Best Practices in Research for Quantitative Equity Strategies

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In this article, we examine the research process and principles underlying successful models used in quantitative equity strategies. The research process is at the heart of the development of successful quantitative strategies. Key factors for their success are the availability of more and better data, advances in computational and econometric methods, and better understanding of how to enhance judgment in the research process. Our discussion does not provide rules to follow, but rather tenets that emerged from our collective experience of researching and developing quantitative models.

By identifying and examining the characteristics of quantitative strategies, we attempt to highlight some best practices in quantitative modeling and aspire to outline a broader paradigm for building successful models. These characteristics may not be strictly statistical or mathematical in nature, but rather they emphasize the integration of market dynamics, data, research design, modeling techniques, and economic and financial judgment.

In *Superforecasting*, Tetlock and Gardner [2015] state that "foresight isn't a mysterious gift bestowed at birth. It is the product of particular ways of thinking, of gathering information, of updating beliefs." In this article, we share some insights on accomplishing this objective by providing a framework and some thoughts on building quantitative forecasting models. Our discussion centers on developing quantitative models regardless of asset class, but our examples draw heavily from equities. Although we focus on quantitative research methodologies, we think that some of these ideas are valuable for a fundamental research process.

WHAT ARE QUANTITATIVE MODELS?

In this article, we refer to quantitative modeling in a broader sense. A quantitative strategy is a systematic, data- and model-based approach to making investment decisions. We can further qualify quantitative strategies by their underlying core characteristics. By examining these core characteristics, we can attempt to identify some best practices in quantitative modeling to develop a paradigm that will lead to building successful models.

The most important characteristic of the quantitative modeling approach is the scientific approach. This approach provides a paradigm that guides and informs empirical work. Similar to other fields that take a scientific approach—including natural sciences, medicine, and social sciences—this approach in quantitative modeling attempts to describe, inquire, and interpret with precision. The characteristics of a scientific approach as it relates to quantitative equity strategy modeling include the following:

- Development of a thoughtful hypothesis or thesis to be evaluated
- Use of empirical work to attempt to put precision around investment decisions and economic reasoning
- Reliance on high standards of analytical rigor
- Use of sensitivity analysis to challenge assumptions and context in which the strategy was developed
- Incorporation of adjustments to the strategy based on judgment
- Ability to explicitly measure results
- Incorporation of revisions or updates to the model as new information becomes available

HOW ARE QUANTITATIVE STRATEGIES DEVELOPED?

Dating back to the 17th century, the scientific method is an approach for examining and understanding phenomena, developing new theories, or modifying or integrating existing theories based on the presentation of empirical and measurable evidence subject to specific principles of reasoning. Research based on the scientific method typically takes steps to 1) define a question, 2) collect information and resources, 3) form an explanatory hypothesis, 4) test the hypothesis by performing experiments and collecting data in a reproducible manner, 5) analyze the data, and 6) interpret the data and draw conclusions. After drawing these conclusions, the researcher may then go back to reformulate the explanatory hypothesis and repeat the (3)–(6) cycle again.

Within the context of investment management, empirical analysis uses data and tools to design, research, and evaluate hypotheses/models. The primary function of empirical research is to create (some) evidence for trading models. A large part of empirical analysis is research design. A well-thought-out research design provides support and credibility for validating the investment insights underlying trading models.

Exhibit 1 lists different types of quantitative strategies. The typical steps in developing these strategies are as follows: 1) formulate trading ideas and strategies, 2) develop signals, 3) acquire and process data, 4) analyze the signals, 5) build the strategy, 6) evaluate the strategy, 7) backtest the strategy, and 8) implement the strategy. We next examine each of these steps.

Formulating Investment Ideas and Strategies

A successful quantitative strategy often starts as an idea based on economic intuition, a market insight, or an anomaly. Background research can be helpful for understanding what others have tried or implemented in the past.

