FINDING ALPHAS

A QUANTITATIVE APPROACH TO BUILDING TRADING STRATEGIES

SECOND EDITION

EDITED BY

IGOR TULCHINSKY et al.

WILEY

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Dedicated to All at WorldQuant —

The Future of Trading

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Preface

Much has changed since we published the first edition of *Finding Alphas*, in 2015. The premise of that edition – that we considered these techniques “the future of trading” – is more true today than it ever was. In the intervening four years, we at WorldQuant have seen remarkable growth in our development of predictive algorithms for quantitative trading – we call them “alphas” – powered by an ever-rising volume and variety of available data, an explosion in computer hardware and software, and increasingly sophisticated techniques that allow us to create and deploy a higher volume and quality of alphas. Today, at WorldQuant, we have produced over 20 million alphas, a number that continues to grow exponentially as we hunt for ever-weaker predictive signals.

Since 2015, we have steadily expanded our outreach to new, diverse talent, adding to the full-time researchers, portfolio managers, and technologists at our 28 offices around the world, as well as to our growing group of research consultants – now more than 2,000 strong. We found many of WorldQuant’s research consultants through our Virtual Research Center (VRC) and its global quantitative finance competitions, such as the WorldQuant Challenge, Women Who Quant, and the International Quant Championship.

Participants who enter our competitions seek to create high-quality alphas using our online portal, WebSim, which provides educational, research, and backtesting tools, including some of the same datasets that WorldQuant researchers use. More broadly, the VRC enables individuals to conduct research and seek to build high-quality algorithms that may be used in WorldQuant’s systematic financial strategies. Research consultants have flexibility in their hours and work location, are compensated based on their activity and productivity, are eligible for additional compensation based on their algorithms’ performance, and may ultimately be considered for full-time positions.

This book, with contributions from 47 current and former WorldQuant staffers, summarizes much of what we have learned about the art and science of alpha development. This edition is not just a new cover slapped on old content. Individual chapters have been extensively rethought and revised. This edition has nine chapters that didn't exist in 2015 – on exchange-traded funds, index alphas, intraday data, and event-driven investing, among other subjects – and extensive additions in most of the rest. Topics like machine learning and automated search have become much more important. But while we've gone deep, we've worked hard to make the material more accessible and useful.

Yet we're only beginning to plumb the possibilities of alphas – and to explore the universe of predictive signals. The years ahead will be full of new challenges, new data, and new techniques. This exponential world forces us to accept that what's here today won't necessarily be here tomorrow. In *The UnRules: Man, Machines and the Quest to Master Markets*, a book I published in 2018, I wrote that I have become convinced that the Age of Prediction is upon us. The more alphas you have, the better you can describe reality and the more predictive you can be. But change is a constant, and the task is never done.

Igor Tulchinsky
June 2019

Preface (to the Original Edition)

This book is a study of the process of finding alphas. The material is presented as a collection of essays, providing diverse viewpoints from successful quants on the front lines of quantitative trading.

A wide variety of topics is covered, ranging from theories about the existence of alphas, to the more concrete and technical aspects of alpha creation.

Part I presents a general introduction to alpha creation and is followed by a brief account of the alpha life cycle and insights on cutting losses.

Part II focuses more on the technical side of alpha design, such as the dos and don'ts of information research, key steps to developing an alpha, and the evaluation and improvement of quality alphas. The key technical aspects discussed in this section are turnover, backtesting, fundamental analysis, equity price volume, statistical arbitrage, overfitting, and alpha diversity.

Part III explores ad hoc topics in alpha design, including alpha design for various asset classes like futures and currencies, the development of momentum alphas, and the effect of news and social media on stock returns.

In Part IV, we introduce you to WebSim, a web-based alpha development tool. We invite all quant enthusiasts to utilize this free tool to learn about alpha backtesting (also known as alpha simulation) and ultimately to create their own alphas.

Finally, in Part V, we present an inspirational essay for all quants who are ready to explore the world of quantitative trading.

Acknowledgments

In these pages, we present a collection of chapters on the algorithmic-based process of developing alphas. The authors of these chapters are WorldQuant's founder, directors, managers, portfolio managers, and quantitative researchers. This book has two key objectives: to present as many state-of-the-art viewpoints as possible on defining an alpha, and the techniques involved in finding and testing alphas. At WorldQuant, we believe that no viewpoint is the best and only answer, and that a variety of approaches is always superior to a single one.

This edition of *Finding Alphas* began to take shape in 2017, after Michael Peltz joined WorldQuant as global head of content. That year, he and then-regional research director Rebecca Lehman met with Igor Tulchinsky – WorldQuant's founder, chairman, and CEO – in his Connecticut office to outline their plan to overhaul the book. *Finding Alphas* had originally been written in 2014; Lehman and Peltz wanted to revise (and in some cases merge) existing chapters and add new ones. The two were instrumental in driving a reconceptualization of the first edition and managing a complex editorial process. We particularly want to thank the authors of the new chapters – Crispin Bui, Mark YikChun Chan, Chinh Dang, Glenn DeSouza, Anand Iyer, Rohit Kumar Jha, Michael Kozlov, Nitish Maini, Aditya Prakash, Prateek Srivastava, Dusan Timotity – as well as the authors of the chapters that were updated. Together they have created a book that should be tremendously useful to anyone interested in quantitative investing and developing alphas.

Every one of these chapters was copy edited by sharp-eyed Ruth Hamel, who juggled the myriad questions and challenges every chapter presented. Then each chapter was carefully vetted by WorldQuant's legal team under Jeffrey Blomberg, whose patience and always sensible suggestions made a major contribution. And, once again, we thank

Wendy Goldman Rohm, our literary agent, who played a major role in getting the first edition of *Finding Alphas* off the ground.

Last, we need to acknowledge with gratitude the support and faith of every colleague at WorldQuant. It takes a team. Thank you all.

DISCLAIMER

About the WebSim Website

At the time of writing, the WebSim information contained in this book is consistent with the WebSim website. Because the website is subject to change, in cases where there are inconsistencies between this book and the website the terms of the WebSim website will govern the most updated and current processes of WebSim. For the most up-to-date version of WebSim and the terms applicable to its use, please go to https://worldquantvrc.com or its successor site.

Registration at WebSim's official website is required to obtain the full functionality of the platform and to have access to the WebSim support team. Successful alphas submitted by research consultants may, in certain cases, be considered for inclusion in actual quant trading investment strategies managed by WorldQuant.

WEBSIM RESEARCH CONSULTANTS

WorldQuant has established a Research Consultant program for qualified individuals to work with our web-based simulation platform, WebSim. This program gives consultants the flexibility to create alphas in their own physical and intellectual environment. This is a particularly ideal pursuit for individuals who are undertaking a college education, as well as those who are ambitious and highly interested in breaking into the financial industry.

Qualified candidates are those highly quantitative individuals who typically come from science, technology, engineering, or mathematics (STEM) programs. However, majors and expertise vary and may include statistics, financial engineering, math, computer science, finance, physics, or other STEM programs.

You can find more details on WebSim in Part IV of this book. More information on the Research Consultant program is available at WebSim's official website.

PART I
Introduction

1
Introduction to Alpha Design

By Igor Tulchinsky

What is an alpha? Throughout this book, you'll read different descriptions or definitions of an alpha. Alpha, of course, is the first letter of the Greek alphabet – as in "the alpha and the omega," the beginning and the end – and it lurks inside the word "alphabet." Over the centuries, it has attached itself to a variety of scientific terms. The financial use of the word "alpha" goes back to 1968, when Michael Jensen, then a young PhD economics candidate at the University of Chicago, coined the phrase "Jensen's alpha" in a paper he published in *The Journal of Finance*. Jensen's alpha measured the risk-adjusted returns of a portfolio and determined whether it was performing better or worse than the expected market. Eventually, Jensen's alpha evolved into a measure of investment performance known simply as alpha, and it is most commonly used to describe returns that exceed the market or a benchmark index.

Since then, the term "alpha" has been widely adopted throughout the investing world, particularly by hedge funds, to refer to the unique "edge" that they claim can generate returns that beat the market. At WorldQuant, however, we use the term a little differently. We design and develop "alphas" – individual trading signals that seek to add value to a portfolio.

Fundamentally, an alpha is an idea about how the market works. There are an infinite number of ideas or hypotheses or rules that can be extrapolated, and the number of possibilities is constantly growing with the rapid increase in new data and market knowledge. Each of these ideas could be an alpha, but many are not. An alpha is an automated predictive model that describes, or decodes, some market relation. We design alphas as algorithms, a combination of mathematical expressions, computer source code, and configuration parameters. An alpha contains rules for converting input data to positions or trades to

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be executed in the financial securities markets. We develop, test, and trade alphas in large numbers because even if markets are operating efficiently, something has to drive prices toward equilibrium, and that means opportunity should always exist. To use a common metaphor, an alpha is an attempt to capture a signal in an always noisy market.

DESIGNING ALPHAS BASED ON DATA

We design alphas based on data, which we are constantly seeking to augment and diversify. Securities prices generally change in response to some event; that event should be reflected in the data. If the data never changes, then there is no alpha. Changes in the data convey information. A change in information should in turn produce a change in the alpha. These changes may be expressed in a variety of alpha expressions. Table 1.1 shows a few simple examples.

Alpha design is really just the intelligent search for price information conveyed by possible changes in the data, whether you think of them as patterns, signals, or a code. The mathematical expression of an alpha should embody a hypothesis or a prediction. Again, just a few examples are shown in Table 1.2.

Table 1.1 Expressions of changes

A simple difference, A – B	Example: today's_price – yesterday's_price
A ratio, A/B	Example: today's_price/yesterday's_price
An expression	Example: 1/today's price. Increase position when price is low

Table 1.2 Expressions and their hypotheses

Expression	Hypothesis
1/price	Invest more if price is low
Price-delay (price,3)	Price moves in the direction of 3-day change
Price	High-priced stocks go higher
Correlation (price,delay(price,1))	Stocks that trend, outperform
(price/delay(price,3)) * rank(volume)	Trending stocks with increasing volume outperform

DEFINING QUALITY IN ALPHAS

Alphas produce returns, which vary over time; like individual stocks, an alpha's aggregate returns rise and fall. The ratio of an alpha's daily return to daily volatility is called the information ratio. This ratio measures the strength and steadiness of the signal, and shows if a strategy is working – whether the signal is robust or weak, whether it is likely to be a true signal or largely noise. We have developed a number of criteria to define the quality of an alpha, though until an alpha is extensively tested, put into production, and observed out of sample, it's difficult to know how good it really is. Nonetheless, here are some traits of quality alphas:

- The idea and expression are simple.
- The expression/code is elegant.
- It has a good in-sample Sharpe ratio.
- It is not sensitive to small changes in data or parameters.
- It works in multiple universes.
- It works in different regions.

ALPHA CONSTRUCTION, STEP BY STEP

We can broadly define the steps required to construct alphas. Although the devil is in the details, developers need only repeat the following five steps:

- Analyze the variables in the data.
- Get an idea of the price response to the change you want to model.
- Come up with a mathematical expression that translates this change into stock positions.
- Test the expression.
- If the result is favorable, submit the alpha.

CONCLUSION

The chapters that follow delve into many of these topics in much greater detail. These chapters have been written by WorldQuant researchers, portfolio managers, and technologists, who spend their days, and often their nights, in search of alphas. The topics range widely, from the nuts-and-bolts development of alphas, to their extensive backtesting, and related subjects like momentum alphas, the use of futures in trading, institutional research in alpha development, and the impact of news and social media on stock returns. There's also a chapter focused on various aspects of WorldQuant's WebSim platform, our proprietary, internet-enabled simulation platform. WebSim's simulation software engine lets anyone backtest alphas, using a large and expanding array of datasets. Last, in this edition of *Finding Alphas*, we've added new material on topics such as machine learning, alpha correlation, intraday trading, and exchange-traded funds.

What is an alpha and how do we find them? Turn the page.

2
Perspectives on Alpha Research

By Geoffrey Lauprete

In the field of finance, an alpha is the measure of the excess return of an investment over a suitable benchmark, such as a market or an industry index. Within the quantitative investment management industry, and in this book, the term "alpha" refers to a model used to try to forecast the prices, or returns, of financial instruments relative to a benchmark. More precisely, an alpha is a function that takes, as input, data that is expected to be relevant to the prediction of future prices and outputs values corresponding to the forecasted prices of each instrument in its prediction universe, relative to a benchmark. An alpha can be expressed as an algorithm and implemented in a computer language such as C++, Python, or any number of alternative modern or classical programming languages.

Attempts to forecast markets predate the digital era and the arrival of computers on Wall Street. For example, in his 1688 treatise on economic philosophy, *Confusion of Confusions*, stock operator and writer Josseph Penso de la Vega described valuation principles for complex derivatives and techniques for speculating on the Amsterdam Stock Exchange. Two hundred years later, in a series of articles, Charles Dow (co-founder of Dow Jones & Co., which publishes *The Wall Street Journal*) codified some of the basic tenets of charting and technical analysis. His writings provide one of the first recorded instances of a systematic market forecasting technique, but investors had to wait until the 1980s for affordable computing power to arrive on the Wall Street scene and change the modeling paradigm: instead of pencil and paper, the main design tools and their hardware were set to become computers and digital data.

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PHDS ON THE STREET

Until the 1960s, all or almost all back-office processes, and stock settlement in particular, were done manually. It took the unprecedented increase in stock trading volumes experienced in the late 1960s (between 1965 and 1968, the daily share volume of the New York Stock Exchange increased from 5 million to 12 million), and the accompanying "traffic jams" in trade processing due to the reliance on pen-and-paper recordkeeping, for the adoption of computers to become a business imperative. By the 1970s, Wall Street had digitized its back offices. Within a few years, computers and programmable devices were ubiquitous on the Street, playing a role in every corner of the financial industry.

The arrival of computing machines on the trading floor of large Wall Street firms allowed previously intractable problems in valuation – the pricing of options and other derivatives, and price forecasting based on databases of digital data – to become practically solvable. But formulating the problems in such a way that the new machines could solve them required a new type of market operator, who historically had not been part of the sales and trading ecosystem: PhDs and other analytically minded individuals, not traditionally Wall Street material, became sought-after contributors to this new and modernized version of the trading floor.

A NEW INDUSTRY

One of the early adopters of computer-based investment methods to exploit systematic alphas was James Simons, an award-winning mathematician and former chair of the mathematics department at Stony Brook University. In 1982, Simons founded Renaissance Technologies, an East Setauket, New York-based firm that became known for the successful deployment of systematic market-neutral strategies. Six years later, former Columbia University computer science professor, David Shaw, launched D.E. Shaw & Co. in New York City. Shaw had spent two years at Morgan Stanley, part of a group whose mandate was to develop stock forecasting algorithms using historical price records. Others followed, either inside banks and brokerages as part of proprietary trading groups or at hedge funds managing pooled investor money.

Over time, quantitative market-neutral investing became known as a scalable and dependable investment strategy, which fared particularly well during the dot-com market crash of the early 2000s.

As the hedge fund industry grew, so did the allocation of investor capital to quantitative investment strategies. As of January 2018, it was estimated that as much as one third of the hedge fund industry's total assets was managed using systematic investment methods, either by firms dedicated to quantitative investing, such as WorldQuant, or by multistrategy hedge funds that invest a portion of their assets in quantitative approaches, according to *The Financial Times*. The hesitation that investors exhibited in the 1990s and early 2000s toward what were often referred to disparagingly as "black box" strategies waned gradually as the strategies' track records held up relative to those of other investment approaches. It's possible that quantitative investment strategies, which emphasize leveraging technology – via algorithms, artificial intelligence, and machine learning – are benefiting from society's growing comfort with automation and the replacement of human intermediaries by machines with increasing levels of free rein. Investing via modeling and smart data processing doesn't seem like much of a stretch 40 years after the launch of the first systematic hedge funds.

Still, the path toward quantitative investing becoming an established strategy was not a straight line. The quant meltdown of 2007 dealt a particular blow to investor and participant confidence in the ability of quantitative investing to produce credible long-term risk-adjusted returns: in August of that year, a market panic prompted a large number of quant funds to liquidate their positions in a short period of time, creating an unprecedented drawdown and causing some participants and investors to head for the exits in what amounted to a stampede. That period was followed the next year by the global financial crisis, which again saw significant investment return volatility. The 2000s were accompanied by a range of structural market changes, from decimalization to the rise of exchange-traded funds. The period also demonstrated the flexibility and resilience of the quantitative investment approach, and showed that the quantitative operators developing alpha forecasts were able to adapt to new market environments, innovate, and ultimately stay relevant.

In the next section, we will take a closer look at the alphas driving the quantitative strategies described above.

STATISTICAL ARBITRAGE

The term "statistical arbitrage" (stat arb) is sometimes used to describe a trading strategy based on the monetization of systematic price forecasts, or alphas. Unlike pure arbitrage, when a risk-free profit can be locked in by simultaneously purchasing and selling a basket of assets, a stat arb strategy aims to exploit relationships among asset prices that are estimated using historical data. Because estimation methods are imperfect, and because the exact relationships among assets are unknown and infinitely complex, the stat arb strategy's profit is uncertain. It is subject to estimation error, overfitting, incomplete information, and shifts in market dynamics that can cause previous relationships to vanish. Nonetheless, the practitioner's goal is to discover, through data analysis and statistical hypothesis testing, which relationships are valid and deserve an allocation of capital and which are bogus and likely to lead to the poorhouse.

In the search for legitimate relationships between asset prices, the academic literature has been and continues to be an important source of ideas. For example, the work of financial economists on the capital asset pricing model (the CAPM, which aims to decompose a stock's return into its market component and an idiosyncratic component) and its derivatives has spawned an enormous, multidecade-long search to prove and/or disprove its validity, and to enhance its explanatory power with additional factors. The initial research on the CAPM was published in the 1960s (e.g. William Sharpe's 1964 article, "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk"), and the debate continued into the 1990s (e.g. Eugene Fama and Kenneth French, "The Cross-Section of Expected Stock Returns"). A 2018 scan of *The Journal of Finance* found at least one entry on the subject of factor pricing ("Interpreting Factor Models," by Serhiy Kozak, Stefan Nagel, and Shrihari Santosh).

But models from academia, even when they provide a foundation for applied research, are often incomplete or based on assumptions that are inconsistent with the real markets in which traders operate. As a result, such models can be difficult or impossible to employ successfully. This observation applies not only to models from financial economics but also to models from the fields of econometrics, applied statistics – such as time-series analysis and machine learning or regression – and operations research and optimization. As an example, many regression models tend to be estimated based on the minimization of mean-squared errors for computational convenience. But mean-squared error is not necessarily the objective that traders have in mind for their stat arb strategies – they may be more interested in generating a steady cash flow and managing the downside risk of that cash flow. The simplicity of the mean-squared error objective is a trade-off against the objective's usefulness. Alternatives are possible but fall into the realm of trade secrets, which quantitative investment firms develop in-house and keep to themselves, never to be published but instead handed down from quant to quant, forming the basis of a deep institutional pool of knowledge that it is in the firm's interest to protect.

