough earnings, the fair value estimate will likely be too low. If Stage I ends with a peak level of earnings, the fair value estimate will likely be too high. The appropriate estimate incorporates a midcycle level of both revenue and margins.

Figure 1: Choosing an EBI Forecast in the Last Year of Stage I



Wrong: trough earnings used as the jumping off point for Stages II-III

Wrong: peak earnings used as the jumping off point for Stages II-III

Right: "mid-cycle" earnings used as the jumping off point point for Stages II-III

Discounted Cash Flow Valuation—Stage II (Standard Methodology)
Our standard Stage II methodology uses a formula to simplify the summation of discounted cash flows.[6] The formula relies on an assumption that EBI growth, return on new invested capital (RONIC), and return on existing invested capital will be constant during Stage II. Analysts are responsible for choosing the growth rate, RONIC, and the length of Stage II, but do not make specific assumptions about revenue, operating costs, and so on.

Stable EBI growth and RONIC also imply stable FCFF growth. Let $FCFF_1$ represent a company's free cash flow in the upcoming year (recall that $FCFF_1=EBI_1+NNI_1$), G represent the growth rate, and WACC represent the discount rate. In this case, the company's fair value (FV) today is given by:

$$FV = \frac{FCFF_1}{WACC - G} = \frac{EBI_1 + NNI_1}{WACC - G}$$

[6] Our Stage II and III formulas were derived independently, but are substantially similar to those found in McKinsey's Valuation (Fifth Edition) by Tim Koller, Marc Goedhart, and David Wessels.

Let us also define the investment rate (IR) as the percentage of EBI that is reinvested in the business and return on new invested capital as the incremental EBI generated from increases in invested capital. That is:

$$IR = -\frac{NNI}{EBI} \quad \text{and} \quad RONIC = \frac{EBI_{t+1} - EBI_t}{-NNI_t}$$

Dividing both the numerator and denominator of the RONIC definition by EBI_t yields:

$$RONIC = \frac{(EBI_{t+1} - EBI_t) / EBI_t}{-NNI_t / EBI_t} = \frac{G}{IR}$$

This can be rearranged as $IR = G / RONIC$. Finally, note that we can factor out EBI from the numerator of the fair value equation above and re-write the equation as follows:

$$FV = \frac{EBI_1(1 + NNI_1/EBI_1)}{WACC - G} = \frac{EBI_1(1 - IR)}{WACC - G} = \frac{EBI_1(1 - G/RONIC)}{WACC - G}$$

We use the right-most version of this formula to value Stage II cash flows. However, because Stage II is assumed to have a finite length, we must subtract the value of cash flows from years beyond the end of Stage II. The final formula becomes:

$$\text{Stage II Value} = \frac{EBI_{T+1}(1 - IR)}{WACC - G} - \frac{EBI_{T+L+1}(1 - IR)}{(WACC - G)(1 + WACC)^L}$$

Where T represents the last year of the Stage I forecast (either five or 10 years from now) and L represents the length of Stage II.

Analysts input their assumptions for Stage II growth and RONIC, and the length of Stage II, in the Stage II-III Methodology box at the top of the Inputs tab. This box also includes the five-year historical average and Stage I projected average values for RONIC and EBI growth to help inform the analyst's choices.

Stage II assumptions are the main way in which our equity valuation models incorporate our analysis of economic moats. In general, companies with wide or narrow economic moats should have RONIC>WACC and a relatively long Stage II. The wider the moat, the longer the company can be expected to outearn its cost of capital. As a rule of thumb, we think of wide-moat companies as being able to earn excess returns on capital for at least 20 years, while narrow-moat companies should be able to earn excess returns on capital for at least 15 years. For no-moat companies, Stage II RONIC normally should be close to or below WACC. If a company's RONIC is below its WACC, it may be appropriate to assume a negative EBI growth rate (that is, the company may rationally choose to disinvest in its business).

Cost of Capital

Because the output of our general model assumptions is free cash flow to the firm--representing cash available to provide a return to both equity and credit investors--we must discount future cash flows using the weighted average cost of capital (WACC), which is a weighted average of the costs of equity, debt, and preferred stock. In most cases, we determine the weights using the book value of debt and preferred stock, and the fair value of equity (using an iterative process). These weights may be adjusted if the company's current capital structure differs from its long-run target capital structure. The cost of debt and preferred stock should be based on observed market rates of return. Because we use a book rather than market value of debt, it may be appropriate to base the cost of debt on a mix of the incremental and historical cost of debt.