To distinguish between a trading idea and a quantitative strategy, we look at the economic motivation for each. A *trading idea* has a shorter-term horizon, often associated with a specific event or mispricing. A *quantitative strategy* has a longer time span and exploits opportunities

EXHIBIT 1
Types of Quantitative Equity Strategies

- *Multifactor strategies*: Models that invest in equities based on multiple characteristics that replicate how investors make decisions. These strategies have an edge in their superior processing of information and identification of differentiated insights.
- *Allocation decisions*: Strategies that make decisions based on allocations to different countries, sectors, factor timing, regime switching, etc.
- *Stock–specific strategies*: Strategies that focus on the information specific to an individual equity security.
- *Factor strategies*: Rule-based strategies that trade well-known equity risk premiums to earn returns.
- *Event studies*: Strategies that generate alpha from specific events.
- *Market microstructure strategies*: Strategies that exploit profitable opportunities arising from the trading flows and dynamics of equity markets.
- *Statistical arbitrage*: Strategies that exploit systematic relationships among equity securities with similar characteristics. In contrast to pure riskless arbitrage, statistical arbitrage is a risky form of strategy.
- *Textual strategies*: Quantitative strategies that trade based on qualitative textual signals, such as news reports, company documents, or Internet searches.
- *Thematic/macro strategies*: Strategies that trade baskets of equity securities based on broad themes in the economic environment, technology, demographics, or other fields.

to process information better, receive premiums associated with anomalies, or identify mispricings.

Developing Signals

After having established the idea of the strategy, we move from the economic concepts to the construction of signals that may be able to capture our intuition. *Signals* provide building blocks for the model used to create an investment strategy.

Built from data, signals are quantitative measures that represent an investment idea. How signals are built varies depending on the investment thesis and the data representing the thesis. For example, a quantitative signal could be based on a stock's underlying characteristics such as its return on equity or valuation ratio. A sentiment signal could be developed from unstructured text from various company-issued reports or news about the company.

Acquiring and Processing Data

Data are critical to a strategy's success. A strategy relies on accurate and clean data to build signals. Data need to be carefully stored in an infrastructure that is scalable and flexible. Upon acquiring new data sources, researchers expand the information set necessary to create new insights.

Analyzing the Signals

Researchers perform a variety of statistical tests and econometric techniques on the data to evaluate the empirical properties of signals. This empirical research is used to understand the risk-and-return potential of a signal. For example, a researcher might be interested in statistically testing whether a signal's Sharpe ratio is larger than 1. This analysis may form the basis for building a more complete trading strategy.

Building the Strategy

A model represents a mathematical or systematic specification of the trading strategy. There are two important considerations in this specification: 1) the selection of the specific signals and 2) how these signals are combined. Both considerations may be motivated by the economic intuition driving the trading strategy.

Evaluating, Testing, and Implementing the Strategy

The final steps involve assessing the estimation, specification, and forecast quality of the model. This analysis includes examining the goodness of fit (often done in sample), forecasting ability (often done out of sample), and sensitivity and risk characteristics of the model.

Empirical validation and testing are key drivers in the development of quantitative trading strategies. They bridge the gap between stylized financial models and the real world represented by the markets. Financial models are often crude approximations of reality—with regimes in which they work acceptably, and regimes in which they do not work at all or work very poorly at best. Careful systematic empirical research can help identify these regimes. The researcher's judgment and experience become a critical factor in this step.

MODELS AND JUDGMENT

The well-known statistician George Box stated, "All models are wrong; some models are useful" (Box [1976]). Models simplify the world around us through idealization. Naturally, this idealization describes the most salient features of markets, and it is important to note that not every market dynamic is included in a model. The construction of idealized representations of the financial markets is a vital part of academic and practitioner research.

Although models are quantitative in nature, the research process is subject to data and design decisions that are more qualitative in nature. Judgment calls include deciding how to cleanse the data, how to select a specific model, how to aggregate signals, and which risk measures to rely on. Researchers make these decisions, of course, based on their experience and preferences. Besides the research process itself, judgment is also prevalent in the *feedback mechanism* of backtesting and running the strategy.