EXISTENCE OF ALPHAS

We could debate whether alphas and stat arb strategies ought to exist at all. In fact, the academic literature in financial economics has tackled this problem exhaustively, qualifying the markets and the nature of information and how it affects prices, and deriving conclusions based on various assumptions about the markets, about market participants and their level of rationality, and how the participants interact and process information. The term "efficient market hypothesis" (EMH) is sometimes used to describe the theory that says market prices reflect all available information. The EMH gained prominence in the 1960s, and empirical studies of prices and of asset manager performance since then have lent credence to the idea that the market is efficient enough to make it impossible to determine whether top asset managers' performance is due to anything but luck. The theory also implies that looking for exploitable patterns in prices, and in other forms of publicly available data, will not lead to strategies in which investors can have confidence, from a statistical perspective.

An implication of the EMH is that prices will evolve in a process indistinguishable from a random walk. However, another branch of financial economics has sought to disprove the EMH. Behavioral economics studies market imperfections resulting from investor psychological traits or cognitive biases. Imperfections in the financial markets may be due to overconfidence, overreaction, or other defects in how humans process information. Empirical studies may have had mixed results in aiming to disprove the EMH, but if no investors made any effort to acquire and analyze information, then prices would not reflect all available information and the market would not be efficient. But that in turn would attract profit-motivated investors to tackle the problem of analyzing the information and trading based on it. Thus, over time, some investors must profit from analyzing information.

Even if we can make an argument in favor of the existence of alphas under various stylized assumptions, the details of prediction in the real world are complex. A prediction with low accuracy or a prediction that estimates a weak price change may not be interesting from a practitioner's perspective. The markets are an aggregate of people's intentions, affected by changing technology, macroeconomic reality, regulations, and wealth – and this makes the business of prediction more challenging than meets the eye. Therefore, to model the markets, investors need a strong understanding of the exogenous variables that affect the prices of financial instruments. That is the challenge that market forecasters and algorithmic traders face, motivated by the expectation that they will be rewarded for their efforts and for their mastery of complexity.

IMPLEMENTATION

Alphas are typically implemented in a programming language like C++, Python, or another flexible and modern language. When implemented in a programming language, an alpha is a function that takes data and outputs a forecast of the price of each instrument in the universe being tested. The simplest forms of data are concurrent and historical prices. Other commonly used data include volumes and other market records, accounting variables in a company's income or cash flow statements, news headlines, and social media-related entries. Data quality is a significant issue in the alpha research process. Bias in the historical data can make the calibration of accurate models impossible. Ongoing data issues, such as technical problems, human error, unexpected data format changes, and more, can sap a model's forecasting power.

Predicting the future price of a financial instrument is a difficult problem. For example, in order to predict the price of an NYSE-listed stock over the next month, a researcher needs to understand not only (1) the idiosyncratic features of that stock, but also (2) what drives the industry that the stock belongs to, and ultimately (3) what drives the market for listed stocks as a whole – that is, the world economy. The complexity of the problem can be reduced dramatically by focusing on relative prices; for example, instead of trying to predict the absolute price of stock XYZ, you can try to predict the price of stock XYZ relative to other stocks in XYZ's industry. By reducing the problem's scope, (2) and (3) can be ignored. In practice, investors can try to monetize such relative value predictions via market-neutral investment strategies.

EVALUATION

What is a good alpha? There is no single metric that will answer that question. The answer depends in part on how the alpha is going to be used. Certain investment strategies require very strong predictors; others benefit, marginally, from weak ones. Here are some pointers for alpha evaluation:

- Good in-sample performance doesn't guarantee good out-of-sample performance.
- Outliers can ruin a model and lead to erroneous predictions.
- Multiple-hypothesis testing principles imply that the more effort spent sifting through evidence and the more alternatives considered, the lower the likelihood of choosing an optimal model.
- An out-of-sample period is necessary to validate a model's predictive ability. The longer the out-of-sample period, the higher the confidence in the model but the less in-sample data available to calibrate the model. The optimal ratio of in-sample to out-of-sample data in model building depends on the model's complexity.

LOOKING BACK

Backtesting involves looking back in time to evaluate how a forecast or trading strategy would have performed historically. Although backtesting is invaluable (providing a window into both the markets and how the alpha would have performed), there are two important points to remember:

- History does not repeat itself exactly. So while an alpha idea may look great in a backtest, there's no guarantee (only a level of confidence) it will continue to work in the future. This is because of the perverse power of computation and the ability of creative modelers to miss the forest for the trees. With computational resources, you can evaluate a very large number of ideas and permutations of those ideas. But without the discipline of keeping track of what ideas were tried, and without taking that into account when evaluating the likelihood that a model is a true model and not a mere statistical artifact (multiple-hypothesis testing principles), you may end up mistaking lumps of coal for gold.

- New algorithmic modelers look back at history and estimate that the market was much easier to trade than it was in reality. This is due to several effects. First, hindsight is 20/20. Second, data scrubbed to polish rough edges can lead to overinflated historical alpha performance. Last, computational power and technology evolve, and today's tools were not available historically. For example, ideas that seemed simple enough to program in a Lotus spreadsheet in the 1980s were actually not so simple to discover and implement back then. Every period has its own market and its own unique market opportunities. Each generation of algorithmic modelers has an opportunity set that includes the possibility of discovering powerful market forecasts that will generate significant profit.

THE OPPORTUNITY

Exploitable price patterns and tradable forecasting models exist because market participants differ in their investment objectives, their preferences (such as risk tolerance), and their ability to process information. Participants work with a finite set of resources and aim to optimize their investment strategies subject to the limits imposed by those resources. They leave to others the chance to take advantage of whatever trading opportunities they haven't had the bandwidth or ability to focus on. Market participants with long-term investment horizons tend not to pay the same attention to short-term price variations as participants with short-term investment horizons. Conversely, traders with a short-term investment horizon can operate efficiently and effectively without having an understanding of the fundamental valuation principles that are used by institutional investors concerned with scalability, tax efficiency, and longer-term performance (or, in some cases, performance relative to an index). Traders who use leverage cannot tolerate volatility and drawdowns to the same extent that a nonleveraged trader can. Firms with larger technology budgets can beat the competition in areas like the monetization of short-term alphas via a low-latency infrastructure, the exploitation of large-scale data processing, or the application of computationally intensive machine learning or artificial intelligence forecasting techniques.

The goal of an alpha researcher is to discover forecastable prices or price relationships that investors may profit from. The fact that the market is continuously evolving and responding to new information and new information sources ensures that the opportunity to find alphas will continue to exist indefinitely. That is good news for the next generation of alpha researchers, but it also implies that models designed for market conditions that no longer exist will cease to function, their forecasting power decreasing inexorably with time. An alpha researcher's job is never finished.

3
Cutting Losses

By Igor Tulchinsky

Man is a creature that became successful because he was able to make sense of his environment and develop rules more effectively than his natural competitors could. In hunting, agriculture, and, later, mathematics and physics, rules proliferated. Today, rules abound in every area of life, from finance to science, from relationships to self-improvement regimens. Man survives because of rules.

An infinite number of possible rules describe reality, and we are always struggling to discover and refine them. Yet, paradoxically, there is only one rule that governs them all. That rule is: no rule ever works perfectly. I call it the UnRule.

It's an accepted scientific principle that no rule can really be proved – it can only be disproved. Karl Popper, the great Austrian philosopher of science, pointed this out in 1934. He argued that although it is impossible to verify a universal truth, a single counterinstance can disprove it. Popper stressed that because pure facts don't exist, all observations and rules are subjective and theoretical.

There are good reasons for this uncertainty. Reality is complicated. People and their ideas are imperfect. Ideas are expressed as abstractions, in words or symbols. Rules are just metaphorical attempts to bring order to this complex reality. Thus, every rule is flawed and no rule works all the time. No single dogma fully describes the world, but every rule describes some aspect of the world. And every rule works sometimes.

We are like artists slowly painting images on canvases. Every stroke may bring an image closer to reality, but the painting will never become a perfect interpretation of reality. There are many examples of this. Newton's laws, which for centuries seemed to describe motion perfectly, turned out to be flawed, giving way to Einstein's theory of relativity. Man's attempts to explain his place in the universe have continually

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evolved, from the belief that the earth was at the center of the cosmos to the realization that we are tiny, fragile beings adrift in a vast universe that eludes our full comprehension. Likewise, various rules have been asserted that purport to describe, even predict, financial markets, from the belief in strongly efficient markets to the development of option-pricing models. All of these have proved flawed, usually after market meltdowns.

So you see the paradox: the only rule that works is the one that says no rule *always* works. Rules are specks of dust, fragments of a larger reality.

This is the reason it's so important to be able to cut your losses when riding the often turbulent seas of the markets, where the UnRule prevails. How can this turbulence and change be weathered? What is the best way to deal with myriad shifting rules, all of them imperfect, many of them conflicting, based on different sets of circumstances and assumptions?

Trading is a microcosm of reality, a dynamic environment of profound complexity in which millions of participants act and react based on rules and beliefs that in turn feed back into and affect the larger environment. The challenge in trading is to derive rules that describe and predict markets, then to use them successfully to earn profits, without changing those markets in ways that might result in the destruction of the rule itself.

We represent trading rules as alphas, algorithms that seek to predict the future of securities returns. Managing millions of alphas, each reflecting some hypothesis about the markets, is a complicated matter and a subject unto itself. In dealing with millions of alphas, certain regularities become apparent. The best, most universal way of dealing with this complexity (and the fact that all rules eventually break down) is knowing when to cut your losses.

The concept of cutting trading losses has been around for a long time. It originated in what may be the oldest type of trading, so-called trend following, in which a trader bets that a rising (or falling) security will continue to rise (or fall). In such a scenario, trades typically are entered when a new high is reached and exited when the accumulated profits exceed some preset limits.

In today's trading world, alphas and strategies are seldom as simple as that. Instead of following a particular security, we apply trend following to the accumulated profit and loss of a strategy as a whole, which may consist of many individual alphas on many securities.

To put it plainly: cutting losses means abandoning rules that no longer work.

Although the logic of cutting losses is easy to see in trading, the principle also holds true in other parts of life, including business, entrepreneurship, and even relationships. Sometimes you just have to admit that whatever you're doing is not working out and move on.

Cutting losses requires discipline and the subjugation of your ego. Typically, emotion plays a big role in any kind of thinking and decision making. Neuroscientists have studied patients suffering from damage to the areas of the brain involved in processing emotions, who are unable to make simple decisions like choosing which shirt to put on in the morning. In our work developing and deploying alphas, we often are driven by emotional confidence. When we are devising a strategy, the process starts with: "I understand how the world works. I believe in my rule. Here is my rule." Because ego and pride are intertwined with this confidence, it may be difficult to let go of the rule that you've come up with, even in the face of evidence that the rule no longer works.

Perhaps the practice of cutting losses is not followed more widely for ego reasons. Or it may be that people lack knowledge of alternative rules that might work. The often high cost of changing a strategy can contribute to resistance to letting go of rules that no longer work.

It's wise to refrain from believing exclusively in any particular theory or rule. You can believe them all, but don't embrace any of them completely. Sometimes they work; sometimes they don't. The best indicator of whether a rule is good is how well it's working *at that moment*. The rest is speculation. If a rule works, we invest in it; if it doesn't, we don't.

We collect all ideas and let time and performance show what works and what doesn't – and when it works and when it doesn't. When we postulate a new idea, rule, or alpha based on historical data and thorough statistical analysis (sometimes with a touch of fundamental wisdom), it then goes into our knowledge base. From this universe of ideas, we seek to construct the closest thing possible to a depiction of financial reality. But to do what we do, we have to be comfortable with the fact that we will never know everything there is to know.

The old saying is that in the land of the blind, the one-eyed man is king. We live in the land of the blind. Particularly in trading and financial markets, accepting that blindness and effectively using that one good eye is a big advantage.

HOW TO APPLY THE PRINCIPLE OF THE UNRULE TO CUTTING LOSSES

We acknowledge that the number of imperfect ideas is unbounded and that reality is unknown and unknowable. But each imperfect idea does describe reality a bit, so the more alphas we possess, the better we can describe an aspect of reality, and the closer we can come to having "one eye" with which we can seek to increase profits.

Because no rule is perfect, a combination of *all* rules may come as close to perfection as possible.

Applying all rules in tandem is a key to success. For example, to cross the street, you might have the following three rules in mind:

1. Look left, look right, look left again, then it is safe to cross.
2. If you hear a loud noise, turn in the direction of the noise.
3. If you see a car headed toward you, run!

You may start crossing the street believing in and comforted by Rule 1, then hear a horn honking, which triggers Rule 2. Rule 1 should be abandoned immediately because the safety conclusion has been challenged by the noise. Then you apply Rule 3.

This has the following implications:

- It is necessary to come up with as many good rules as possible.
- No single rule can ever be relied upon completely.
- It is necessary to develop a strategy for using rules simultaneously.

How do you know when an investment strategy isn't working? When the strategy performs outside its expected returns. This usually is accompanied by the following signals:

- A drawdown exceeds the typical drawdowns observed previously.
- The strategy's Sharpe ratio falls significantly.
- Rules that were initially observed in historical simulation are no longer valid in live trading.

It is important to pursue different strategies simultaneously and to shift your efforts into those that are working. Suppose you have a theory describing when gold prices will rise. The theory works 50% of the time. Suppose you have 10 other equally solid theories. A combination of theories should describe reality better than any one of them. And the best way to manage which one of them is most accurate is by observing which ones are working at the moment.

Then comes the discipline of cutting losses.

When a strategy stops working, determine the belief that initially motivated the activity. If the belief was obviously false, you are playing with dice. Best to terminate the activity and engage in more productive efforts.

Say you hire someone to renovate your house. They promise to do the job for $50,000, but less than halfway through the project they've already spent $45,000. At this point, you should cut that builder loose if switching to a new one can be done cheaply enough.

Suppose we are engaged in an activity – let's call it X – that starts to lose money. The activity can be anything, perhaps a trading strategy or a business. We need to ask the following questions:

- Am I losing money in activity X?
- What is the maximum acceptable loss? (Call the maximum acceptable loss Y.)
- What is the observed loss amount? (Call the observed loss Z.)

Before starting activity X, we should identify the maximum acceptable loss, Y. If the observed loss, Z, exceeds the maximum acceptable loss, Y, and the exit cost is not too high, cut the loss.

SUMMARY

Examine each potential action before embarking on it. Determine:

- What's the objective?
- What are the normal, expected difficulties?

Plan in advance how to get out of the strategy cheaply.

Pursue multiple strategies simultaneously.

Cut all strategies that fall outside expectations.

PART II
Design and Evaluation

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4
Alpha Design

By Scott Bender and Yongfeng He

This chapter will lay out the process of designing an alpha, starting with raw data. We will discuss some of the important design decisions you need to make when creating an alpha, as well as how to properly evaluate an alpha. At the end of this chapter, we will highlight some issues that can arise after alphas have been developed and put into production.

DATA INPUTS TO AN ALPHA

Alphas are fueled by data. The edge sought for an alpha may come from identifying high-quality pieces of publicly available data, superior processing of the data – or both. Some typical data sources are:

- Prices and volumes. Technical analysis or regression models may be built based on this data.
- Fundamentals. By automating the analysis of key metrics for each company, you can build alphas that typically have very low turnover.
- Macroeconomic data, such as GDP numbers and employment rates, that have market-wide effects upon their release.
- Text, such as Federal Open Market Committee minutes, company filings, papers, journals, news, or social media.
- Multimedia, notably relevant videos or audio. There are mature techniques to process such data – for example, converting audio into text that can be used to build models.

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Sometimes data sources aren't used to generate a directional signal but to attempt to reduce noise in predictions and refine other alpha signals. Examples are:

- Risk factor models. By controlling risk exposure or eliminating exposure to some risk factors, one can seek to improve the alpha's performance.
- Relationship models, such as instruments that typically are correlated with each other to some extent. Some may lead or lag others, thus generating potential opportunities for arbitrage.

Today, with information growing explosively, extracting signals from an expanding ocean of data is more and more challenging. The solution space is nonconvex, discontinuous, and dynamic; good signals often arise where they are least expected. How can we extract such signals? By limiting the search space and using methods previously employed by treasure hunters:

- Searching in the vicinity of previous discoveries.
- Conserving resources to avoid digging too deeply.
- Using validated cues to improve the probability of a find.
- Allocating at least some resources (computational power) to test wild theories.

ALPHA UNIVERSE

An important step in designing an alpha is choosing the target set of assets to be traded; this set of assets is called the universe of the alpha. The universe may be restricted along one or more dimensions, such as:

- Asset class (stocks, exchange-traded funds, futures, currencies, options, bonds, etc.)
- Region or country
- Sector or industry
- Individual instruments

The universe choice typically is driven by the coverage of the input data or the alpha idea, but alphas can be designed and tuned specifically for a certain universe even if the data has wider coverage.

ALPHA PREDICTION FREQUENCY

Another important design decision when creating an alpha is the prediction frequency. This defines the times at which the alpha will generate new predictions.

Some typical frequencies:

- Tick. New predictions are triggered by events such as a trade in the market.
- Intraday. Predictions are generated multiple times at predetermined points during the day.
- Daily. One prediction per day, of which there are several typical subtypes:
  - Delay 1. Only data available before the current trading day may be used to make a prediction.
  - Delay 0 snapshot. Data before a specific time may be used to make a prediction.
  - MOO/MOC. Predictions are tied to the opening or closing auction.
- Weekly or monthly.

As with the choice of universe, this decision often is guided by the frequency of the input data.

VALUE OF AN ALPHA

The ultimate test of alpha value is how much risk-adjusted profit the alpha adds to the strategy in which it is trading. In practice, this is difficult to precisely measure because:

- There is no canonical strategy in which an alpha may be used, and the exact strategy in which the alpha will be used may not be known at the time of its design.
- There are often nonlinear effects in the combination that make it difficult to precisely attribute profit to individual alphas.

All that said, we can still make useful predictions about whether an alpha will add value in strategies, and we can provide a reasonable estimate of how much an alpha contributed to the strategy's performance.

PRACTICAL ALPHA EVALUATION

Because the target trading strategy may not be known when the alpha is being designed, when considering an alpha on its own, how can we know if it will be useful? Alternatively, when an alpha is changed, is it really improved? To answer these questions, good quantitative measurements are required.

A typical method for collecting measurements about trading strategies is to run a simulation (that is, backtest) and measure characteristics of the result, such as the information ratio. One way to make analogous measurements for an alpha is to do a mapping of its predictions to a trading strategy and then run such a simulation. There are different ways to do this mapping, but the simplest is to assume the prediction strength of an alpha is the dollar position taken by the trading strategy. One issue with this mapping method is that alphas often will not map to good strategies on their own because they are designed to predict returns, not to make profitable trades net of costs. One way to address this issue is by charging reduced transaction costs in the simulation.

Once the simulation has been constructed, some useful measurements that can be taken are:

- **Information ratio**. The mean of the alpha's returns divided by the standard deviation of the returns, this measures how consistently the alpha makes good predictions. Combining the information ratio with the length of the observation period can help us determine our level of confidence that the alpha is better than random noise. A reasonable annualized information ratio for a unique alpha with little fitting, observed over a five-year period, would be 1.0. In practice, alphas have some fitting and some correlation to existing alphas, so the information ratio is typically a bit higher than this.
- **Margin** is the amount of profit the alpha made in the simulation divided by the amount of trading that was done. This is an indicator of how sensitive the alpha is to transaction costs. A higher margin means the alpha is not much affected by trading costs. Alphas with low margins won't add value unless they are very different from the other alphas in the strategy. For an average daily alpha, a margin of 5 basis points typically is acceptable.
- **Correlation** measures the uniqueness of an alpha and often is measured against the most correlated alpha that exists in the alpha pool.