The cost of equity (COE) presents the greatest challenge in calculating the WACC because it is unobservable. The most common methodology for estimating the COE is the Capital Asset Pricing Model (CAPM). However, we find that the CAPM raises more questions than it answers, by replacing one unobservable input with three (the risk-free rate, the equity risk premium, and beta). While interest rates on U.S. Treasury bonds can serve as a reasonable proxy for the risk-free rate, there is significant disagreement about appropriate values for the equity risk premium and beta. For this reason, we have chosen a greatly simplified COE methodology that captures the essence of the CAPM while avoiding precise estimates of inherently unknowable quantities.

The central insight of the Capital Asset Pricing Model is that investors will only be rewarded, on average, for taking on systematic or non-diversifiable risk. We sort the companies in our coverage universe into four buckets based on their level of systematic risk. The buckets correspond to cost of equity values as follows:

Systematic Risk	**COE**
Below Average	8%
Average	10%
Above Average	12%
Very High	14%

The choice of a systematic risk bucket must be approved by the analyst's director or associate director. When deciding on a systematic risk bucket, the analyst should consider the question: "If aggregate global economic output unexpectedly and permanently increased (decreased) by 5%, what would happen to this company's sustainable operating earnings?"

If the answer is that the company's operating earnings would increase (decrease) by about as much as the average firm in the S&P 500, the company has average systematic risk. Most companies should fall in this bucket. If the answer is that the company's operating earnings would change by significantly less than most other firms, the company has below-average systematic risk. For example, most regulated utilities and soft-drink manufacturers would fall in this bucket. Finally, if the company's operating earnings would be expected to change by significantly more than most other firms, it has above-average or very high systematic risk. These buckets include economically sensitive businesses such as metal fabrication, hotels, oil and gas drilling, and asset management.

Viewed in another way, systematic risk to equity has three components: revenue cyclicality, operating leverage, and financial leverage. Table 1 provides a rough guide for assigning companies to systematic risk buckets based on an assessment of these underlying drivers. Importantly, company-specific, diversifiable (that is, nonsystematic) risks *do not* contribute to the systematic risk rating. For example, companies with a high degree of product or customer concentration, pending legal or regulatory issues, concerns about management execution, and so on would not be allocated to a higher systematic risk bucket. In contrast, the uncertainty rating should incorporate both systematic and company-specific risks. For this reason, the uncertainty rating should be at least as high as the systematic risk rating (where below-average systematic risk corresponds to low uncertainty, and so on). Additionally, company-specific risks should be incorporated in fair value estimates through base-case cash flow forecasts, which represent the expected value of future cash flows, or by explicitly probability-weighting scenario-based fair value estimates.

Table 1: Assigning Companies to Systematic Risk Buckets

Revenue Cyclicality	**Operating Leverage**	**Financial Leverage**	**Systematic Risk to Equity**	**Cost of Equity**
Low	Low	Low	Below Average	8%
Low	Low	Medium	Below Average	8%
Low	Low	High	Average	10%
Low	Medium	Low	Below Average	8%
Low	Medium	Medium	Average	10%
Low	Medium	High	Average	10%
Low	High	Low	Average	10%
Low	High	Medium	Average	10%
Low	High	High	Above Average	12%
Medium	Low	Low	Below Average	8%
Medium	Low	Medium	Average	10%
Medium	Low	High	Average	10%
Medium	Medium	Low	Average	10%
Medium	Medium	Medium	Average	10%
Medium	Medium	High	Above Average	12%
Medium	High	Low	Average	10%
Medium	High	Medium	Above Average	12%
Medium	High	High	Very High	14%
High	Low	Low	Average	10%
High	Low	Medium	Average	10%
High	Low	High	Above Average	12%
High	Medium	Low	Average	10%
High	Medium	Medium	Above Average	12%
High	Medium	High	Very High	14%
High	High	Low	Above Average	12%
High	High	Medium	Very High	14%
High	High	High	Very High	14%

The 8%,10%,12%, and14%, COE values refer to companies whose primary business is in the U.S. For international companies, we may add a premium to the baseline COE to account for differences in country risk and inflation. The analyst should be sure that the impact of inflation on future cash flow forecasts is consistent with the inflation rate implied by the cost of equity.

The country premium should be based on the location of the company's operations. This may be different from the company's headquarters. For companies with operations in multiple countries with different risk premiums, a blended rate may be appropriate.