Generally, most quantitative models are based on two approaches of thinking—hypothesis based (deductive) and pattern based (inductive). Each approach requires a different model-building research process. For the hypothesis-based approach, the starting point is some insight about why a trading opportunity exists. It is dependent on an economic thesis or hypothesis on how the market works or why the opportunity exists. Frequently, the "story" precedes the empirical work.

The second approach is inductive or pattern based. This approach is exploratory in nature, and the discovery of insights emerges from the empirical work. A key feature is that learning occurs throughout the process. In this approach, it is critical to be able to distinguish between correlation and causation. Are measured statistical correlations spurious or causal? Understanding underlying economic mechanisms and theory may provide insights to this question.

Best practices involve understanding how to make better decisions in the research design process. It is useful to draw on sciences from other disciplines that study decision making, often in experimental settings; these include psychology, philosophy, and organizational behavior.

A good question to ask is, "How do we make better decisions in the development of quantitative strategies?" We compiled the following list of attributes from the research of various experts in the areas of decision sciences, including Leamer [1978, 1983], Tetlock and Gardner [2015], and Tversky and Kahneman [1974], as well as from our own personal experience:

- Start a research project with scientific caution.
- Understand the assumptions underlying the research methodology decisions and why those assumptions were chosen.
- Formulate an alternative hypothesis.
- Make (reasonable) changes to key assumptions to evaluate their robustness.
- Look for contrary evidence of the findings.
- Tweak the research question being asked and try answering this revised question as a way of gaining additional perspective.
- Focus on causation and probabilities, rather than statistical correlations.
- Break down the investment thesis into its underlying assumptions and scrutinize each assumption.
- Examine what you know about the investment thesis from what you do not know or cannot know.

The benefits of using quantitative models extend beyond pure quantitative trading. These models provide valuable analytical tools in a traditional, fundamental investment decision-making process. It is important to differentiate between how purely quantitative investors use model forecasts and how fundamental investors use them. For quantitative investors, model forecasts produce an expected return forecast on a security or a set of securities. For fundamental investors, model forecasts create new insights to synthesize with other qualitative information (e.g., management meetings and industry strategy) being acquired to make investment decisions. Working with fundamental investors, we apply quantitative models to understand complex relationships, to verify investment theses, and to discover new opportunities.

Collaboration of quantitative researchers with fundamental investors is a social experience that can create an "investment edge." The process of building a quantitative model jointly produces unique investment insights. Numerous studies and anecdotes provide evidence that combining computer-based forecasting and human judgment results in better outcomes. We can draw on the literature from other disciplines to assist in providing insight into how to better integrate the two. For example, in "freestyle chess," a chess tournament in which players are open to consult any resource available to assist them, the winners of tournaments are humans paired with machines—beating machines only, or human experts alone, or machine alone (Cowen [2013]). The key to the winners' success is being able to synthesize information from multiple sources, while recognizing the strengths and weaknesses of each approach.

TAXONOMY OF QUANTITATIVE EQUITY STRATEGIES

Quantitative strategies exist across different markets. The characteristics underlying these strategies vary substantially. We categorize strategies along a number of dimensions, such as the asset class, type of securities, horizon, trading style, and investment philosophy. Each of these categories influences the quantitative modeling process, often starting with the research design, data, modeling techniques, and evaluation methods.

Commonality in these traits allows us to classify strategies into groups. In Exhibit 1, we attempt to create a simple taxonomy of quantitative strategies. There is some overlap in this classification because strategies share common traits. We also considered how investors implement the strategies.

Quantitative investment strategies differ in their motivation to trade, the frequency of trading, information used to trade, and the markets traded. The strategies employ different holding periods and trading frequencies—the latter of which can occur in milliseconds, or extend to months or years. Separately, the holding period of each trade varies along similar horizons. Both trading frequencies and holding periods are functions of the investment theory underlying the strategy and the empirical results uncovered in research.