Lower correlation indicates that the alpha is more unique and therefore more desirable. For an alpha whose characteristics are otherwise average, the following interpretation of the maximum correlation is reasonable:

- More than 0.7: Too high unless the alpha is significantly better than the existing alpha.
- 0.5 to 0.7: Borderline. The alpha should be exceptional in some other metric.
- 0.3 to 0.5: Generally acceptable.
- Less than 0.3: Good.

The measurements above can be made more complex. For example, it can be useful to test whether the alpha has good information ratios on both liquid stocks (stocks with high trading volume) and illiquid stocks. If the alpha is only predictive on illiquid stocks, it may have limited usefulness in a strategy that intends to trade very large sizes.

FUTURE PERFORMANCE

All of the measurements in the preceding section are intended to evaluate an alpha when there is no information other than the actual predictions. However, additional information, such as how the alpha was constructed, can be useful in determining whether the alpha will make good predictions going forward. Ultimately, what is important is whether the alpha makes usable future predictions, not historical predictions.

Consider an alpha that has a high information ratio but was built by optimizing parameters that have no economic explanation to historical data. For example, suppose the alpha had 12 parameters, one for each month (x1. . .x12), and suppose the alpha rule is simply to buy x1 dollars of all stocks in January, x2 dollars of all stocks in February, and so forth. If x1–x12 was optimized over the past year, the alpha would make good predictions for the past year, but there is no reason to think they would work going into the next year.

In general, each optimization or improvement made to an alpha after observing historical data will improve the alpha's historical performance by some amount and its future performance by some different, usually smaller, amount. The alpha designer should take special care to ensure that changes are expected to improve the alpha going forward, not just historically.

When changes to the alpha yield very small (or even negative) improvements to the future predictions compared with large improvements of historical predictions, the alpha is being overfit to the historical data. Alpha designers can measure the effect of this overfitting by looking at the performance of their alphas on data that was not used in alpha construction (out-of-sample data) and comparing it with the data used to improve the alpha (in-sample data). The comparison of in-sample to out-of-sample performance is useful not only on the alpha level but also in aggregate across all alphas from a given designer or on groups of alphas from a given designer. These comparisons on groups of alphas can measure the tendency of a designer's methodology to overfit.

CONCLUSION

This chapter discussed the major elements of alpha design, including practical approaches to evaluate alphas. Some potential issues that arise after alphas are developed also were addressed. By harnessing the exponential growth of computing power and data sources, combined with a solid alpha design framework, we can generate alphas and trading strategies that evolve with the market.

5
How to Develop an Alpha: A Case Study

By Pankaj Bakliwal and Hongzhi Chen

In this chapter, we explain how to design an alpha, the logic behind an alpha, how to convert an alpha idea into a mathematical predictive formula by using appropriate information, and how to improve the idea. We will also introduce some important concepts on evaluating the performance of an alpha.

Before we talk more about alpha development and design, let's study a simple example to get a better understanding of what an alpha looks like.

Let's say we have $1 million in capital and want to invest continuously in a portfolio consisting of two stocks: Alphabet (GOOG) and Apple (AAPL). We need to know how to allocate our capital between these two stocks. If we do a daily rebalancing of our portfolio, we need to predict the next few days' return of each stock. How do we do this?

There are a lot of things that can affect the stocks' prices, such as trader behavior, price trends, news, fundamental corporate change, and a change in holdings by big institutions or corporate insiders – officers, directors, or shareholders with more than 10% of a class of the company's registered equity securities. To make things simple, we can deconstruct the prediction process into two steps: first, we predict the stock returns of each instrument, using a single factor like news or price trends; second, we aggregate all the different predictions.

Let's try to develop an alpha using recent price trends, employing available data in the form of the daily historical prices of these two stocks. The next step is to come up with a sensible idea. Let's say that, based on the historical prices, we observe that the two stocks have trended upward during the past week. Logic says that in the absence of any additional information, when stock prices rise, investors tend

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to book profits and close their long positions, which in turn pushes the stock prices downward. At the same time, when stock prices fall, investors see an opportunity to buy shares at a cheaper rate, which in turn pushes the stock prices upward.

Converting an idea into a mathematical expression is not always straightforward. In the above case, though, it can be done simply as follows:

$$\text{Alpha} = -\left(1 \text{ week returns}\right)$$

The negative sign indicates that a short position is taken when the trend is upward and a long position when the trend is downward. The dollar amount of the long–short position in a particular financial instrument is determined by the magnitude of the value given by the formula. This means that the stronger the price trend, the greater the likelihood the price will revert. Suppose our algorithm produces the following values for two stocks, respectively:

$$\text{Alpha}\left(\text{GOOG}\right) = 2$$

$$\text{Alpha}\left(\text{AAPL}\right) = -1$$

The values above have a ratio of 2 to –1. This means we want to hold twice as much of GOOG as we do of AAPL; the positive number means we want to hold a long position, while the negative number means we want to hold a short position. Thus, using $1 million of capital as an example, we want to be long $1 million of GOOG and short $500,000 of AAPL at the end of today's trading. This example, of course, assumes zero transaction costs.

So the alpha model is actually an algorithm that transforms input data (price-volume, news, fundamental, etc.) into a vector, which is proportional to the money we want to hold in each instrument.

$$\text{Alpha}\left(\text{input data}\right) \rightarrow \text{alpha value vector}$$

Now that we understand what an alpha is, let's write our first alpha.[1] We will introduce more concepts along the way. Above all, we need

[1] The sample alphas and returns described in this chapter are included for illustrative purposes only and are not intended to be indicative of any strategy utilized by WorldQuant or its affiliates.

to define a universe – that is, the set of financial instruments on which we want to build the alpha model. Let's focus on the US equity market. There are different ways to select equity instruments, such as using components of the S&P 500 index. Suppose we use the most liquid 3,000 stocks in the US as our research universe (call it TOP3000).

Next we need an idea to predict the stock price. We can use the same mean-reversion idea mentioned above and express it in terms of a mathematical expression as follows:

$$\text{Alpha1} = -\left(\text{close}\left(\text{today}\right) - \text{close}\left(5\_\text{days}\_\text{ago}\right)\right)/\text{close}\left(5\_\text{days}\_\text{ago}\right)$$

To find out if this idea works, we need a simulator to do backtesting. We can use WebSim for this purpose.

Using WebSim, we get the sample results for this alpha, as shown in Figure 5.1.

Table 5.1 shows several performance metrics used to evaluate an alpha. We focus on the most important metrics.

The backtesting is done from 2010 through 2015, so each row of the output lists the annual performance of that year. The total simulation book size is always fixed at $20 million; the PnL is the annual PnL.

Figure 5.1 Sample simulation result of Alpha1 by WebSim

Table 5.1 Evaluation of Alpha1 simulation graph

Year	Book size	PnL	Ann. return	Information ratio	Max drawdown	% profitable days	Daily turnover	Profit per $ traded
2010	2.0E7	4.27E6	46.44%	1.32	16.63%	46.52%	62.69%	0.15¢
2011	2.0E7	6.93E6	68.70%	1.42	39.22%	50.79%	64.72%	0.21¢
2012	2.0E7	2.01E6	20.08%	0.96	14.66%	51.20%	63.36%	0.06¢
2013	2.0E7	1.04E6	10.34%	0.60	9.22%	46.83%	63.26%	0.03¢
2014	2.0E7	1.48E6	14.72%	0.61	28.67%	51.19%	62.36%	0.05¢
2015	2.0E7	−158.21E3	−32.96%	−1.38	4.65%	41.67%	64.34%	−0.10¢
2010–15	2.0E7	15.57E6	31.20%	1.00	39.22%	49.28%	63.30%	0.10¢

Note: Provided for illustrative purposes only.

Annual return is defined as:

$$\text{Ann\_return} = \text{ann\_pnl}/\left(\text{booksize}/2\right)$$

The annual return measures the profitability of the alpha.

The *information ratio* is the single most important metric we will look at. It is defined as:

$$\text{Information\_ratio} = \left(\text{average daily return}\right)/\left(\text{daily volatility}\right) * \text{sqrt}\left(256\right)$$

The information ratio measures the information contained in the alpha, which roughly means the stability of the alpha's profitability: higher is better.

Max drawdown measures the highest peak-to-trough loss from a local maximum of the PnL to a subsequent local minimum as a percentage of book size divided by two (the long or short side of the book).

Percent profitable days measures the percentage of positive days in each year.

Daily turnover measures how fast you rebalance your portfolio and is defined as:

$$\text{Daily\_turnover} = \left(\text{average dollars traded each day}\right)/\text{booksize}$$

Profit per dollar traded measures how much you made for each dollar you traded and is defined as:

$$\text{Profit\_per\_\$\_traded} = \text{pnl}/\text{total\_traded\_dollar}$$

For this alpha, the total information ratio is about 1, with a high return of about 31.2% but with a very high max drawdown of 39.22%. This means the risk is very high, so the PnL is not very stable. To reduce the simulated max drawdown, we need to remove some potential risks. We can achieve this by using some risk neutralization techniques. Industry risk and market risk are the biggest risks for the equity market. We can partially remove them by requiring our portfolios to be long–short balanced within each industry.

We neutralize our alpha by requiring:

$$\text{Sum}\left(\text{Alpha2 value within same industry}\right) = 0$$

By doing this, we get a new sample result, as seen in Figure 5.2.

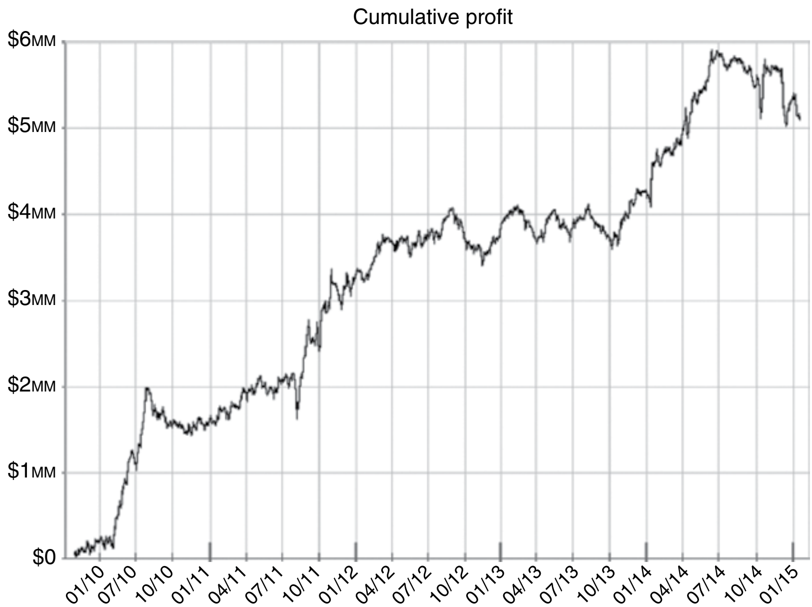

Figure 5.2 Sample simulation result of Alpha2 by WebSim

As Table 5.2 shows, the information ratio is increased to 1.37 and the return is decreased to 10.22%, but the max drawdown is decreased significantly, to less than 9%. This is a big improvement.

The magnitude of our alpha is five days' return, which is not very accurate as a predictor; the relative size may be more accurate. To improve the alpha, we introduce the concept of cross-sectional rank, which means using the relative rank of the alpha values as the new alpha values.

$$\text{Alpha3} = \text{rank}\left(\text{Alpha1}\right)$$

$$\text{Sum}\left(\text{Alpha3 value within same industry}\right) = 0$$

The results are reflected in Figure 5.3.

As can be seen from Table 5.3, we get another significant improvement. Now the performance looks much better, but the turnover is still a little high. We can try to decrease it by using decay. Decay means averaging your alpha signal over some time window.

Basically, it means:

$$\text{New\_alpha} = \text{new\_alpha} + \text{weighted\_old\_alpha}$$

When we try three days' decay in WebSim, we get the results shown in Figure 5.4.

Table 5.2 Evaluation of Alpha2 simulation graph

Year	Book size	PnL	Ann. return	Information ratio	Max drawdown	% profitable days	Daily turnover	Profit per $ traded
2010	2.0E7	1.59E6	17.30%	2.44	5.44%	51.30%	63.73%	0.05¢
2011	2.0E7	1.66E6	16.50%	1.81	5.27%	49.21%	63.85%	0.05¢
2012	2.0E7	518.24E3	5.18%	0.90	6.66%	55. 20%	63.12%	0.02¢
2013	2.0E7	450.88E3	4.47%	0.80	4.97%	51.59%	62.99%	0.01¢
2014	2.0E7	1.11E6	11.02%	1.24	8.73%	53.17%	62.86%	0.04¢
2015	2.0E7	−231.40E3	−48.21%	−5.96	2.88%	33.33%	62.30%	−0.15¢
2010–15	2.0E7	5.10E6	10.22%	1.37	8.73%	51.92%	63.29%	0.03¢

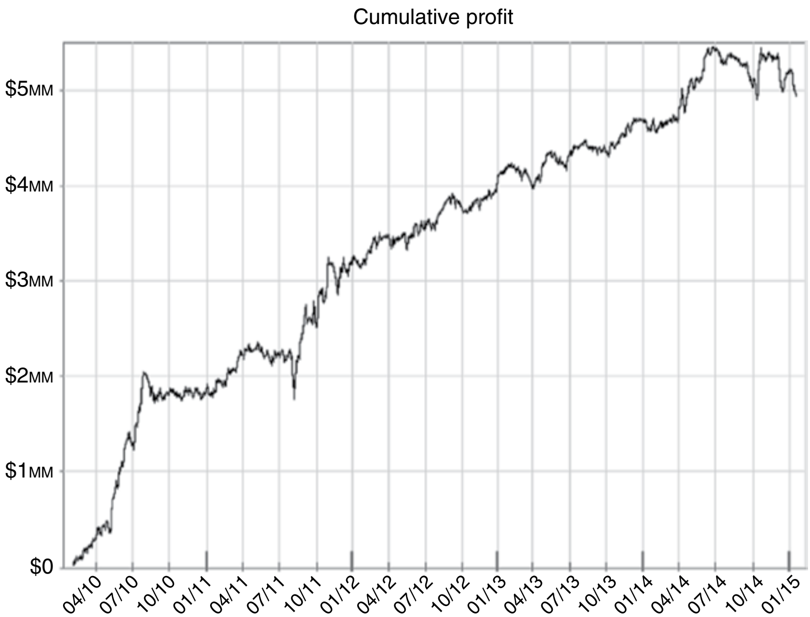

Figure 5.3 Sample simulation result of Alpha3 by WebSim

Figure 5.4 Sample simulation result of New_alpha by WebSim

Table 5.3 Evaluation of Alpha3 simulation result

Year	Book size	PnL	Ann. return	Information ratio	Max drawdown	% profitable days	Daily turnover	Profit per $ traded
2010	2.0E7	1.83E6	19.94%	3.43	3.11%	56.52%	59.43%	0.07¢
2011	2.0E7	1.34E6	13.30%	1.70	5.82%	53.17%	59.49%	0.04¢
2012	2.0E7	801.74E3	8.02%	1.89	1.93%	55.20%	58.94%	0.03¢
2013	2.0E7	692.73E3	6.87%	1.94	2.49%	53.57%	58.69%	0.02¢
2014	2.0E7	518.06E3	5.14%	0.93	5.43%	52.38%	59.20%	0.02¢
2015	2.0E7	−251.40E3	−52.37%	−10.45	2.78%	33.33%	59.59%	−0.18¢
2010–15	2.0E7	4.94E6	9.89%	1.76	5.82%	53.93%	59.15%	0.03¢

Table 5.4 Evaluation of New_alpha simulation result

Year	Book size	PnL	Ann. return	Information ratio	Max drawdown	% profitable days	Daily turnover	Profit per $ traded
2010	2.0E7	1.72E6	18.66%	3.09	4.11%	53.91%	42.48%	0.09¢
2011	2.0E7	1.61E6	15.94%	2.01	4.87%	51.19%	42.28%	0.08¢
2012	2.0E7	814.03E3	8.14%	1.90	2.05%	57.20%	42.09%	0.04¢
2013	2.0E7	643.29E3	6.38%	1.88	2.48%	54.76%	41.87%	0.03¢
2014	2.0E7	599.21E3	5.94%	1.03	7.74%	51.59%	42.09%	0.03¢
2015	2.0E7	−194.34E3	−40.49%	−7.20	2.58%	33.33%	41.82%	−0.19¢
2010 –15	2.0E7	5.19E6	10.39%	1.82	7.74%	53.53%	42.15%	0.05¢

Table 5.4 looks great. Not only is the turnover decreased, but the information ratio, return, and drawdown are also improved. Note that at each point, after evaluating the performance of the alpha, you can go back to the raw idea and make meaningful changes to further improve the alpha.

CONCLUSION

In this chapter, we have explained the logic behind an alpha, provided some examples of ideas, and discussed how to convert those ideas into mathematical expressions and translate them into instrument positions. We have also explained how to analyze and improve an alpha's performance. The entire alpha logic is nicely summarized by the flow chart in Figure 5.5.

You can think of more ways to improve an alpha – just be creative.

The next step is to explore other ideas and datasets, hunting for something really unique. A unique idea is good because you can trade it before others do, potentially leading to more profit.

Good luck!

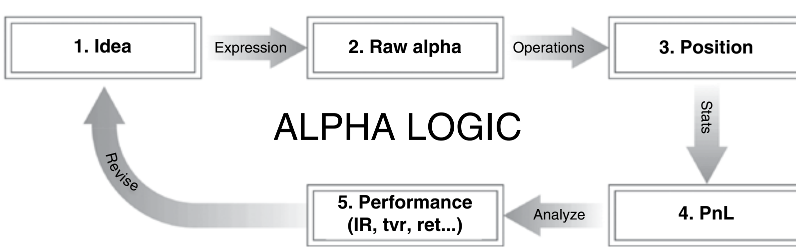

Figure 5.5 Five steps to creating alphas

6
Data and Alpha Design

By Weijia Li

Data plays a central role in alpha design. First, basic data, such as the price and volume of a security, is necessary to run a backtesting simulation. No matter what kind of alpha idea one wants to backtest, this basic information is required to calculate performance statistics like return, Sharpe ratio, and turnover. Without these statistics, we will never know whether an alpha idea is good. Second, data itself can inspire alpha ideas – every alpha idea is associated with some sort of data. By observing the price–volume plots of some stocks, for example, we may find repeating patterns in the history that can be used to make predictions for the future. If we also have access to company earnings data, one idea would be to trade stocks based on fluctuations in earnings.

In this chapter, we will discuss the effective use of data in alpha design. Usually, finding data is the first step in alpha research. After the data is obtained, some sanity checks should be made to verify the data's usability. Then we may start alpha research.

HOW WE FIND DATA FOR ALPHAS

Finding new data is a critical skill for an alpha researcher. We prefer alphas with good performance and low correlation; a new dataset can serve both purposes. Sometimes we can get signals from one set of data, but they may not be strong enough even after we have tried our best to improve them. If we can get another set of data and look at companies from a different angle, we may improve on the original signals. We always want to create uncorrelated alphas to diversify the alpha pool. However, even when the alpha ideas are different, signals from the same dataset may still be highly correlated. There can be an intrinsic correlation between the signals because the same data has been used. If we

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have a new dataset, it will inspire new ideas and new ways of using the dataset. Ideally, the alpha signals found in the new dataset will have a low correlation to signals that are based on different types of data. By using new data, we may achieve both performance improvement and diversification.