The following table provides a guideline for country premiums as of January 2012. We revise this table approximately every six months.[7] Please consult Allan Nichols (allan.nichols@morningstar.com) for up-to-date values or for any countries not shown.

Table 2: International Cost of Equity Premiums

Argentina	9%	Greece	11%	Peru	3%
Australia	1%	Hong Kong	none	Philippines	4%
Austria	none	Iceland	3%	Portugal	4%
Bahamas	2%	India	3%	Russia	3%
Belgium	1%	Indonesia	4%	Singapore	none
Bermuda	1%	Ireland	4%	South Africa	2%
Brazil	3%	Israel	1%	South Korea	1%
Canada	none	Italy	2%	Spain	1%
Chile	1%	Japan	-1%	Sweden	none
China	1%	Lithuania	2%	Switzerland	none
Colombia	3%	Mexico	2%	Taiwan	1%
Denmark	none	Netherlands	none	Thailand	2%
Finland	none	New Zealand	none	Turkey	4%
France	none	Norway	none	United Kingdom	none
Germany	none	Panama	3%		

[7] Country risk premiums are adapted from research by Aswath Damodaran and are based on differences in nominal sovereign debt rates. See http://pages.stern.nyu.edu/~adamodar/.

Appendix C: The Morningstar Analyst-Driven Moat Methodology

Sustainable competitive advantages can take many forms, and some companies are better at developing them than others. But more than anything, the principle of sustainability is central to an evaluation of a company's economic moat. A company with a wide economic moat is one best suited to prevent a competitor from taking market share or eroding its margins.

Here is how Morningstar defines the five main types of economic moats.

Low-Cost Producer: Firms that can figure out ways to provide goods or services at a lower cost than anyone else have an advantage because they can undercut their rivals on price. **Wal-Mart** WMT is a textbook example of a low-cost producer because it can use its size to acquire merchandise on the cheap, passing part of the savings to its customers.

Switching Costs: Switching costs are those one-time inconveniences or expenses a customer incurs to change from one product to another. Customers facing high switching costs often won't switch unless they are offered a large improvement in either price or performance. Otherwise, the switch isn't worth it. As they say time is money. Companies whose customers have switching costs can charge higher prices (and reap more profits) without the threat of losing business.

Many financial-services companies enjoy the benefits of customer switching costs. Just ask anyone who has contemplated moving a checking account from one institution to another. Is it worth the hassle to open a new account, order new checks, switch direct deposit, and transfer automatic billing just to save $1 on ATM transactions?

The Network Effect: The Network Effect occurs when the value of a particular good or service increases for both new and existing users as more people use that good or service. For example, the fact that there are literally millions of people buying and selling things on **eBay** EBAY makes its service incredibly valuable to existing users—and makes it all but impossible for another company to duplicate its service. Imagine if you started a competing auction site tomorrow—there would be nothing for sale, so no buyers would be interested in your site. And without any buyers, there would be no sellers, either. It's a virtuous circle for eBay, but a vicious one for competitors.

Intangible Assets: Intangible assets generally refer to the intellectual property that firms use to prevent other companies from duplicating a good or service. Of course, patents are the most common economic moat in this category, critical for drugmakers, such as **Pfizer** PFE and **Johnson & Johnson** JNJ. A strong brand name can also be an economic moat—just consider consumer-product companies such as **Coca-Cola** KO and **Procter & Gamble** PG.

Efficient Scale
This dynamic primarily occurs when a limited market size is effectively served by one or a small handful of companies. In many of these situations, the incumbents have economic profits, but a potential competitor has less incentive to enter because the limited opportunity would cause returns in the market to fall well below the cost of capital, not just down to the cost of capital itself. The companies that benefit from this phenomenon are efficiently scaled to fit a market that only supports one or a few competitors, limiting rivalry. **International Speedway** ISCA is a great example; there is simply not enough demand for more than a single NASCAR racetrack in any given city. Airport companies like **Grupo Aero del Sureste** ASR (a Mexican airport operator) also benefit from efficient scale because, for most cities, it makes sense to have just a single commercial airport.

Companies can sometimes fall into just one of these buckets, while others may have two or more sources of advantage. Take Grupo Aero del Sureste: Even though efficient scale alone would keep competitors at bay, the company also sources its moat from intangible assets in the form of government concessions that limit new airports from being built in geographies where it operates. Or consider Coca-Cola: The company obviously benefits from the intangible assets represented by its brands. But even if these brands were to lose their value and the company were to produce generic cola, Coke would still have a major cost advantage because of its distribution network.