TECHNIQUES FOR EMPIRICAL WORK

In addition to insights about the market, quantitative computational methods are critical for success. Many of the traditional financial econometric techniques continue to be widely used. Their success results from their tractability—being well understood and fairly straightforward to implement. These include regression-based techniques, such as Fama–MacBeth and generalized least squares, and nonparametric techniques, such as portfolio sorts. Our understanding of how to effectively apply and interpret these techniques has matured.

Researchers continue to extend and innovate upon traditional computational approaches. For example, Patton and Timmermann [2010] propose new ways to test for monotonicity (in portfolio sorts) in the expected returns of securities sorted by characteristics that theory predicts should earn a systematic premium. They provide a summary statistic for monotonicity, allowing researchers to decompose the results to better diagnose the source of a rejection of (or failure to reject) the theory being tested.

New computational methods continue to emerge and flourish. An increasingly popular computational field among quantitative researchers is statistical learning (sometimes referred to as *machine learning*). These analytical tools—which can be classified into supervised and unsupervised methods—are valuable for building models because they reveal the structure of data, incorporate nonlinearities into the model, and provide robust predictions. In our view, these approaches should not be viewed or used as "black boxes" but rather as analytical tools.

Researchers in finance are applying these newer methodologies to create insights into the dynamics of equity markets. Moritz and Zimmermann [2014] address the research question of which variables provide independent information about the cross-section of stock returns. Their computational approach, called *deep conditional portfolio sorts*, is designed to deal with a large number of variables and potential nonlinearities and interactions. When estimating the model, the authors incorporate concepts from the statistical learning literature, mirroring methods used to estimate decision tree and ensemble methods.

Ogneva, Piotroski, and Zakolyukina [2015] use the lasso (*least absolute shrinkage and selection operator*) model by Tibshirani [1996] to select a parsimonious set of fundamental variables for a probability of recession given a failure model. Lasso estimates a sparse solution of a regression problem by setting some of the regression coefficients to zero. They are primarily interested in the out-of-sample classification ability of a proposed model, using cross-validation as a performance measure.

Unstructured data have become more valuable in developing quantitative signals for equities. Textual analysis of corporate disclosures such as financial statements, earnings releases, and conference call transcripts are sources of unstructured, qualitative data. Li [2010] provides a survey of various techniques to extract signals from textual data, showing that the communication patterns of management could reveal certain management characteristics that have an impact on understanding corporate decisions and forecasting stock returns. Focusing on research related to earnings quality, stock market efficiency, and corporate financial policies, he highlights two general approaches for conducting content analysis using a rule-based dictionary approach and statistical approach, such as the naïve Bayesian machine-learning algorithm.

Equity markets react to news flow. Although it is potentially rich in information, this source of data also contains substantial noise. Heston and Sinha [2015] compare different methods of textual analysis using news reports from Dow Jones to predict cross-sectional stock returns. They analyze the horizons over which returns are realized for sentiment signals created using different computational methods. Some signals provide a forecasting horizon of up to a quarter, whereas others forecast returns over shorter horizons, such as a day.

A growing amount of information comes from Twitter, Internet searches, and other sources of text-based social media. These data sources can also be useful for building quantitative measures of investor sentiment. For example, Da, Engelberg, and Gao [2015] use daily Internet search volume to construct a measure of market-level sentiment. They show that this measure is useful in predicting short-term reversal, increased volatility, and fund flows.

It is important to understand the intuition, assumptions, and strengths and weaknesses of computational approaches. The choice of a method involves trade-offs. The computational approach should align with the data structure, research design approach, and underlying investment strategy being research and traded. For example, research that uses a hypothesis-based (deductive) approach to modeling typically relies on more traditional computational approaches, such as regression and information coefficients. Pattern-based approaches are applied to unstructured data sources and/or data that contain nonlinearities or other unusual features.