Data from Literature

It is nice to have new data to make new alphas, but how do we get new data? There are many possible sources. The most common is academic literature. If we search for “stock returns” on the internet, we can find thousands of papers that are trying to establish ways of capturing “abnormal returns” (i.e. alphas). In those papers, we learn about the data used in their studies: price–volume, fundamentals, earnings, and so forth. Once we get that data, we can try the same methods used in the paper to develop an alpha. It is also possible to find information by scanning for publicly available content on the internet. Bear in mind that the less well known the data, the more valuable it can be. If the data is well known, many people may have similar alpha models, which can gradually arbitrage away the alpha. However, there is a possibility that even if the data is popular, no one has applied it the way we will, so it may still be useful.

Data from Vendors

Data is valuable, and providing it is a business. There are many vendors that specialize in collecting, parsing, processing, and delivering data. If the data is simple, vendors may provide only the raw data they have collected, such as price and volume. Sometimes vendors do parsing and processing before providing data to their clients; fundamental data is an example. For unstructured yet sophisticated data, such as news, Twitter posts, and so on, vendors typically apply natural language processing techniques to analyze the content of the raw data. They provide machine-readable data to their clients instead of raw data that is only human-readable. Some vendors even sell alpha models directly – this means the data itself is the output of alpha models. The clients need only to load the data and trade according to it. Such alpha models are risky, however, because they may be overfit and/or overcrowded, with many clients of the same vendor trading the same model. To avoid these risks, the users of these models must test them carefully out of sample (OS), after the data is point-in-time, and use them in nontrivial ways.

DATA VALIDATION

When alpha researchers get new data, the first thing they need to do – before checking alpha signals on it – is check the data's usability. In alpha simulation, the data delivery time is a very important factor. Any piece of data is useless if it does not have a timestamp. This is because without knowing the time a data point is created, we cannot effectively chart its progression; essentially, we are using the data blindly. Only with the correct timestamp can we do correct simulations. If we attempt to use the data before it is available, we will have forward-looking bias, which will make the alpha's performance look amazing in simulation but will be unrealizable in live trading. If we do not use the data promptly, the alpha will not perform up to its potential. For example, if Apple's earnings exceeded expectations, its stock price most likely would increase, all other things being equal; the earnings announcement would be a good time to buy. If, however, we waited a week to buy Apple, we would not be able to realize those gains because the good news already would have been priced into the stock. So for every dataset we want to use in alpha research, we need to learn about the data delivery timeline and take care to access the data only when it is available, to make sure that we do not have forward-looking bias and that we get meaningful simulation results. We also need to ensure that the data can support alpha production – that the data will be generated in the future following a reliable schedule. Sometimes we learn that the data producer will cease to generate the data. In this case, the data is not usable for an alpha because there is no way to get more data in real time.

Another possible problem is survival bias. Even if a data vendor provides an alpha model that performs well when it is tested, this does not mean the model will perform well in the future. That is because we do not know how many models the vendor developed before this single model was selected. If the vendor tried 1,000 models and only one survived, we may face survival bias. The bias is introduced by the vendor and out of our control. In this case, some out-of-sample testing period for the dataset might be useful. Out-of-sample testing is helpful because it is not conducted in a controlled universe and strong performance is a good indicator of an alpha's robustness.

In historical simulations, one bad data point can kill the entire alpha signal. In live production, it is very dangerous to assume that the data always is correct. If the data goes wrong, it can distort the alpha signals and potentially cause significant losses. When using data in alpha design, we always should consider conducting a sanity check. We should do some basic checking, such as removing outliers in the alpha code. These basic safeguards help ensure that our alpha will be more robust.

UNDERSTAND THE DATA BEFORE USING IT

Serious alpha research is based on a deep understanding of the data. For some simple data, just crunching the numbers to create an alpha may be fine. For complicated data, however, a deep understanding makes an essential difference in alpha research. Sometimes we need to acquire extra knowledge. To understand hundreds of fundamental factors, we need to learn some concepts of corporate finance. Only when we fully comprehend the data can we come up with alpha ideas that will be more robust and more likely to survive.

EMBRACE THE BIG DATA ERA

Nowadays, the available data is growing explosively, in variety, volume, and velocity. In the past, traders might have considered only price–volume and fundamental data in predicting stock price movements. Today there are many more choices, which allow many interesting ideas. Kamstra et al. (2002) presented a "SAD" (seasonal affective disorder) effect: stock market returns vary seasonally with the length of the day. Hirshleifer and Shumway (2003) found that the morning sunshine at a country's leading stock exchange could predict the market index returns that day. Preis et al. (2013) made use of Google trend data to develop an alpha that beat the market significantly: a 326% return versus a 16% return.

A huge amount of data is created every day. Take the US equity market: the Level 1 tick data is about 50 gigabytes per day, and the Level 2 tick data exceeds 100 gigabytes per day. Social media also contribute lots of data, with Twitter users sending out 500 million tweets, on average, every day.

Today, data is created quickly. The latency for high-frequency trading firms can be measured in single-digit microseconds. Data vendors are trying to push the data speed to the limit in hopes of gaining more clients.

More data is always better, as long as we can handle it. It is very challenging to manage the rapid growth of data. There may be cost considerations for storage devices, computing machines, customized databases, and so forth. Yet, if data can be used correctly and efficiently, we can target better alphas.

CONCLUSION

In alpha research, the search for data is always a high priority. Given the many types of data available, it is challenging to find the most suitable data for alpha research, but when we succeed, the rewards can be considerable. One information-rich dataset can inspire many alpha ideas and generate many alphas. A single good data source can make a big difference in the performance of an alpha or a portfolio. Therefore, investment in data searching, data cleaning, and data processing is an important part of alpha creation.

7
Turnover

By Pratik Patel

We generally measure the accuracy and quality of an alpha's predictions by metrics such as the information ratio (IR) and the information coefficient (IC). The IR is the ratio of excess returns over a benchmark to the variability of those returns; the idea behind it is that an alpha with high excess returns and low variability consistently predicts future returns over a given time period. The IC measures the correlation between the predicted and actual values, in which a value of 1.0 represents perfect forecasting ability.

In the context of evaluating the strength of an alpha, a high IR and a high IC are obviously desirable, but we usually measure an alpha's return prediction ability irrespective of real-world constraints. We assume liquidity is endless, trading is free, and there are no other market participants but ourselves. However, as actual trading strategies must abide by certain constraints, an alpha that often makes predictions correctly will be more easily leveraged if it also satisfies reasonable assumptions about market conditions.

ALPHA HORIZON

Predictions change as new information becomes available. Whether a stock moved one tick, an analyst revised his recommendation, or a company released earnings, this change in information can be a catalyst for trading activity. We measure this trading via turnover: the total value traded divided by the total value held. A company's stock price changes much more often than its earnings per share, so it follows that an alpha based on price movements (e.g. price reversion) will usually have a higher turnover than an alpha based solely on company fundamentals. Because more trading opportunities provide more opportunities to

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capture returns, we typically find the IR and IC tend to be higher for price-movement alphas than for fundamental alphas.

More specifically, the turnover of an alpha is related to its prediction horizon – that is, the amount of time in the future for which the price movement is being predicted. For example, an alpha with a horizon of five days aims to predict the price movement from now until five days from now. We find that the longer the horizon, the greater the uncertainty; a meteorologist can predict the weather tomorrow much more accurately than the weather two months from now, and we can predict what we will be doing next week better than what we will be doing at this time next year. The ability to take advantage of rapidly changing information and react accordingly typically increases the quality of the prediction. Similarly, in alpha research we expect a higher-turnover alpha with a shorter forecast horizon to have better predictive power than a lower-turnover, longer-term alpha.

However, it is also clear that execution time becomes a constraint as the horizon becomes shorter. A trader using an alpha with a five-day horizon would need to trade into the position today and trade out of it five days later to fully capture this price movement. In comparison, an alpha with a horizon of three months allows for a much longer time between trades to capture the price movement, resulting in fewer trades and lower turnover over the same time period. For very short-term alphas (e.g. seconds to minutes), it may even be necessary to cross the spread to get into the desired position, incurring high transaction costs. With their longer execution times, longer-horizon alphas allow better execution optimization, as well as higher capital capacity. It is possible to invest more capital in the alphas before the profits are outweighed by the market impact costs.

THE COST OF A TRADE

Every trade has a cost. When buying a stock, we not only pay a commission to the broker, we also pay a spread cost. The highest price a buyer is offering for a stock (the bid) is usually below the lowest price a seller is willing to accept (the ask); this is the bid–ask spread. To realize a positive return, you must sell what you bought at a higher price than you purchased it at, or, in the case of a short trade, buy back the borrowed shares at a lower price than you sold them at.

We expect these costs to be proportional to the liquidity of the universe or market in question. Spreads are kept tight in liquid markets because there is plenty of interest from buyers and sellers at any point in time; when a buyer crosses the spread to move the bid price up, a seller is typically readily available to take advantage of the favorable price move and bring the ask price back down. On the other hand, when liquidity is low or investor interest piles up on one side, prices are more easily moved, increasing volatility and widening the spread. The top 500 most liquid stocks in the US equity market have an average spread of about 5 basis points (bps). In comparison, smaller markets, like those in Southeast Asia, may have average spreads as wide as 25–30 bps.[1] Clearly, the cost of trading is much higher in these markets, so it becomes more important to understand whether the alpha's horizon and turnover profile are suitable for the market. An argument can be made that these markets are less efficient (i.e. have higher volatility), leaving larger opportunities for return, and this is certainly true as long as the return of the alpha justifies the cost of its trading.

When we charge trading costs to alphas, we will likely see that longer-horizon alphas have lower overall trading costs than shorter-horizon alphas. Moreover, it's possible that the lower trading cost of a longer-horizon alpha may also improve its overall performance compared with a shorter-horizon alpha, even though the opposite may be true before costs. The picture can look very different once real-world constraints are imposed, so it is beneficial to be mindful of this during the research process.

To illustrate this effect in the context of alpha construction, consider two hypothetical alphas that use price and volume data to predict prices on the following day. Both alphas operate on the same set of instruments, and let us assume that both alphas have the same return and IR. The first invests in instruments based on their recent volatility, while the second invests based on their current market volume.

$$\alpha 1 = \text{std(returns)}$$
$$\alpha 2 = \log(\text{volume})$$

We see that the first alpha is investing in more-volatile instruments, but as high-volatility stocks tend to have lower volume and wider

[1] These are estimates based on our WebSim simulation results. For reference only.

spreads, it is difficult for a strategy to allocate a large amount of capital given the challenge in turning those returns into actual profits. The second alpha, meanwhile, is investing in more-liquid large-cap instruments and is likely to perform better when subjected to more-realistic trading assumptions. If we also pretend that volume data is more stable over time relative to volatility, we would expect turnover for the second alpha to be lower, further increasing its appeal.

THE CROSSING EFFECT

So should we only look at after-cost performance when evaluating alphas? Why even bother with evaluating alphas before cost? Just charge trading costs on all alphas and the problem is solved, right? Unfortunately, it's not that simple. Typically, an individual alpha is too weak and unlikely to perform well as a strategy on its own; to build a potentially profitable trading strategy, a portfolio manager generally needs to combine multiple alphas. Combining many diverse alphas results in a stronger, more informed prediction that is more likely to overcome transaction costs and other trading constraints. A diverse alpha pool requires diverse ideas, methods, and data, resulting in alphas with a wide range of turnover profiles. To put it another way: there is diversity in alpha turnover. Alphas with different horizons are likely taking into account different types of information, and this may result in lower correlations.

When alphas are combined in a single strategy, the alphas' opposing trades "cross." Consider an alpha that is looking to buy 200 shares of IBM and is combined with another that has a contrarian view and suggests selling 300 shares of IBM. Assuming both alphas have equal weights of 1, the resulting combined alpha will sell 100 IBM shares. Two hundred shares of IBM "cross" and no transaction costs are incurred; the trade never goes out to the market and is therefore cost-free. Costs are incurred only on the 100 shares that the combined alpha will be trading.

If there is adequate crossing among a set of alphas, the turnover and overall trading costs of the resulting combined alpha may be lower than the turnover and trading costs of the individual alphas. In this way, we can still make use of higher-turnover alphas to increase prediction power while keeping trading costs under control. Although charging trading costs on the individual alphas and seeing how those alphas perform would be a viable test, making this a strict requirement would be overly restrictive. With the understanding that turnover should still be controlled on the individual alphas, their after-cost performance is less meaningful if their contributions to the combined alpha performance are significantly better due to this crossing effect.

CONTROLLING TURNOVER

Information is changing all the time, but (1) not all types of information change at the same rate, and (2) not all information is particularly useful. For the sake of illustration, let us assume that our alpha signal is just the underlying data, with no special transformations, i.e.

$$\alpha = \text{data}$$

The data is the prediction, and it is clear that the data frequency drives the alpha's turnover: The more the data changes, the higher the turnover.

At one extreme, suppose our data is the daily price of each stock. We will buy if the price previously went up and we will sell if it previously went down. Prices change on almost every executed trade, so we can expect our alpha to have very high turnover. But we understand that most of the trades in the market are inconsequential and we will likely be trading a lot more than we'd like. As a result, it's very likely that our alpha will lose money, on average.

Quarterly company announcements, meanwhile, occur only a handful of times per year, and an alpha making its predictions based solely on this data will naturally have few trading opportunities and low turnover. But this data is inherently sparse. If we do not pay any attention to this fact, plotting the daily turnover of the alpha may show spikes of trading activity around these quarterly events. This suggests that the alpha may be trading into the position very quickly and potentially trading out too soon. We understand that such an alpha has a longer horizon, so such trading spikes may be suboptimal. Thus, even naturally low-turnover alphas may have room for improvement by smoothing the data and spreading out the trading over a longer period. Entire books have been written in signal processing and similar fields on various methods for processing and transforming data. For our purposes, a few simple, high-level approaches should suffice.

First, it is useful to determine whether very large values in the data are meaningful or if they are just anomalies (i.e. outliers). If tests show that they are indeed outliers, one way to reduce them is to simply clamp the data by reducing the large data points to predefined minimum and maximum values, e.g.

$$\alpha = \text{clamp}(\text{data}, \text{min\_value}, \text{max\_value})$$

The bounds can be chosen in a variety of ways, such as some percentile of the data distribution or some number of standard deviations. The approach and the associated parameters will depend on the nature of the data and can be evaluated via backtesting, taking caution to try only a few sensible approaches and to avoid overfitting.

On the other hand, it could be the smallest changes in the data that cause unnecessary trading. The assumption here is that these small movements are just noise that we need to remove from our data. Suppose that tests show that the small changes in data are completely unnecessary and the desired course of action is to not trade at all unless the change is significant. One simple approach could be to require the change to exceed a threshold (or "hump") and otherwise preserve the previous value.

$$\text{delta} = \text{data}_{t-1} - \text{data}$$

$$\text{humped\_delta} = \text{hump}(\text{delta}, \text{threshold})$$

$$\alpha = \text{data}_{t-1} + \text{humped\_delta}$$

Here, the humped delta is 0 if abs(delta) is less than the threshold. This ultimately removes all changes in the data less than the provided threshold, which should provide a significant reduction in turnover for our alpha. However, the hump approach results in a more concentrated trading profile; alpha values will remain unchanged for a period of time until the threshold is crossed, at which point a large trading event will occur. There's nothing wrong with this if it's the desired effect. In other cases, the trades can be smoothed (decayed) rather than stopped completely by using an exponential moving average

$$\alpha = \beta * \text{data}_t + (1 - \beta) * \alpha_{t-1}$$

or a simple or weighted moving average

$$\alpha = \beta * \text{data}_t + \beta_1 * \text{data}_{t-1} + \ldots + \beta_n * \text{data}_{t-n}$$

These approaches can provide a similar reduction in turnover, but with a smoother trading profile. When slowing down the signals in this manner, deciding which method and parameters to use will depend on the data and the alpha's horizon. With careful experimentation and backtesting, we can choose an optimal point where the outliers and noise are reduced, the signal is smoothed, the turnover is lowered, and the performance is increased. However, reducing the turnover too much (i.e. beyond the alpha's horizon) will result in degraded performance, as the signal will be slowed beyond the point necessary to capture the return. Faster-moving signals with shorter horizons can tolerate less decay than those with longer horizons, so it is important to optimize the trade-off between the return and turnover.

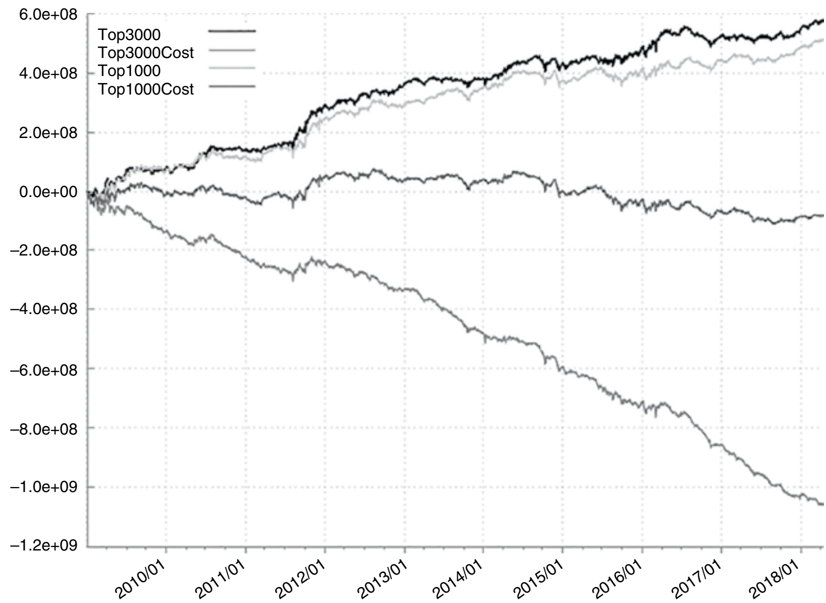
EXAMPLES

To illustrate the effect of turnover on costs, consider the well-known five-day reversion alpha, which assumes all prices will eventually revert to the average price. A simple implementation of such an alpha is to sell stocks whose prices have gone up over the past five days, and vice versa:

$$\alpha = -1 * \left(\text{close}_t - \text{close}_{t-5}\right)$$

Two versions of the alpha are shown in Figure 7.1. The first is run on the top 3,000 most liquid stocks in the US market, neutralized by industry. The second is run on only the top 1,000 most liquid stocks. The graph shows the performance before and after cost (i.e. charging half of the spread cost to every trade in the backtest).