Measuring Moats
At Morningstar, we classify moats as either wide, narrow, or none. To determine which bucket a company fits into, we spend a lot of time getting to know the industries we cover, combing through financial statements, and talking to management. Before we assign a company a narrow or wide economic moat, we want to be confident that sustainable competitive advantages will allow it to generate returns on capital in excess of its cost of capital for at least one decade. To attain a wide moat rating, we must expect a company's competitive advantage period to last at least two decades.

It is not easy for a company to meet our wide-moat criteria. Of the approximately 2,000 securities to which we assign moat ratings, only about 10% are classified as wide-moat. This is all the more impressive when you consider Morningstar's coverage universe skews toward large and successful firms; most companies in the overall economy don't have any sort of moat whatsoever. By focusing on this select group of wide-moat firms, we are focusing on the at least the top decile in terms of company quality.

Appendix D: Breakdown of Quantitative Coverage by Country of Domicile

Country of Domicile	Equities Covered	Country of Domicile	Equities Covered	Country of Domicile	Equities Covered
USA	18012	GRC	302	COL	12
CAN	10116	IRL	284	HRV	11
JPN	6544	TUR	254	PER	11
DEU	4390	LUX	249	MCO	10
CHN	3400	POL	240	MUS	10
AUS	3259	PRT	235	CZE	8
GBR	2726	VGB	215	FRO	7
CYM	2371	JEY	212	KAZ	7
THA	2007	NZL	189	LIE	7
BMU	1877	RUS	186	ATG	6
FRA	1863	KOR	145	ISL	6
TWN	1584	LVA	134	BGD	5
ITA	1345	LTU	129	BHS	5
SGP	1297	MHL	118	MLT	5
CHE	1146	ARG	108	PAK	4
SWE	1103	IMN	79	PNG	4
HKG	927	CHL	78	QAT	3
IND	892	CYP	67	UKR	3
NLD	856	EST	52	GRL	2
ZAF	687	GGY	45	MWI	2
NOR	678	EGY	26	NAM	2
ESP	672	CUW	21	ZWE	2
FIN	594	MYS	21	AIA	1
DNK	545	PAN	21	BHR	1
BEL	516	PRI	20	KEN	1
AUT	501	PHL	18	NGA	1
MEX	449	HUN	17	ROU	1
BRA	361	LBR	17	COL	12
IDN	338	GIB	16	HRV	
ISR	325	ARE	12	PER	

Appendix E: Breakdown of Quantitative Coverage by Exchange

Exchange	Equities Covered	Exchange	Equities Covered
EX$$$$XFRA	9226	EX$$$$XHAN	335
EX$$$$XBER	9002	EX$$$$XASE	317
EX$$$$XETR	8339	EX$$$$XNGO	317
EX$$$$XSTU	5159	EX$$$$XMIL	312
EX$$$$PINX	4316	EX$$$$XNSE	307
EX$$$$XMUN	4168	EX$$$$XJSE	304
EX$$$$XLON	4015	EX$$$$XOSL	217
EX$$$$XNAS	2480	EX$$$$XBUE	205
EX$$$$XTKS	2254	EX$$$$XBRU	203
EX$$$$XTSX	2177	EX$$$$XCSE	177
EX$$$$XDUS	2108	EX$$$$XAMS	163
EX$$$$XNYS	2027	EX$$$$XMCE	150
EX$$$$XSHE	1474	EX$$$$XHEL	146
EX$$$$XHKG	1439	EX$$$$XLUX	146
EX$$$$XBKK	1429	EX$$$$XBSP	140
EX$$$$XASX	1303	EX$$$$XWAR	117
EX$$$$XTSE	1142	EX$$$$XIST	112
EX$$$$XHAM	1010	EX$$$$XNZE	112
EX$$$$XSHG	976	EX$$$$XCNQ	111
EX$$$$XJAS	843	EX$$$$XWBO	85
EX$$$$XTAI	824	EX$$$$XATH	65
EX$$$$XOTC	805	EX$$$$XLIS	61
EX$$$$XSES	776	EX$$$$XDUB	42
EX$$$$XOSE	743	EX$$$$XRIS	31
EX$$$$ROCO	651	EX$$$$XLIT	29
EX$$$$XPAR	521	EX$$$$XTAL	12
EX$$$$XMEX	489	EX$$$$XICE	6
EX$$$$XBOM	392	EX$$$$ARCX	1
EX$$$$XSTO	377	EX$$$$XHAN	
EX$$$$XSWX	340	EX$$$$XASE	