EXAMINING SOME CRITICAL ASPECTS OF QUANTITATIVE STRATEGIES

There are many advantages to using a quantitative model. The scientific approach to developing models bring advantages such as rigor, creativity, avoidance of biases, and process.

Rigorous analysis is an underlying principle of the scientific approach. A rigorous approach allows one to validate ideas through a framework incorporating statistical rigor by employing backtests, in-sample/out-sample comparisons, and Monte Carlo analysis to study the robustness and sensitivity of a strategy to a given choice of parameters. This verification should also incorporate new market and theoretical developments. New assumptions (paradigms/theories) require the reconstruction of prior assumptions and the reevaluation of prior facts.

The numerous computational tools—from statistical learning to traditional statistical approaches—and the expanding set of data sources provide tools and raw materials to explore new trading ideas. Similar to an artist who has access to paints and canvases, a researcher benefits from creativity—which results from hard work, introspection, and inspiration. This creativity is the driver for new investment ideas. With the right tools, researchers have the ability to develop ideas about investing strategies and create models.

All decisions are subject to biases. In investing, the behavioral biases are well documented—confirmation bias, optimism bias, and overconfidence, to name a few. Quantitative models give us more objective benchmarks to measure our decisions and to (partially) eliminate these biases.

The decisions we make to build quantitative strategies are also affected by biases. We sometimes see data and construct a story to explain what happened. Taleb [2007] calls this "narrative fallacy"— looking backward and creating a story to fit events. Being aware of potential biases and understanding how our assumptions drive our choices in the modeling process are key to building successful strategies.

Quantitative strategies are systematic; that is, the underlying strategy is consistently applied to identify and implement trading opportunities in a structured framework. A framework brings structure and logic to a disorderly and complex activity of identifying opportunities in the markets. This framework provides a process—a common plan of direction and action to use in developing, evaluating, and implementing investment ideas through quantitative models. In markets filled with near-constant information flow, not all information influences asset prices. The benefit of having a systematic model is having a consistent process to focus efforts on information that influences prices—and to avoid reacting to noise (useless information).

Empirical research is often based on historical data, and there is a limit to how much information about the future we can infer from the past. Sometimes, quantitative investors are at risk of being too systematic in their approach. There is always the risk of low-probability events that will challenge the underlying assumptions. Because markets change and the current environment looks different from the past, we need to evaluate whether those changes are structural or transitory. It is important to understand how both types of changes will impact the performance of quantitative models. We need to continually evaluate our models and the markets they operate in, revising a model when our judgment and experience indicate it is no longer effective or a different opportunity set for alpha arises.

At the Core of a Quantitative Model: The Data

At the heart of a quantitative model is data. Quantitative analysis relies on nonexperimental inference. How the data are used and the source of the data are of critical importance. "Garbage in and garbage out" is a commonly used phrase referring to how the data inputs of a model can affect its output. For researchers of quantitative strategies, this means that a quantitative process is only as good as its data.

Data impact the outcome of a research project. In any dataset, there are some data features we understand, and some we do not. For researchers, it is critical to *explore data features and expose unexpected features of the data*.

We can classify data in a number of different ways. More recently, it has become common to characterize data as *structured* or *unstructured*. Structured data are organized into tables with clearly identified and organized information. Unstructured data, such as text containing natural language, do not have a formal structure. It requires specialized processes to extract the important attributes that can be used in various computational techniques—and thereby, it introduces new opportunities and challenges for researchers. The infrastructure to store and access this information is still evolving; thus, it requires substantial effort to utilize this information in modeling.

Data containing errors, missing values, and other flaws affect the validity of the analysis. For example, Kothari, Sabino, and Zach [2005] find that nonsurviving firms tend to be either extremely bad or extremely good performers. Survivor bias implies truncation of such extreme observations. The authors show that even a small degree of such nonrandom truncation can have a strong impact on sample moments of stock returns.