When we evaluate an alpha before cost, we typically see that a wider universe will improve the information ratio; in a larger universe, there are more "bets" to make, which helps to diversify the portfolio and decrease potential risk. We can see, however, that the performance looks quite different when we consider the additional cost of the trades. The effect of this cost is much larger on the wider, less-liquid universe. Comparing the margins ($pnl/$traded) in the table of statistics below the graph, we see a deterioration of about 4 bps in the after-cost margin of the top 1,000 version. Because the top 3,000 version contains stocks



Top3000

date	long	short	pnl	ret	tvr	sharpe[	ir]	vol	dd	mgn
20090102-20180413	500.36	−499.64	576.24	12.33%	63.01%	1.26[	0.08]	9.82%	−13.50%	3.92

Top3000Cost

date	long	short	pnl	ret	tvr	sharpe[	ir]	vol	dd	mgn
20090102-20180413	500.36	−499.64	−1061.69	−22.69%	63.01%	−2.33[	−0.15]	9.74%	−212.02%	−7.22

Top1000

date	long	short	pnl	ret	tvr	sharpe[	ir]	vol	dd	mgn
20090102-20180413	500.01	−499.99	512.45	10.97%	62.98%	1.02[	0.06]	10.73%	−13.19%	3.48

Top1000Cost

date	long	short	pnl	ret	tvr	sharpe[	ir]	vol	dd	mgn
20090102-20180413	500.01	−499.99	−82.38	−1.75%	62.98%	−0.16[	−0.01]	10.69%	−37.68%	−0.56

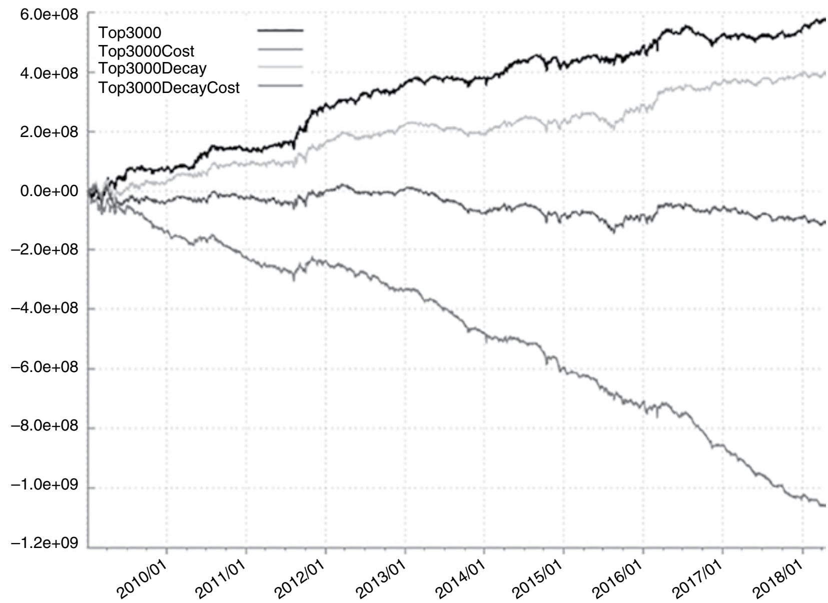
Figure 7.1 Example of a five-day reversion alpha run on the top 3,000 most liquid stocks in the US market, neutralized by industry, and on the top 1,000 most liquid stocks

that are less liquid and therefore have a higher cost, we see a much larger deterioration of nearly 10 bps, even though both versions have roughly similar turnover. It follows that the liquidity of the alpha plays a significant role in determining the cost of turnover.

The daily turnover of this alpha is roughly 63%. Let's see how the alpha characteristics change when we attempt to control the turnover of the signal by using the linear decay method over the past 20 time periods:

$$\alpha = \beta * \text{data}_t + \beta_1 * \text{data}_{t-1} + \ldots + \beta_n * \text{data}_{t-n}$$

Figure 7.2 shows the before- and after-cost performances of the decayed version of the alpha. As expected, the turnover is significantly



Top3000

date	long	short	pnl	ret	tvr	sharpe[	ir]	vol	dd	mgn
20090102-20180413	500.36	−499.64	576.24	12.33%	63.01%	1.26[	0.08]	9.82%	−13.50%	3.92

Top3000Cost

date	long	short	pnl	ret	tvr	sharpe[	ir]	vol	dd	mgn
20090102-20180413	500.36	−499.64	−1061.69	−22.69%	63.01%	−2.33[	−0.15]	9.74%	−212.02%	−7.22

Top3000Decay

date	long	short	pnl	ret	tvr	sharpe[	ir]	vol	dd	mgn
20090102-20180413	500.14	−499.86	396.93	8.50%	18.84%	0.86[	0.05]	9.83%	−14.33%	9.02

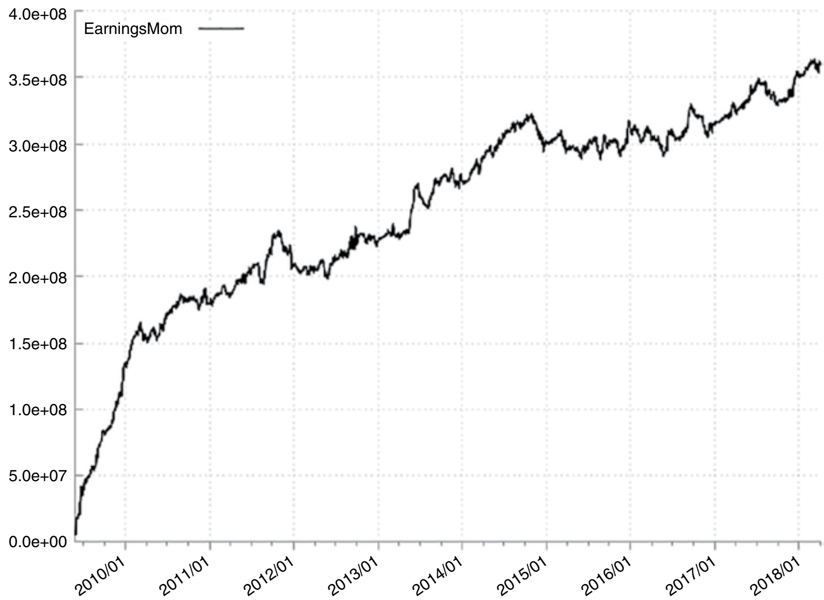
Top3000DecayCost

date	long	short	pnl	ret	tvr	sharpe[	ir]	vol	dd	mgn
20090102-20180413	500.14	−499.86	−105.42	−2.22%	18.84%	−0.23[	−0.01]	9.81%	−33.04%	−2.40

Figure 7.2 The before- and after-cost performances of the five-day reversion alpha's decayed version

lowered (from 63% to 19%) at the expense of some of the performance before cost; IR and returns are both lower than in the original version. More important, the decay increases the margin substantially (from 3.9 bps to 9.02 bps), which significantly improves the after-cost performance.

However, it is important to note that although the top 1,000 after-cost alpha outperforms the top 3,000, and the top 3,000 version does not perform particularly well on its own after cost, even after reducing turnover, this does not imply that the top 3,000 alpha is less useful. As mentioned previously, an individual alpha typically is not strong enough to perform well after costs on its own. The key factor in strategy construction is the effect of crossing among alphas when they are combined. A universe with more instruments will naturally have a higher probability of crossing, and



date	long	short	pnl	ret	tvr	sharpe[	ir]	vol	dd	mgn
20090601-20180403	498.99	−499.21	359.68	8.08%	35.27%	1.59[	0.10]	5.10%	−7.28%	4.59

Figure 7.3 The performance of the alpha run on the top 3,000 most liquid US stocks, neutralized by industry

just as the before-cost performance of wider universes typically exceeds that of smaller ones, the same is true on the strategy and portfolio levels.

The frequency of crossing also depends on the turnover profile of the alphas. Alphas with sparser trading profiles will have fewer crossing opportunities, on average, than those with more uniform trading. A five-day reversion alpha, for example, will generally trade a similar amount each day as long as the market volatility remains constant. An earnings–momentum alpha, meanwhile, will likely exhibit a cyclical turnover pattern, with spikes in activity around the most common times of earnings announcements. Consider the following alpha, which takes long positions on stocks N days before the earnings announcement:

$$\alpha = 1 \text{ if } \left(0 < \text{days\_until\_earnings\_announcement} < N\right) \text{ else } 0$$

The performance of the alpha run on the top 3,000 most liquid stocks in the US, neutralized by industry, is shown in Figure 7.3. The average turnover of 35% is well below the 63% turnover of our reversion alpha.

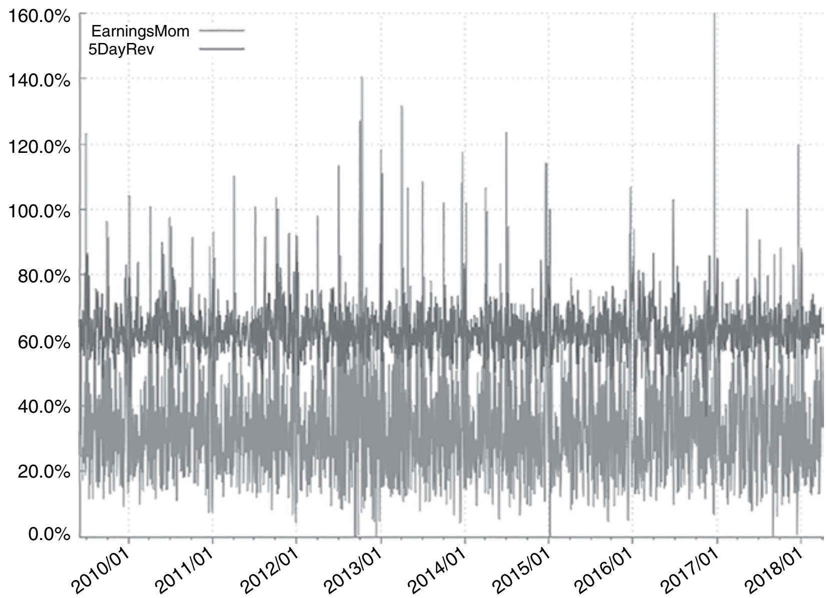


Figure 7.4 The daily turnover of two alphas run on the top 3,000 most liquid US stocks

However, Figure 7.4, showing the alphas' daily turnover, illustrates that although the earnings–momentum alpha has a lower turnover, on average, it has much higher turnover spikes several times each year.

Visualizing and analyzing the liquidity, turnover, and trading patterns of alphas can provide useful insights. In this example, it would be worth examining whether the trades on the lower-turnover days are generating any meaningful value or should be filtered out, or whether the spikes can be smoothed out by gradually trading into the position over several days rather than making abrupt (binary) trades. Understanding the characteristics and trading behavior of the alpha can reveal more opportunities to improve its predictive power, as well as useful feedback on how the alpha can be used in a strategy under real-world constraints.

TUNING THE TURNOVER

Smoothing methods such as linear decay may actually improve the performance of sparse signals with very few trading events. Winsorizing (limiting extreme values) or decaying the data itself may also help to reduce the turnover in cases where excessive sensitivity to changes in information leads to unnecessary changes in position. The utility of any single technique will ultimately depend on the alpha. Regardless of the result, an understanding of how the alpha behaves at various turnovers gives us a sense of its tradability. An alpha that maintains most of its return is generally more easily leveraged than one that loses all its return after a slight turnover reduction.

To understand the robustness and tradability of an alpha idea, it is important to test it on a variety of universes of instruments and to understand the liquidity of each market. A given level of turnover might be acceptable in the most-liquid universes but become untradable when extended to include less-liquid instruments; a level that works in one country might not work in a less developed market. For example, an alpha that trades the top 500 most liquid US equities with X% turnover may be perfectly acceptable, but for a similar alpha for a larger universe with less-liquid instruments (e.g. the top 3,000 most liquid stocks in the US), or an alpha trading a developing market, it would be wise to evaluate the performance at lower turnovers, keeping in mind the cost of trading.

A good level of turnover is one that maximizes the ratio between the profit or IR and the turnover. More important, the exercise of testing and analyzing an alpha's performance across different liquidity sets and under varying turnover levels can provide insights and confidence in that alpha's robustness and tradability. In the end, it's all relative.

8
Alpha Correlation

By Chinh Dang and Crispin Bui

Alphas are evaluated by many different metrics, such as the information ratio, return, drawdown, turnover, and margin. These metrics are derived mainly from the alpha's profit and loss (PnL). For example, the information ratio is just the average returns divided by the standard deviation of returns. Another key quality of an alpha is its uniqueness, which is evaluated by the correlation coefficient between a given alpha and other existing alphas. An alpha with a lower correlation coefficient normally is considered to be adding more value to the pool of existing alphas.

If the number of alphas in the pool is small, the importance of correlation is low. As the number of alphas increases, however, different techniques to measure the correlation coefficient among them become more important in helping the investor diversify his or her portfolio. Portfolio managers will want to include relatively uncorrelated alphas in their portfolios because a diversified portfolio helps to reduce risk. A good correlation measure needs to identify the uniqueness of one alpha with respect to other alphas in the pool (a smaller value indicates a good uniqueness). In addition, a good correlation measure has the ability to predict the trend of movement of two alpha PnL vectors (time-series vectors). The correlation among alphas can be computed based on alpha PnL correlation or alpha value correlation.

ALPHA PnL CORRELATION

Given two alpha PnL vectors (we use bold letters for vectors):

$$\begin{aligned} \mathbf{P}_i &= \left[P_{i1}, P_{i2}, \ldots, P_{in}\right]^T \in \mathbb{R}^n \\ \mathbf{P}_j &= \left[P_{j1}, P_{j2}, \ldots, P_{jn}\right]^T \in \mathbb{R}^n \end{aligned} \tag{1}$$

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where P_{it} and P_{jt} denote the PnLs of i^{th} and j^{th} alphas on the t^{th} day, n is the number of days used to measure correlation, and T denotes the matrix transposition. Note: tests usually select the number of days for correlation as two or four years instead of a full history, to save computational resources.

Pearson Correlation Coefficient

The Pearson correlation coefficient, also known as the Pearson product-moment correlation coefficient, has no units and can take values from −1 to +1. The mathematical formula was first developed by Karl Pearson in 1895:

$$r = \frac{\operatorname{cov}\left(\mathbf{P}_i, \mathbf{P}_j\right)}{\sigma_{\mathbf{P}_i}\sigma_{\mathbf{P}_j}} \tag{2}$$

where $\operatorname{cov}\left(\mathbf{P}_i, \mathbf{P}_j\right) = \mathrm{E}\left[\left(\mathbf{P}_i - \mu_{\mathbf{P}_i}\right)\left(\mathbf{P}_j - \mu_{\mathbf{P}_j}\right)\right]$ is the covariance and $\sigma_{\mathbf{P}_i}$ and $\sigma_{\mathbf{P}_j}$ are the standard deviations of $\mathbf{P}_i$ and $\mathbf{P}_j$, respectively. For two vectors of PnLs, the coefficient is computed by using the sample covariance and variances. In particular,

$$r = \frac{\sum_{t=1}^{n}\left(P_{it} - \overline{P_i}\right)\left(P_{jt} - \overline{P_j}\right)}{\sqrt{\sum_{t=1}^{n}\left(P_{it} - \overline{P_i}\right)^2}\sqrt{\sum_{t=1}^{n}\left(P_{jt} - \overline{P_j}\right)^2}}. \tag{3}$$

The coefficient is invariant to linear transformations of either variable. If the sign of the correlation coefficient is positive, it means that the PnLs of the two alphas tend to move in the same direction. When the return on $\mathbf{P}_i$ is positive (negative), the return on $\mathbf{P}_j$ has a tendency to be positive (negative) as well. Conversely, a negative correlation coefficient shows that the PnLs of the two alphas tend to move in opposite directions. A zero correlation implies that there is no relationship between two PnL vectors. Figure 8.1 shows the variation of maximum correlation as a function of trading signals, using two years' worth of data.

Alphas seek to make predictions about the future movements of various financial instruments. As a result, the analysis needs to be extended into a time series, which includes a sequence of random variables with the time index. In the case of an alpha PnL vector, the observation is the profit (+) or loss (−) of the alpha in one day. Below we briefly review the dot product, then discuss the temporal-based correlation.

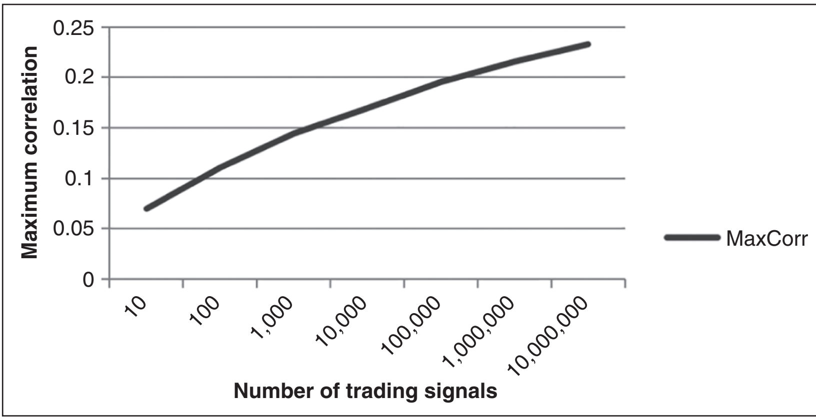

Figure 8.1 Variation of maximum correlation as a function of trading signals

Temporal-Based Correlation

The dot (inner) product is defined as the sum of the products of the corresponding entries of the two sequences of numbers.

$$\mathbf{P}_i.\mathbf{P}_j = |\mathbf{P}_i||\mathbf{P}_i|\cos(\theta) \tag{4}$$

where $|\mathbf{P}|$ is the modulus, or magnitude, of the PnL vector and θ is the angle between the two vectors. One important application of the dot product is to find the angle between two vectors because the angle θ can be found via

$$\cos(\theta) = \frac{\mathbf{P}_i.\mathbf{P}_j}{|\mathbf{P}_i||\mathbf{P}_i|} = \frac{\sum_{t=1}^{n} P_{it}P_{jt}}{\sqrt{\sum_{t=1}^{n} P_{it}^{2}}\sqrt{\sum_{t=1}^{n} P_{jt}^{2}}}. \tag{5}$$

When the angle is zero, the two PnL vectors fall on the same line and $\cos(\theta) = \pm 1$. When the angle is $\frac{\pi}{2}$, the vectors are orthogonal and $\cos(\theta) = 0$.

The temporal-based correlation considers each alpha's PnL vector as a time-series sequence and assigns weight to the values on each day. The correlation between two PnL vectors is thus defined as:

$$r = \frac{\sum_{t=1}^{n} w_t P_{it} P_{jt}}{\sqrt{\sum_{t=1}^{n} w_t \left(P_{it}^{2}\right)}\sqrt{\sum_{t=1}^{n} w_t \left(P_{jt}^{2}\right)}}. \tag{6}$$

Naturally, larger weights are assigned to recent PnL values ($w_t > w_{t+1}$, $t = \overline{1,\ldots,n}$). For example, $w_t = 1 - \frac{t}{n}$, which is inversely proportional to the time index t. The formula transforms input pairs of vectors $(\mathbf{P}_i, \mathbf{P}_j)$ into time-scaled vectors and then computes the angle between the two scaled vectors:

$$\begin{aligned} \mathbf{P}'_i &= \left[\sqrt{w_1}P_{i1}, \sqrt{w_2}P_{i2}, \ldots, \sqrt{w_n}P_{in}\right]^T \in \mathbb{R}^n \\ \mathbf{P}'_j &= \left[\sqrt{w_1}P_{j1}, \sqrt{w_2}P_{j2}, \ldots, \sqrt{w_n}P_{jn}\right]^T \in \mathbb{R}^n. \end{aligned} \tag{7}$$

As a result, the temporal-based correlation still preserves many desirable aspects of the traditional dot product, such as commutative, distributive, and bilinear properties.

The Pearson correlation coefficient can be computed here for the two scaled vectors in Equation 7. We can see that the centered variables have zero correlation or are uncorrelated in the sense of the Pearson correlation coefficient (i.e. the mean of each vector is subtracted from the elements of that vector), while orthogonality is a property of the raw variables. Zero correlation implies that the two demeaned vectors are orthogonal. The demeaning process often changes the angle of each vector and the angle between two vectors. Therefore, two vectors could be uncorrelated but not orthogonal, and vice versa. For further information about linear independent, orthogonal, and uncorrelated variables, see Joseph Rodgers et al. (1984).

Generalized Correlation

Data transformation can be an important tool for proper data analysis. There are two kinds of transformations: linear and nonlinear. A linear transformation (such as multiplication or addition of a constant) preserves the linear relationships among the variables, so it does not change the correlation among the variables. Below we will consider nonlinear transformations, which typically modify the correlation between two variables.

The two correlation formulas above compute correlation coefficients using daily PnL values. The generalized correlation creates a matrix $\boldsymbol{M}^{k\times n}$, then transforms the two PnL vectors to a different Euclidean space:

$$\begin{aligned} \mathbf{Q}_i &= \boldsymbol{M}^{k\times n}\mathbf{P}_i \in \mathbb{R}^k \\ \mathbf{Q}_j &= \boldsymbol{M}^{k\times n}\mathbf{P}_j \in \mathbb{R}^k. \end{aligned} \tag{8}$$

The regular correlation now is computed in the transformed domain, with some additional features added by the transformed matrix $\boldsymbol{M}^{k\times n}$. If $\boldsymbol{M}^{k\times n} = \boldsymbol{I}^{n\times n}$ is the identity matrix, we obtain the regular correlation scheme. Here we take a look at some other particularly useful transformations.

The weekly PnL correlation is computed for weekly instead of daily PnL vectors. In this case, $k = \left\lceil \frac{n}{5} \right\rceil$ and the transformation matrix becomes

$$\boldsymbol{M}^{k\times n} = \left[m_{i,j} \right]_{\left\lceil \frac{n}{5} \right\rceil \times n} \tag{9}$$

where $m_{i,(i-1)*5+t} = \frac{1}{5} \left(i \in \left[1, \left\lceil \frac{n}{5} \right\rceil \right] \text{ and } t \in [1,5] \right)$ and all other elements are zero. The weekly correlation is usually higher than daily values, but it is another way to understand alphas. The monthly PnL correlation is computed using a similar approach.

The temporal-based correlation is another form of generalized correlation, corresponding to the square diagonal transformation matrix:

$$\boldsymbol{M}^{k\times n} = \left[m_{i,j} \right]_{n\times n} \tag{10}$$

where $\begin{cases} m_{i,j} = \sqrt{w_i} & \text{if } i = j \\ m_{i,j} = 0 & \text{otherwise} \end{cases}$. Under this transformation, the input PnL vectors are transformed into time-scaled vectors, as in Equation 7.

The sign PnL correlation is another form of PnL vector correlation, in which the correlation is computed over the signs of the PnL values instead of the values themselves. The transformation matrix now is a data-dependent diagonal matrix and its element values depend on input PnL vectors. As a result, the input pairs $(\mathbf{P}_i, \mathbf{P}_j)$ are transformed into the following form:

$$\begin{aligned} \mathbf{Q}'_i &= \left[\operatorname{sgn}(P_{i1}), \operatorname{sgn}(P_{i2}), \ldots, \operatorname{sgn}(P_{in}) \right]^T \in \mathbb{R}^n \\ \mathbf{Q}'_j &= \left[\operatorname{sgn}(P_{j1}), \operatorname{sgn}(P_{j2}), \ldots, \operatorname{sgn}(P_{jn}) \right]^T \in \mathbb{R}^n \end{aligned} \tag{11}$$

where $\operatorname{sgn}(x)$ is the sign (or signum) function and takes the values $(1,0,-1)$, corresponding to (positive, zero, negative) values of x.

ALPHA VALUE CORRELATION

Denote the alpha position vector on the t^{th} day by

$$\boldsymbol{\alpha}_i^{(t)} = \left[\alpha_{i1}^{(t)},\ \alpha_{i2}^{(t)},\ \ldots,\ \alpha_{im}^{(t)}\right]^T \in \mathbb{R}^m \tag{12}$$

where m is the number of instruments, $\alpha_{ik}^{(t)}\left(\leq k \leq m\right)$ is (or is proportional to) the amount of money invested in k^{th} instrument, and $\sum_{k=1}^{m} \alpha_{ik}^{(t)}$ is (or is proportional to) the total amount of money invested in the portfolio. It is sometimes useful to consider the alpha position vectors as well as the PnL vectors. In particular, portfolio managers often consider two correlation measures based on positions: the position correlation and the trading correlation.

The position correlation between two alphas over a period of d days is computed by forming the following two vectors:

$$\begin{aligned} \boldsymbol{\alpha}_i &= \left[\boldsymbol{\alpha}_i^{(1)},\ \boldsymbol{\alpha}_i^{(2)},\ \ldots,\ \boldsymbol{\alpha}_i^{(d)}\right]^T \in \mathbb{R}^{(m*d)} \\ \boldsymbol{\alpha}_j &= \left[\boldsymbol{\alpha}_j^{(1)},\ \boldsymbol{\alpha}_j^{(2)},\ \ldots,\ \boldsymbol{\alpha}_j^{(d)}\right]^T \in \mathbb{R}^{(m*d)}. \end{aligned} \tag{13}$$

The trading correlation between two alphas over a period of d days is computed by forming the two difference vectors:

$$\begin{aligned} \boldsymbol{\alpha}_i &= \left[\boldsymbol{\alpha}_i^{(1)} - \boldsymbol{\alpha}_i^{(2)},\ \boldsymbol{\alpha}_i^{(2)} - \boldsymbol{\alpha}_i^{(3)},\ \ldots,\ \boldsymbol{\alpha}_i^{(d)} - \boldsymbol{\alpha}_i^{(d+1)}\right]^T \in \mathbb{R}^{(m*d)} \\ \boldsymbol{\alpha}_j &= \left[\boldsymbol{\alpha}_j^{(1)} - \boldsymbol{\alpha}_j^{(2)},\ \boldsymbol{\alpha}_j^{(2)} - \boldsymbol{\alpha}_j^{(3)},\ \ldots,\ \boldsymbol{\alpha}_i^{(d)} - \boldsymbol{\alpha}_j^{(d+1)}\right]^T \in \mathbb{R}^{(m*d)}. \end{aligned} \tag{14}$$

Normally, it is enough to take $d = 20$ days, so the alpha vector is of dimension 20 * the number of instruments in the universe. If two alphas take positions on different universes of instruments, the intersection of the two universes is used for the calculations.

CORRELATION WITH ALPHA POOL

The above correlation methods are used for checking the correlation between two individual alphas. Naturally, given a pool of alphas, the maximum correlation has been used as a measure of the value added by

Table 8.1 A histogram of correlation

Bins	cnt(%)	count_in_number
0.9	c9	0
0.8	c8	0
0.7	c7	0
0.6	c6	0
0.5	c5	0
0.4	c4	167
0.3	c3	5,102
0.2	c2	70,294
0.1	c1	283,436
0	c0	438,720
−0.1	c_1	286,478
−0.2	c_2	36,889
−0.3	c_3	1,293
−0.4	c_4	59
−0.5	c_5	0
−0.6	c_6	0
−0.7	c_7	0
−0.8	c_8	0
−0.9	c_9	0
−1	c_10	0

a given alpha. As the number of alphas increases, the average correlation becomes more important than a single max correlation.

T-corr is defined as the sum of the correlations of the given alpha with all other alphas. The average correlation and *T-corr* provide additional powerful measures of alpha value addition, along with the max correlation.

A correlation density distribution is more important than a singular maximum value or even the average correlation value. Table 8.1 shows a sample histogram of correlation density (20 bins of size 0.1). Numerous features can be extracted from the histogram in addition to the maximum correlation and the average correlation. For example, the scaled average score of one alpha with the pool could be defined as $\sum_{j=-10}^{9} c_j * \frac{j}{10}$ (c_j is taken from Table 8.1). The score ranges in $[-1, 1]$, which increases if the number of alphas with positive correlation increases or the number of alphas with negative correlation decreases.

CONCLUSION

We have surveyed several different approaches to evaluating the correlations between the PnLs and positions of alphas and pools of alphas. There are, of course, more statistical and less algebraic approaches to evaluate correlation, such as Spearman's rank correlation and the Kendall rank correlation. Within the scope of this chapter, we have covered only some of the most common methods for evaluating alpha correlation. PnL correlation can be evaluated over a longer period of time (2–4 years or longer) in comparison with alpha value correlation (which requires a short, recent period of time) because of the limitations of computational resources.

One reasonable idea often can be used to develop numerous alphas, depending on different techniques and datasets. Because they are developed using a single idea, these alphas have a tendency to be highly correlated. Sometimes there are instances when it is beneficial to combine some or all of these highly correlated alphas instead of selecting only one alpha and removing all others. Two alphas may have highly correlated historical performance, but the future is uncertain and it is not always clear which one may add more value in the future. Therefore, in terms of resource allocation for two high-correlation alphas (e.g. A and B), one can divide resources (not necessarily equally) between A and B instead of allocating all of the resources to a single alpha. A single alpha cannot fully describe every aspect of one idea, but each alpha represents that idea in a different way; hence, using all these alphas at once may provide a more complete view of the idea and make the overall strategy more robust.

The ultimate objective of alpha correlation is to find the true value of adding one new alpha, given a pool of existing alphas, which becomes increasingly important as the number of alphas grows toward the sky. Using multiple correlation approaches leads to a better understanding of the alpha signals in recent history as well as over a longer past period. An alpha based on a completely novel trading idea is generally unique and adds the most value to the alpha pool.

9
Backtest – Signal or Overfitting?

By Zhuangxi Fang and Peng Yan

INTRODUCTION

Over the past decade, quite a few quant funds have gained tremendous success in the financial markets through their alpha portfolios. But does that mean an alpha can effectively predict stock prices? More specifically, can quants predict the price of a given stock on a given date in the future? Unfortunately, we probably cannot make single predictions with any reasonable confidence. It is the nature of statistical arbitrage that prediction is possible only in a "statistical" sense: only over a large number of predictions do random errors average out to a usable level of accuracy in the aggregate. More interestingly, there are many ways of making such statistical price predictions.

STATISTICAL ARBITRAGE

The key underlying assumption of statistical arbitrage is that the prices of financial instruments are driven by consistent rules, which can be discovered from their historical behavior and applied to the future. The prices of financial instruments are influenced by multiple factors, including trading microstructures, fundamental valuation, and investor psychology. Therefore, it is to be expected that various kinds of price-driving rules can be discovered and used to create alphas. As the prices of securities are determined by multiple rules, or factors, not every rule will apply to any particular instrument at any given moment.

A real price-driving rule – and a good alpha based on this rule – should appear to be predictive with statistical significance when applied

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to the collection of all investigated securities over all available trading days. A simple example is the well-known mean-reversion rule, which states that a stock's price will tend to revert to its average price over time. Within a stock market, it is still easy to find stocks whose prices keep going up or down in some periods, with the average price consistently trending in a particular direction. Yet aggregating over a collection of N stocks over M trading days, if N and M are sufficiently large, you will find more than 50% of these $N \times M$ sample points obeying the mean-reverting rule.

Furthermore, even though they are based on the same underlying price-driving rule, different alphas can be created as long as they use different implementations of the rule. For example, to take advantage of the mean-reversion rule, using a variety of methods to calculate the mean and diverse ways to define the tendency of reversion could result in different alphas, all of which could be profitable and relatively uncorrelated. It is important to distinguish between the essential constraints that define an idea and specific implementation choices. Consider the wheel. Wheels are commonly round, but why do they have to be round? The real restriction on the shape of a wheel is that it must be convex and planar, with constant width. Under this rule, it is possible to make wheels in shapes other than round, as explained by the theory of the Reuleaux triangle. Because different implementations often have different strengths and weaknesses, a good ensemble of implementations is generally more robust than any individual instance.

BACKTESTING

There are two basic ways of generating signals: through ideas or through data. In the idea-driven process, the seed of an alpha design idea can be a hypothesis, a paper, a story, an inspiration, or just a random idea. In the data-driven process, signals come from datasets collected in-house or from data providers, but any potentially valuable signals found must be verified. Most research follows some form of hybrid methodology: an initial idea is revised based on the data, or a new data source motivates a new direction of reading and research. For both methodologies, backtesting is a critical component of the process.

As in academic research, many assumptions are wrong and many trials futile. Only a few of them have the potential to generate consistent profits in the real environment. In many cases, a researcher will have a strong belief that a model will work but will find after testing that it does not – or, conversely, the initially skeptical researcher may find great empirical value in an idea discovered by serendipity or a contrarian hypothesis. The underlying force may be present in the market but have a weak effect that is outweighed by other factors, or the initial idea may simply be wrong because markets often behave counterintuitively.

Simulation and Backtesting

There are many possible methods to test the validity of a hypothesis, including:

- A Monte Carlo simulation, which simulates the various sources of uncertainty that are affecting instrument values to get a range of resultant outcomes.
- Pricing models, which calculate asset prices (for example, the Black–Scholes options pricing model).
- Explanatory models, which analyze what happened historically.

In our working environment, simulation means backtesting: the process of applying a specific model to unbiased historical data under certain market assumptions and risk constraints to test its simulated historical performance. The implicit assumption of backtesting is that if the idea worked in history, then it is more likely to work in the future. A model will generally not be considered unless it has been validated in simulation.

Backtesting results are used for preselecting models, comparing different models, and judging the potential value of such alphas. These results can be assessed using various measures, such as returns, Sharpe ratio (return over risk), turnover (trading frequency), and correlation with other alphas.

Good backtesting results are not sufficient for a profitable strategy, however; many other factors will affect investment performance. As a general matter, investors should not invest capital based solely on backtesting simulation results. Some of the reasons are:

- The current market may not be the same as the historical period. Market rules are always changing, the balance of market participants shifts over time, and new theories and new technologies can affect market behavior.

- The assumptions behind the simulation may not be realistic. To buy or sell assets, investors must execute trades that may affect the market, and they need to pay transaction costs or commissions. Reasonable estimates for those numbers are crucial when evaluating a simulation result.
- There could be possible forward-looking bias. If you saw someone following a trend and making a profit last year, you might think to test a trend-following model, and perhaps you could get a good historical simulation over the same year. Without a better understanding, you might or might not make a profit in future investments.
- It could be a case of overfitting. Sometimes investors see good simulation results that are simply due to random chance and have no predictive power.

OVERFITTING

The word "overfitting" comes from the statistical machine learning field. In the quant world, overfitting, or the apparent discovery of a price-driving rule that turns out to be incorrect, is an inherent risk in any backtesting framework. A spurious relationship may appear to be statistically significant in the historical data on which it was developed, then disappear in the future and never show up again. An alpha such as "Stocks with the letter 'C' in their tickers tend to rise on Wednesdays" is probably not a good one to invest in – even if it appears to have been profitable in the past.

This kind of phenomenon is frequently seen in a field closer to everyday life. An apparent "3,964" formula was discovered before the 2006 World Cup soccer competition. Argentina had won the championship in 1978 and 1986, years that added up to 3,964; Germany won in 1974 and 1990, which added up to the same number; Brazil won in 1970 and 1994, and again in 1962 and 2002. This formula looked beautiful until "statisticians" tried to use it to predict the 2006 championship. They contended that the World Cup would go to Brazil, which had won in 1958 – but it went to Italy instead. Not surprisingly, the "rule" also failed in 2010, when Spain became a new member of the champions' club. But instead of simply laughing at this false alpha, we can learn something sensible: among all the national teams, those that have won the championship tend to be more powerful than their rivals, so they may have a higher chance of winning again. The lesson is that purely playing with numbers may help you find some significant results, but to create good alphas it is important to recognize the underlying price-driving principle and separate it from spurious noise.

Every day, professional investors run huge numbers of simulations on historical data to seek patterns of price moves, using supercomputers, clusters, and now the cloud. The risk of overfitting, or the discovery of spurious relationships, is especially high given the enormous computational power of modern graphics-processing units. When you see especially good simulation results, you need to be careful to evaluate the overfitting risk of the models.

Suppose that a researcher is looking to identify at least one two-year-long backtesting period with an annualized Sharpe ratio higher than 1. If he tries enough strategy configurations, he will eventually find one even if the strategies are actually random, with an expected out-of-sample Sharpe ratio of 0. By trying a large enough number of strategy configurations, a backtest can always be fitted to any desired performance for a fixed sample length.

A signal can be defined as a strategy configuration whose last M days' daily PnL Sharpe ratio was higher than S. In Table 9.1, a minimal Sharpe requirement runs across the top and the number of random simulations within which one can expect to see a signal satisfying the requirement runs down the left column. The numbers are generated by: (1) randomly produced 1 billion-length M normalized distribution vectors; (2) checking how many of such random tries have absolute Sharpe ratios higher than S (if one signal has a very negative ratio, it can be flipped); and (3) calculating the expected number of simulations needed by dividing 1 billion by the number observed in no. 2.

Table 9.1 The number of backtest days required to meet various Sharpe ratio targets

		Target	Sharpe			
No. of days	0.5	1.0	1.5	2.0	2.5	3.0
20	1.12	1.27	1.46	1.70	2.00	2.38
60	1.24	1.59	2.12	2.97	4.32	6.58
120	1.37	2.03	3.28	5.82	11.31	24.14
250	1.61	3.11	7.29	20.87	73.45	317.53
500	2.07	6.25	28.34	196.60	2,104.14	34,698.13
1,000	3.13	21.39	345.77	13,700.13	1,340,483	500,000,000

HOW TO AVOID OVERFITTING

To reduce overfitting risks, multiple technologies have been proposed, such as ten fold cross-validation, regularization, and prior probability. Tenfold cross-validation is a process that breaks the data into ten sets of size *n*/10, trains the model on nine datasets, and tests on one, then repeats the process ten times and takes the mean accuracy. In statistics and machine learning, regularization is used in model selection to prevent overfitting by penalizing models with extreme parameter values. Recently, papers have been published on overfitting issues in the quantitative investment field, including Bailey et al. (2014a), Bailey et al. (2014b), Beaudan (2013), Burns (2006), Harvey et al. (2014), Lopez de Prado (2013), and Schorfheide and Wolpin (2012).

Borrowing concepts from the statistical machine learning field, here are some specific guidelines on how to avoid overfitting:

Test out of sample: To evaluate an alpha model, an out-of-sample test needs to be a true out-of-sample test. That is, we build a model, test it daily in a real environment, and monitor how it performs. It is not a true out-of-sample test if (1) models are backtested based on the most recent *N* years' data, then data from an earlier *N* year period is used as out-of-sample data; or (2) the model is backtested on a subset of the trading instruments and other instruments are used as out of sample. In the first case, the market history of the recent *N* years was influenced by prior history, so models that worked recently may also tend to work in that history. In the second case, different instruments are correlated; models with good performance in one universe tend to perform well in another.

Note: as the number of alphas being tested out of sample increases, the out-of-sample test becomes more biased. An alpha can perform randomly well due to luck. Out-of-sample performance at the single-alpha level is inadequate when many alphas are tested.

Increase the in-sample Sharpe ratio requirement: A higher Sharpe ratio reduces the risk of overfitting. If possible, it is better to test the model on a wider universe, where it should have a higher Sharpe, following the fundamental law of Sharpe ratios: the information ratio equals the information coefficient times the square root of breadth (Grinold and Kahn 1999). In the real world, unfortunately, there are often constraints on the total number of relevant tradable instruments or the subset of instruments covered by the dataset.