Data are often available from multiple sources, and the number of available data sources is increasing. It is well known that different data sources maintain a different level of detail. These differences can have a large impact on strategy development. It is important to understand the comparative characteristics of databases. In particular, the researcher needs to explain how discrepancies between databases affect the research output. The issue is to determine whether the use of a particular data source might have influenced the results.

Characteristics of good data include the following:

- Clear and consistent definitions of what the data represent
- Reasonable detail underlying the data
- Appropriate data availability: length, frequency, timeliness
- Consistent view of history
- Free from survivorship bias
- Free from look-ahead bias

Successfully working with data means understanding the nuances of data sources. The following are a few best practices for data.

- *Understand how the database evolves over time.* Most databases change over time, and those changes include what data were collected, how the data were collected and its coverage.
- *Understand how the database's standard procedures work and how they differ among different data sources.* Most databases have standardized procedures for reporting certain items in their system in order to ensure comparability.
- *Beware of potential biases in the data.*
- *Choose one data source to build the model and a second data source to confirm the model.*
- *Include statistics that describe and compare the usability of data items with regard to standard empirical applications in finance.*
- *Look for economic explanations of any outliers.* For example, Brown, Lajbcygier, and Li [2008] examine the economic significance of outliers in their dataset. In their work, they show that the outliers result from firms with materially different financial situations. In contrast to outliers caused by bad data, this set of outliers had material implications for the conclusions of their results.

There may be opportunities in using less clean data sources or data with shorter history, and so on. This type of data might provide a source of alpha that others overlook because of the work and patience required to make the data usable for a research process.

How does poor data affect strategies? High-quality data are critical to success. The validity and power of the results rely on well-prepared datasets. For example, Ljungqvist, Malloy, and Marston [2009] document changes in the collection and recording of historical I/B/E/S analyst stock recommendations. They show that these changes are nonrandom, and the consequences of these changes affect returns generated on trading signals using these data.

WHAT DO WE MEAN BY "GOOD" MODELS AND STRATEGIES?

In this section, we describe five key properties of "good" quantitative models. We leverage the work of Gabaix and Laibson [2008], who describe critical properties for building economic models. These properties are intended to be broad guidelines.

Parsimony: Parsimony means models with few assumptions. All models are only approximations of reality, and some features will always be omitted. Our assumptions are based on the results of empirical research (parameter estimates), economic intuition, and judgment and theory (for example, priors, structural assumptions). Having too many assumptions tends to lead to overfitting. When overfitting occurs, our models are unable to provide accurate out-of-sample predictions.

Tractability: Tractable models are easy to analyze, providing transparency to the user. We should have explicit descriptions of our research choices for data, research design, and computational choices. Having tractability enables us to question our model assumptions and make changes when necessary.

Conceptual insightfulness: Our model should align with market dynamics, investor behavior, and investment theory. The empirical analysis and our hypothesis about why the strategy works should be mutually reinforcing.

Predictability: We desire models that give us robust forecasts. As practitioners, we are primarily concerned with the profitability and risk of a strategy and how well the model's motivation fits economic theory and market behavior.

Adaptability: Financial markets are constantly evolving, subject to sudden, unpredictable changes. Market changes challenge the assumptions of models. It is important to understand and forecast the potential impact of those changes. For example, change may be the result of innovation of financial products, change in the preferences of market participants, and/or responses to exogenous financial and economic shocks. Flexibility in our thinking and our models is necessary to adapt to changing market conditions.

CONCLUSIONS

In this article, we discussed a number of principles, insights, and experiences for building successful quantitative equity strategies. To build these successful strategies, we need to combine judgment with the scientific approach to identify and validate new opportunities in ever-changing markets. Understanding the data and computational techniques is necessary for obtaining empirical evidence to support our investment ideas. Without doubt, the research and development of successful quantitative models are a blend of science and art. Our endeavors in model building require constant innovation and rigorous analytics to be successful.

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