Test the model over a longer history: As Table 9.1 shows, lengthening the backtesting period decreases the probability of accidental overfitting. However, longer is not always better because data may not be available for a long enough period or the market may have changed too much for the older history still to be meaningful.

Cross-validate on different instruments: Good alpha models generally work across assets and regions. For example, equity models developed in the US can be applied to Europe and Asia.

Make the model elegant: An alpha is better if (1) it is simple and easy to understand; (2) it has a good theory or logic behind it, not just empirical discoveries; and (3) it can be explained and you can tell the story behind it. For example, "Alpha = returns" may have the potential to be a good model, but "Alpha = returns + $\Delta(\text{volume})$" does not. The latter would not work because you cannot meaningfully add two different units (for example, returns use dollars and volume uses a whole number, such as shares).

Minimize parameters and operations: As in machine learning, models with fewer degrees of freedom are less sensitive to parameter change. This can help reduce the overfitting risks. The added value of spending extra time on fitting parameters or operations is generally small and at a certain point becomes negative as the risk of overfitting outweighs the benefit of the improved fit.

CONCLUSION

The prices of financial instruments are driven by various rules and factors, which can form the basis of statistical arbitrage alphas. All alphas have failure modes, and no alpha works on all instruments under all conditions, but a reasonable combination of real alphas covering different aspects of true price-driving rules is more likely to result in successful profit-generating portfolios. Backtesting is necessary to develop and validate signals, but it runs the risk of overfitting. There are many ways to control the risk of overfitting; the all-encompassing idea is to find robust alphas that work as general principles and are not too sensitive to specific parameters or conditions.

Keep in mind that people glean ideas from academic research papers and sell-side research reports, but these papers and reports describe only good results; they cannot publish if the performance is not good enough. They don't say how many times they have tried, and they don't report failures. In many cases, their models cannot be reproduced.

In addition, financial markets have memory effects. Many quantitative investors are looking at the same historical data. Some patterns occur in history for no discernible reason or for reasons that are outside the scope of what quantitative models can handle. Such patterns can be captured by not just one but a large number of noise models. Trading such highly fitted patterns can push market prices against the model to lose profit, especially at large trade sizes.

10
Controlling Biases

By Anand Iyer and Aditya Prakash

INTRODUCTION

Investment biases have been well studied, as is clear from both the academic literature and the field of behavioral finance, which is dedicated to understanding them. Although a quantitative investment process offers investors a means of managing and arbitraging such biases, many quantitative portfolio managers wind up introducing bias, systematically or otherwise. This chapter is a practitioner's reflection on how to control bias and is aimed at quantitative portfolio managers and researchers.

We start by identifying two categories of bias, then explore various types of bias that exist within these categories. We conclude with some practical suggestions for quantitative practitioners and firms.

CATEGORIES OF BIAS

We broadly categorize bias as systematic or behavioral. Investors introduce systematic bias by inadvertently coding it into their quantitative processes. By contrast, investors introduce behavioral bias by making ad hoc decisions rooted in their own human behavior. Over a period of time, both systematic and behavioral bias yield suboptimal investment outcomes.

SYSTEMATIC BIASES

There are two important sources of systematic bias: look-ahead bias and data mining.

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Look-Ahead Bias

In a simulation or backtest, when a signal or investment strategy at a given point in time uses data from a future point that would not have been known or available, it introduces look-ahead bias. This often makes the simulation results appear better than they actually are. Although it is well understood, look-ahead bias is surprisingly prevalent in the quantitative arena.

Look-Ahead Bias in Timestamping

One of the key causes of look-ahead bias is poor timestamping of data. Every datum should be dual timestamped with the occurrence datetime and the arrival datetime. The occurrence datetime identifies when the event associated with the data occurred. For example:

Analyst XYZ upgraded stock PQR to a buy on 20171017 10:00:00 EST

The arrival datetime is when the researcher received the information of the aforementioned event from the data distributor or vendor. For example:

Vendor ABC delivered information of the above analyst upgrade on 20171018 15:00:00 EST

Any signal keyed off the occurrence datetime instead of the arrival datetime will ignore the real-world delays associated with getting the data, which may result in unrealistic simulations.

In quantitative parlance, dual-timestamped data is also called point-in-time data. Many time series, such as GDP estimates, are subject to frequent revisions by the economists gathering and analyzing the data. Data vendors may also correct data errors over a period of time. In all such cases, dual timestamping reconstructs the data available at a point in time so that an accurate simulation may be conducted for that point in time.

Another form of poor timestamping relevant to global strategies is the failure to record the time zone in which the data is timestamped. This is especially relevant for strategies that trade different time zones simultaneously – for example, London and New York. Simulations of signals that trade simultaneously across different time zones can be accurately reconstructed by normalizing the data datetimes across time zones to a single time zone.

Last, quantitative portfolio managers rely on data vendors. Any look-ahead bias introduced in the vendor's own data collection and dissemination process can make it into an investment model. Therefore, quantitative investors should accept only historical data that is dual timestamped and thoroughly vet any data source that is subject to frequent revisions. Models should be tested for consistency between the vendor's in-sample period (before it began delivering the data in real time) and the subsequent out-of-sample period.

Look-Ahead Bias in Machine Learning

Researchers using machine learning techniques also can introduce look-ahead bias. In particular, they may tune some hyper-parameters on the entire data sample and then use those parameters in the backtest. Hyper-parameters should always be tuned using only backward-looking data. Similarly, in the area of sentiment analysis, researchers should take note of vendor-supplied sentiment dictionaries that may have been trained on forward-looking data.

Data Mining

A researcher may data mine a signal by tinkering with its construction until it has favorable in-sample performance; this is commonly called overfitting. The standard approach to controlling data mining involves a holdout, which withholds data in the simulation and takes one of two broad forms: a time-series holdout or an asset holdout. In a time-series holdout, researchers do not conduct the backtest on a given section of time. Similarly, in an asset holdout researchers do not conduct the backtest on a certain set of assets. After the holdout is incorporated into the backtest, a separate backtest is conducted solely on the holdout to validate whether the performance is consistent.

There are two common approaches when using a time-series holdout:

1. Omit a continuous stretch of time. Typically, this is toward the end of the time series.
2. Hold out several interleaved stretches of time within the entire backtesting window. For example, hold out periods every alternate week within that window. When using interleaving, we need to ensure that any seasonality or autocorrelations in the data do not bias our results.

For an asset holdout, we have to make sure that the holdout sample of assets has the same broad characteristics as the overall asset universe. There should be no country, industry, size, or liquidity bias in the holdout relative to the overall asset universe. The holdout sample should be relatively independent of the other assets; if they are highly correlated, the holdout is of limited value.

Data mining carries the risk of formulation bias, which relates to the choice of which signal formulation to use on the same set of data. For example, should a momentum signal consume 3, 6, or 12 months of price returns data? Should a signal that consumes historical trading volume data use mean historical volume or its root-mean-squared historical volume? Although signal characteristics such as turnover and an in-sample Sharpe ratio can help drive formulation decisions, it is hard to tell which formula will work best out of sample. One mitigating approach is to diversify across formulations by mixing them using some unbiased weighting scheme, such as equal weighting or risk parity weighting.

BEHAVIORAL BIASES

There are several behavioral traps that are germane to the quantitative investment space, as detailed below.

Storytelling

Quantitative researchers and portfolio managers are at risk of storytelling, the tendency to fit an unverifiable story to justify performance. A researcher may explain the sensibility of a signal based on a theory – a phenomenon called theory-fitting. A researcher may also make a claim that is correct for a given sample window but falls apart outside that window – say, that mean-reversion signals don't work for French stocks. Similarly, portfolio managers may attempt to explain portfolio drawdowns based on redemption flows among correlated managers without rigorously validating this hypothesis. If they reshape their portfolios based on a biased story, they simply incur additional costs and degrade investment performance.

Confirmation Bias

Confirmation bias is the tendency to believe information that aligns with the practitioner's prior probability distribution and to disbelieve its opposite. The availability of unverifiable information on the internet to support almost any set of priors makes it easy to fall prey to this bias. For quantitative researchers, a classic trap is the fallacy that the latest research is the greatest. Buzzwords, especially those espoused by the larger investment community, also feed confirmation biases.

Familiarity Bias

Familiarity bias is the tendency to invest in familiar assets. Research shows that individual investors have a tendency to invest in companies with geographical proximity. For example, an investor is more likely to invest in technology stocks if she is based in Silicon Valley. Though this goes against the grain of the quantitative investment approach, which is grounded in diversification, quantitative investors may unknowingly introduce this bias into their models. Many practitioners construct universes using the familiar S&P 500 constituents instead of a broader universe of potentially unfamiliar names. Another form of familiarity bias is to pursue exclusively a certain style of signals, such as statistical arbitrage, factor- and event-driven strategies, and so forth.

Narrow Framing

Narrow framing is the tendency to make investment decisions without considering the larger portfolio. One example is a portfolio manager who shifts capital allocations without considering overall correlations and associated costs. Another example is a portfolio manager who changes models amid, and in response to, a drawdown.

Availability Bias

Availability bias is the tendency to judge a future event as more likely given a recent memory of a similar event. Consider the portfolio manager who, on the eve of the U.K.'s Brexit vote, surmised that Brexit would not happen because Greece's Grexit never did. Similarly, a quantitative investor may overallocate to a strategy based on its recent outperformance.

Herding Bias

Herding is the propensity of investors to crowd into the same positions and has been identified as a key driver of financial bubbles. Quantitative investors in particular are known to have high correlation with one another, suggesting that herding bias may be incorporated in their models. This likely happens because many investors use similar data sources to construct similar investment strategies inspired by the same academic research. Although it is easier said than done, the best way to guard against this bias is to have differentiating investment research.

CONCLUSION

Biases, while impossible to eliminate, can be better controlled by personal awareness. Portfolio managers should control their behavioral biases by committing to reduce ad hoc intervention, especially amid drawdowns, when the tendency to act on a bias is most pronounced. Writing up a drawdown playbook beforehand can be an effective solution. Similarly, researchers need to restrain behavioral biases around their own recent work. Containing systematic biases, by contrast, requires a sustained commitment of time and technological sophistication to ferret out look-ahead bias and overfitting.

11
The Triple-Axis Plan

By Nitish Maini

The world of quantitative investing is growing extremely rapidly. Quants are developing new ways of predicting market fluctuations by using mathematics, computer programming, and an ever-proliferating array of datasets. Discovering new alphas can be a formidable challenge, however, particularly for new quants. An efficient exploration of the vast universe of possible alphas – what we call the alpha space – requires a structured strategy, an anchoring point, and an orientation technique, otherwise known as the Triple-Axis Plan (TAP).

TAP can help new quants define the alpha space by providing a framework for conceptualizing the search for alphas. It can also help more-experienced quants, who have the ability to define the entities that constitute each axis and then analyze existing alphas in their portfolios, to target their efforts with greater efficiency.

New quants can easily be overwhelmed by the challenge of trying to develop alphas. They ask themselves, "How do I find alphas? How do I start the search?" Even experienced quants working with many alphas can miss key components required to build a robust, diversified portfolio. For instance, one of the most difficult aspects of alpha portfolio construction is the need to optimize the level of diversification of the portfolio. In automated trading systems, decisions on diversification make up a major area of human intervention. It's not easy to visualize the many pieces of the portfolio, which contain hundreds or thousands of alphas, and their interactions.

TAP emerged from those concerns. When new quants start conducting alpha research, many begin by searching the internet for articles about developing alphas. Most of those articles focus on reversion and momentum, and as a result, beginners may initially spend a lot of time building reversion or momentum alphas. But as new quants grow more skilled, they begin to wonder whether they are actually creating much value when they add a new alpha to their portfolios. Though they think they are

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diversifying their portfolios, they may just be developing the same kinds of alphas over and over again. Although they may appear to have low correlation, variants of the same alpha types tend to have the same failure modes and do not provide the full benefit of a truly diversified portfolio.

Nearly everyone falls into this trap when they begin to research alphas. Every successful quant has a gold mine; he digs deeper and deeper in his mine to extract as much as he can. One person develops a very strong momentum site; another has a very strong fundamental site; a third builds a very strong reversion site. They often forget, however, that there are multiple gold mines out there. After they play out one area, they need to move on to find and explore other mines.

TAP is really just a tool to organize the complex, multidimensional alpha space. It offers a number of advantages for portfolio diversification. The alpha space is vast, with a high and growing number of degrees of freedom, and there is an almost unlimited number of possible alphas, with each region or cluster of alphas possessing different topographies that require discovery and exploration. A quant has a plethora of choices. She can make predictions to trade over intervals ranging from microseconds to years. She can make predictions on different asset classes, most commonly equities, bonds, commodities, and currencies. But the set of possible elements that a quant can manipulate is growing all the time – more datasets, more parameters, more ideas.

With the available data expanding at such rapid rates – in fact, *because* there's so much data – it is important to develop a plan to organize this complex landscape that has a reasonable probability of success. Every successful quant needs a strategy to identify viable signals within a world of noise, to target specific regions within the possible universe, and to select the kind of data and the specific financial instruments that are most appropriate to the purpose. You need a model to structure your search. TAP is such a model.

The motivation behind TAP was the need to generalize individual alphas to the widest possible family of analogous alphas. Three particularly useful categories, or axes for generalization, are Ideas & Datasets, Performance Parameters, and Regions & Universes.

THE TAP

The process of searching for alphas in this complex landscape can vary widely as a function of the ideas behind the alphas and the desired objective function, which may include attributes of the signal, such

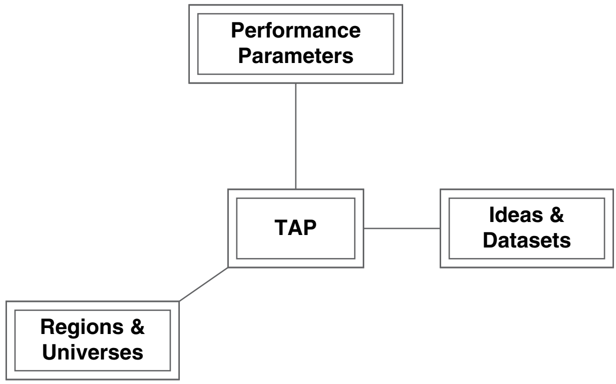

Figure 11.1 The three axes of the Triple-Axis Plan

as turnover, trading frequency, or universe of tradable instruments. To make this easier to visualize, TAP structures alphas within an asset class in a three-dimensional space (see Figure 11.1).

The ideas used to develop alphas may range from traditional indicators, like reversion, momentum, or pairs trading; to less common ones, like machine learning, lead-lag, or seasonality. With increasing computing power, the number of datasets that we can use to implement these ideas has grown so much that we can measure the diversity of a pool of signals by the number of different datasets used. The most widely used datasets include price and volume data, company fundamentals, analyst recommendations, stock sentiment, social media, and options, but there are many others.

These ideas can be generated and implemented on different groups of financial instruments in different regions. The market capitalization of individual stock exchanges and the regulatory environment in a specific region or country usually define the choice of region for a quant. The US and Europe have traditionally seen the heaviest trading, although Asian markets have attracted increasing interest in recent years. Trading instruments may be defined in terms of their liquidity, classification characteristics like sector or industry, or other criteria, depending on the alpha idea.

To seek success under different market conditions, a quant can construct a diverse, robust portfolio by developing alphas that try to achieve one or multiple objective functions, usually related to attributes that explain their performance. Quants aim to generate profits by maximizing the Sharpe ratio and returns or by minimizing drawdowns and trading costs. The TAP approach is one way to orient yourself in this world, with each axis providing a different lens through which to focus your

Table 11.1 Some of the ideas, datasets, regions, universes, and performance parameters that TAP spans

The three axes		
Ideas & datasets	Regions & universes	Performance parameters
Ideas • reversion • momentum • seasonality • learning • lead-lag	**Regions** • US • Europe • Asia (Japan or ex-Japan) • Americas • global	• high returns • high Sharpe ratio • lower costs • lower drawdowns
Datasets • fundamental • analyst • sentiment • social media • options	**Universes** • can be defined using the liquidity profile, such as TOP50, TOP100, TOP200, TOP1500 • any particular sector or industry • any selected instrument or group of instruments	

research. Many elements can be added to each axis, depending on the approach. Table 11.1 provides a simplified schematic of the three axes. The possible constituent entries in each axis can be much more extensive, of course.

IMPLEMENTING TAP

TAP employs a relatively simple, mechanical process that both reflects and organizes the complex financial reality of alpha space. It allows a strategist to fill in the blanks on the three axes, thus revealing possible missing components of the portfolio.

TAP operates on three levels. The first involves identifying an initial area to focus on. The user can start with a relatively generic focus on a single axis – say, on momentum as an idea; or on a particular regional area, like the US or Europe; or on performance parameters such as a high Sharpe ratio or minimal drawdowns. The second level involves refining the focus by systematically filling in the elements of the other axes. TAP allows the quant to choose a target on one axis and maintain the flexibility to manipulate the other two axes. Working on each target independently helps the quant develop skills and gather the knowledge necessary to build alphas in that area. The third level involves execution: implementing the algorithm in code, testing the initial idea, and then going back to refine the basic concept by working across the three axes.

Consider this relatively simple example. Suppose that a quant is exploring ideas that might work in a predominantly liquid universe of stocks. He chooses to focus first on the Regions & Universes axis and selects the liquid universe – the top 500 or 300 companies in the US. Later, to diversify geographically, he will need alphas and strategies for Asia and Europe as well as the US. This should be relatively easy because after already developing momentum and reversion alphas and becoming familiar with the properties of liquid universes, it is natural to apply this knowledge to Europe and Asia. At the same time, the researcher realizes that it is not enough to focus only on reducing the cost of the alphas or increasing their Sharpe ratios; it is also important to generate high returns. Getting higher returns, however, often requires a trade-off against the effects of the other parameters. Thus, it takes a higher level of skill to seek higher returns. Now the quant can iterate again through his previous work and continue aiming to develop a high-return momentum alpha, a high-return reversion alpha, and a high-return liquid alpha.

To achieve a desired level, diversification requires systematically mastering the use of TAP's three axes:

- The choice to focus on a momentum alpha freezes the Ideas & Datasets axis. In this case, the next steps are to diversify on the other two axes by choosing different Regions & Universes of financial instruments to develop momentum alphas, and to target alphas to optimize different kinds of performance parameters.
- Similarly, the choice to develop an alpha on the US financial sector fixes the Regions & Universes axis but retains the flexibility to use different ideas or datasets to optimize different performance parameters.
- The choice to develop a high-return alpha fixes your Performance Parameters axis, leaving the flexibility to vary the other two axes on any kind of dataset, idea, region, and universe to seek the desired return target.

The complexities of financial markets allow for a vast range of granularity and precision, which are what provide richness to the alpha space and excitement to the challenge of finding new alphas. It is important to recognize that there is no single fail-safe solution. The world of finance is shaped by idiosyncratic differences among individuals' valuations of assets, returns, and risk. Therefore, potential value lies in exploring the known landscape as extensively as possible, even in areas often dismissed as noise; they could potentially turn out to be infinite sources of knowledge. The quant just needs to make deliberate choices about where to begin that search and how to organize the effort.

CONCLUSION

TAP is a tool that visualizes the various dimensions that affect alpha performance. As a result, it can provide a quant with greater clarity and insight into the complex alpha space. TAP is not a secret weapon that ensures success, but it does help less experienced quants begin their search and understand the underlying issues, and it helps more-experienced strategists enhance the diversification of very complex portfolios of alphas. To be most effective, TAP should be integrated into all the necessary steps of alpha development, refining, testing, and execution.

12
Techniques for Improving the Robustness of Alphas

By Michael Kozlov

INTRODUCTION

The main goal of alpha research is to predict and try to outperform the market. However, most investors desire not only returns but also low risk exposure and some confidence in their ability to anticipate trading results. With these requirements in mind, we have defined a robust alpha.

A robust alpha should have the following properties:

- **Invariance** under modification of the traded universe: An alpha should reflect a statistical property that is independent of the choice of specific instruments to trade. Changes to the instrument set are frequently imposed by the market as a result of regulatory changes, customer preferences, liquidity decreases, short bans, etc.
- **Robustness** to extreme market conditions: An alpha should not have excessively sharp declines in any of its performance benchmarks. The most common benchmarks used for alpha performance measurement include information ratio, maximum drawdown, and return.

METHODS FOR ROBUSTNESS IMPROVEMENT

In this section, we will introduce the most common and established techniques for improving the robustness of an alpha. In general, our goal is to ensure stable alpha performance that is not unduly affected by input data outliers or other small departures from model assumptions.

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Methodologies for robustness improvement can be classified into three categories: ordering methods, approximation to normal distribution, and limiting methods. Below we will discuss all three methods in detail.

Ordering Methods

The powerful motivation for applying ordering methods in alpha research is to improve the alpha property of invariance, meaning that the test results do not change when the input data or traded universe is transformed in some way.

An ordinal scale of measurement is one that conveys order alone. These scales indicate only that one value is greater or less than another, so differences among ranks do not have meaning.

Generally speaking, ordering-based procedures are a subset of nonparametric methods, which in many circumstances have advantages in robustness over parametric methods. They are preferred when certain assumptions of parametric procedures (for example, t- and F-tests) are grossly violated. That may happen, for example, when the normality assumption is not satisfied by a dataset with extreme outliers. In addition, alphas based on nonparametric methodologies by nature require fewer assumptions and control parameters than their parametric alternatives.

Ranking: Ranking is an operation that replaces a vector's elements with their ranks under some sorting criterion. Usually, the elements of the vector are rescaled to be in the interval [0,1]. If two values are the same, they are supposed to have the same rank, equal to the average of their corresponding positions.

Ranking can be used to define the Spearman's rank correlation (Spearman 1904). In many cases, the Spearman correlation is much more stable than the Pearson correlation measure (Pearson 1895). For instance, the Pearson correlation is known to be unstable for nonstationary and/or nonlinear inputs.

It is obvious that any statistics based on the ranks of the data must be invariant to monotone transformations because such transformations do not affect the relative rankings of observations. Thus, rank-based statistics do not depend on whether the outcome is measured on the original scale or on any other arbitrary scale.

Quantiles approximation: Quantiles are points taken at regular intervals from the cumulative distribution function of a random variable. Splitting a set of ordered data into equal-size data subsets is the motivation for q-quantities; the quantities are the data values marking the boundaries among consecutive subsets.

For example, ordinary least squares regression may be unstable for nonstationary and/or nonlinear inputs. However, it can be replaced by least quantile of squares (LQS), in which the objective is to minimize some quintile of the squared residuals. Among the various LQS methods, the most popular is median squares minimization.

Approximation to Normal Distribution

The normal distribution is the random variable distribution defined by the following probability density function:

$$f(x \mid \mu, \sigma^2) = \frac{1}{\sqrt{2\pi\sigma^2}}\; e^{-\frac{(x-\mu)^2}{2\sigma^2}}$$

where μ is the mean of distribution, σ is the standard deviation, and σ^2 is the variance. The normal distribution has special importance in statistics because of the so-called central limit theorem, which states that under certain conditions the sum of many random variables will have an approximately normal distribution.

We will illustrate several methods of transforming an arbitrary distribution function to an approximately normal distribution function. When the underlying distribution is roughly normal but contaminated with outliers and heavy tails, the following robust methods can help maintain stable performance, even under extreme market conditions.

Fisher Transform formula: Assuming that a random variable x is bounded by 1, the Fisher Transform can be defined as follows:

$$F(x) = \frac{1}{2}\ln\left(\frac{1+x}{1-x}\right) = \operatorname{arcth}(x)$$

If *F(x)* is the Fisher transformation of x and N is the sample size, then *F(x)* approximately follows a normal distribution with standard error $1/\sqrt{N-3}$.

Z-scoring: Z-scoring of data results in a distribution with zero mean and unit standard deviation. The Z-score is defined as follows:

$$Z = \frac{x - \mu}{\sigma}$$

In other words, the Z-score represents the distance between the raw score and the population mean in units of the standard deviation.

Limiting Methods

Extreme values can have a significant and generally harmful effect on the statistical properties of observed quantities. Therefore, one aim of robust methods is to reduce the impact of outliers.

Trimming: With trimming, we simply remove a certain fraction of the data above or below some threshold.

Winsorizing: Winsorization is a transformation that limits extreme values in the data to reduce the effect of possibly spurious outliers, as originally suggested by Hastings et al. (1947) and later argued more systematically by Rousseeuw and Leroy (1987). Winsorizing is similar to trimming, but we replace the extreme values with cutoff values rather than throwing them out.

Let us illustrate how trimming and winsorizing will affect the calculation of simple estimators on a sample set of numeric data $\{3,5,7,10,100\}$. Consider the mean, median, k-trimmed mean, and k-winsorized mean as defined below.

a. mean: arithmetic mean of sample data

$$\text{mean} = (3 + 5 + 7 + 10 + 100) / 5 = 25$$

b. median: the value separating the higher half of a data sample from the lower half

$$\text{median} = 7$$

c. k-trimmed mean: trim a given proportion α from both ends of the dataset and then take the mean.

$$20\% \text{ trimmed mean} = (\ 5 + 7 + 10) / 3 = 7.33$$

d. k-winsorized mean: replace a proportion k from both ends of the dataset by the next closest observation and then take the mean.

$$20\% \text{ winsorized mean} = (5+5+7+10+10)/5 = 7.4$$

From the above example, we can see that both the k-trimmed mean and the k-winsorized mean are much more stable with regard to outliers than the arithmetic mean. The k-trimmed mean and the k-winsorized mean are also very close to the median, which is a well-known robust estimator.

All of the above estimators (mean, median, k-trimmed mean, and k-winsorized mean) can be considered particular cases of L-statistics, or linear combinations of order statistics. For example, for particular sample values the smallest order statistic is the minimum of the sample: $X_{(1)} = \min\{X_1, \ldots, X_n\}$, and the largest order statistic is the maximum of the sample: $X_{(N)} = \max\{X_1, \ldots, X_n\}$. The kth order statistic is the kth data point when the points are ordered.

CONCLUSION

As argued by Bertsimas et al. (2004), robust methods can significantly improve several benchmarks that measure alpha behavior in extreme market conditions. These days, more and more practitioners are exploiting the advantages offered by robust methodologies developed over the past decades. Most standard statistical software packages include a variety of tools for robust data analysis.

It's important to remember that robust methods assume that the underlying distribution is roughly normal but contaminated with outliers and heavy tails. The methods can produce misleading results if they are applied to data that is inherently skewed or if a large proportion of the data is identical in value.

For further details about robust methods, refer to *Robust Statistics* by Peter J. Huber and Elvezio M. Ronchetti (2009).

13
Alpha and Risk Factors

By Peng Wan

In this chapter, we will review the practice of seeking alphas from a historical perspective. We will examine a few well-studied alphas and observe that some evolve to become "hedge fund betas," or risk factors.

Building on Markowitz's work (1952) on the expected returns and variance of returns of a portfolio, Treynor (1962), Sharpe (1964), Lintner (1965), and Mossin (1966) developed the capital asset pricing model (CAPM) in the 1960s. According to CAPM, a stock's expected return is the investor's reward for the stock's market risk:

$$\text{Expected return} = \text{Risk-free rate} + \text{Stock's market beta} * \text{Market risk premium}$$

Since its birth, CAPM has been challenged for its restrictive assumptions and inconsistency with empirical data. The arbitrage pricing theory (APT), developed chiefly by Ross (1976), does not require the stringent assumptions of CAPM. APT states that in a market with perfect competition, a stock's expected return is a linear function of its sensitivities to multiple unspecified factors:

$$\text{Expected return} = \text{Risk-free rate} + \sum \left(\text{Stock's factor beta} * \text{Factor's risk premium}\right)$$

CAPM and APT provided the theoretical foundation of stock return analysis and alpha evaluation. In practice, the factors in APT can be constructed as stock portfolios, and most of them can be constructed as both dollar-neutral and market-beta-neutral portfolios. Each of these beta-dollar-neutral factors can be evaluated as a potentially tradable alpha.

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In the 1980s, several important factors were reported. Banz (1981) documented the size factor, which says that small-cap stocks tend to outperform large-cap stocks. Basu (1983), as well as Rosenberg et al. (1985), published various forms of the value factor, including earnings to price ratio (E/P) and book equity to market equity (BE/ME). Fama and French (1992, 1993) analyzed multiple documented factors that could explain stock returns and summarized them as the Fama–French three-factor model; the model cites market risk, size, and value factors. It's worth mentioning that investment managers may have profited from these factors before academics analyzed them in a theoretical framework. For example, value investing was promoted by Benjamin Graham and David Dodd in the 1930s, well before modern portfolio theory was formulated. As another example, the Magellan Fund had high small-cap exposure in the early 1980s, when Peter Lynch was the fund's manager (Siegel et al. 2001).

The Fama–French three-factor model did not end the search for factors. Instead, in parallel with the rapid expansion of the quantitative investment industry, researchers published many more factors; Fama and French tried to absorb some of them into the Fama–French five-factor model (2015). Besides the market risk, size, and value factors, the new model added profitability and investment. The profitability factor says that stocks with more robust operating profitability, such as high gross profits to assets, have higher expected returns. The investment factor says that, all else being equal, more conservative reinvestment of company earnings (i.e. issuing dividends and/or buying back stock) implies higher expected returns of the stock.

Not absorbed into Fama and French's expanded model were a number of important factors, such as the momentum effect that recent winners tend to outperform recent losers (Jegadeesh and Titman 1993), the liquidity effect that less liquid stocks have higher expected returns (Amihud and Mendelson 1986; Pástor and Stambaugh 2003), and the accrual anomaly that higher accruals in accounting are associated with lower expected returns (Sloan 1996).

These and other well-studied risk factors have played important roles in the theory and practice of finance. Any alpha we find may unintentionally load some risk factors because they are expected to continue to drive a large portion of the relative returns of stocks in the future. For instance, a raw alpha built from news sentiment may load the momentum factor because news writers get excited by high-flying stocks, even if the alpha construction does not involve any of the price information from which the original momentum factor was built.

It is hard to tell whether each factor is the result of irrational investor behavior or the reward for bearing some systematic risk. For practitioners, it may be more important to know whether these factors' risk premiums will persist in the future. Unfortunately, this is also hard to predict, but we might get some insights from the adaptive market hypothesis (AMH), which was proposed by Andrew Lo (2004) to reconcile financial theories based on the efficient market hypothesis with behavioral economics. AMH does not view the market as being in equilibrium. Instead, it tries to explain market dynamics by evolutionary processes. It compares profit opportunities in the market to food and water in a local ecology, for which different species compete. Drawing insights from evolutionary processes, AMH predicts that the risks and rewards of market opportunities are unlikely to be stable over time and that investment strategies may wax and wane. Opportunities may disappear, then reappear years later. Lo's hypothesis implies that in a competitive environment the best opportunities are likely to be available for only a short time before other "animals" find them. In the adaptive market, the wide publication of these factors could change their behavior in the future because market participants would act on the newly broadcast information.

As an example, Figure 13.1 shows the long-term cumulative return of a value factor. (The factor is constructed by shorting the bottom 30% of US stocks ranked by BE/ME and buying the top 30% ranked by BE/ME. The monthly return series were downloaded from Kenneth French's website, http://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html#Research.) The factor achieved positive returns over the long term but occasionally suffered big losses, including after the late 1990s tech bubble and during the 2008 financial crisis. Another observation is that the annualized Sharpe ratio was 0.56 between 1950 and 1989 but only 0.11 between 1990 and 2017; this may be a sign that the wide publication of the factor changed its behavior.

In our research process, we need to be aware of a few issues concerning these risk factors:

- As we have discussed, their Sharpe ratios cannot be high, given how well known they are. Smart money could quickly pile in until the performance became less attractive.

Figure 13.1 Long-term cumulative return of a value factor (1950–2017)

- Some of these risk factors, such as size and liquidity, require a large imbalance of liquidity between the long and short sides of factor expression. This is not desirable in actual trading and is also a concern for risk management because it would be difficult to liquidate both sides in a balanced way, particularly under market crisis conditions.
- These risk factors generally realize higher volatility per dollar size. They may suffer long-term drawdowns as a result of macro trends. Moreover, there is a trend in the industry to package some of these risk factors as alternative beta products, which may increase their volatility in the future. Figure 13.2 shows the long drawdown caused by the market reversal in 2009 of a momentum factor, as calculated by French and his team.
- The well-studied risk factors are popularly implemented by many firms across the quant investment industry. If some large holders suddenly deleverage their holdings, the price impact may be high enough to force others to follow and thus exacerbate the losses. This danger was most vividly demonstrated in the August 2007 "quant crisis": popular quant risk factors suffered large losses, most likely as a result of some large players' aggressive unwinding (Khandani and Lo 2007). Figure 13.3 shows the sudden loss of a hypothetical quant factor during the 2007 crisis. The factor is constructed by combining the momentum and value factors. The daily return series for the construction were downloaded from French's website, and the combo factor

is leveraged to target 10% annualized volatility. The way to avoid this kind of catastrophic risk is to be different from others and to control the exposure to common risk factors.

Therefore, even though these well-studied market effects may continue to generate positive returns in the long run (for either rational risk-rewarding reasons or irrational investor behavioral reasons), we tend to call them hedge fund betas, or risk factors, rather than alphas in our research process.

Figure 13.2 Cumulative return of a momentum factor (2008–2012)

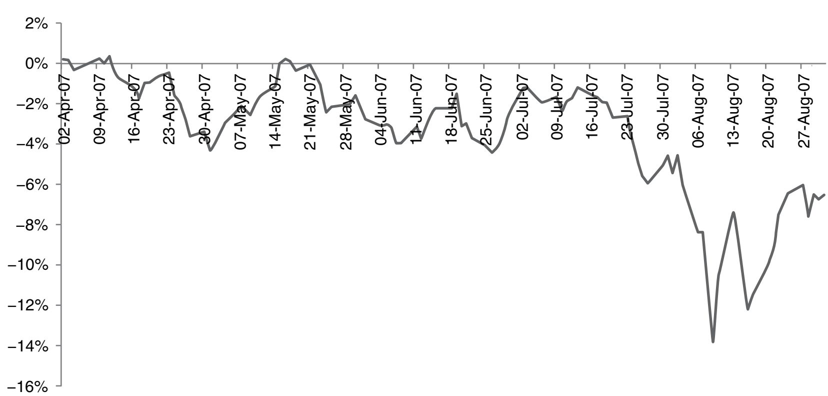

Figure 13.3 Cumulative return of a hypothetical factor during the 2007 quant crisis

From a historical perspective, there is not a clear distinction between alphas and hedge fund betas. The transition has been part of the evolving process of the adaptive market. In the era of CAPM, any market anomalies, such as the size and value factors, might have been considered alphas. After the Fama–French three-factor model was widely adopted, the momentum factor was still an alpha. Nowadays, however, more "alphas" have evolved to become hedge fund betas, or risk factors.

In the process of new alpha research, it is better to avoid high loadings of risk factors. We can evaluate the strength of an alpha by neutralizing these factors. The most common way is to perform a multivariate regression on the alpha portfolio against the risk factor portfolios. A good alpha tends to yield a higher Sharpe ratio after risk factor neutralization, even though its per-dollar return may be reduced in some cases. As an example, Table 13.1 shows the impact of this factor neutralization process on a hypothetical alpha built with Bloomberg price–volume data for 3,000 stocks traded in the US. The alpha is constructed as a dollar-neutral long–short portfolio of fixed size, for the period from January 2011 to December 2016. Before factor neutralization, the original alpha had an annualized average return of 16.8% (relative to the long-side size of the alpha) and an annualized Sharpe ratio of 1.55. We performed factor neutralization with three Barra USE3S (a US equity risk model) risk factors: momentum, size, and value. After each operation, the per-dollar return was lower and the Sharpe ratio was higher. The Sharpe ratio was highest after simultaneous neutralization of the three factors.

In summary, finding alphas is a constantly evolving process in a competitive market. Some alphas may become less powerful over the years. Because of the risks involved, it is wise to avoid high loadings of risk factors in our portfolios.

As predicted by the AMH, innovation is the key to survival.

Table 13.1 Example of factor neutralization on an alpha

	Annualized return	Annualized volatility	Sharpe ratio
Original alpha	16.8%	10.9%	1.55
Neutralized momentum factor	13.3%	7.4%	1.79
Neutralized size factor	14.4%	8.1%	1.77
Neutralized value factor	14.6%	8.1%	1.81
Neutralized all three factors	13.4%	7.3%	1.84

14
Risk and Drawdowns

By Hammad Khan and Rebecca Lehman

Finding alphas is all about returns over risk. Everyone knows what returns are, but what is risk? Researchers often conflate different types of risk, which require different forms of measurement and control. In truth, the set of potential types of risk is unbounded. At the far end are Knightian uncertainty and black swans – risks that are a priori unknowable but can be rationalized and overfit after the fact. The only constructive thing that can be said about these risks is that they exist and any attempt to rationalize them after they have occurred is an exercise in futility. Overly complex risk models may contain epicycles upon epicycles that are intended to mitigate the last black swan event but will do nothing for the next one except make the models more brittle. Slightly closer to home are asset-specific and operational risks, which the practitioner can and should take into account but are not amenable to a broad treatment. This chapter will focus on the near end of the risk spectrum – the most well defined and commonly considered types, which can be broadly classified as extrinsic and intrinsic risks.

Many alphas are exposed to extrinsic, or external, factors that are not related to their source of returns, such as the behavior of a given industry or the market as a whole. Other risk factors include alpha strategies that have been largely arbitraged away but are still highly traded and prone to momentum periods and liquidation runs, such as the Fama–French and Barra factors. These factors constitute extrinsic risk to the alpha, which can be partially or completely neutralized without destroying performance. One special type of external danger is event risk, when the usual drivers of an alpha's performance are temporarily outweighed by some external factor, such as a sudden news announcement, which may or may not be anticipated. But even after neutralizing all known external factors, an alpha still contains its own intrinsic risk, and that is what ultimately drives its return, assuming limits to arbitrage. Although

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intrinsic risk cannot be eliminated, it can and should be estimated and controlled. Different measures of intrinsic risk – such as volatility, value at risk, and expected tail loss – can be used to select the appropriate level of leverage or capital allocation for each alpha. One type of intrinsic risk that is particularly challenging to estimate is drawdown risk. For many investors, drawdowns are critical – perhaps even more important than historical volatility – because excessive drawdowns pose a risk to their firms' continued operations. Drawdowns are particularly difficult to estimate empirically because they are nonlinear and more likely to be overfit in sample than other risk measures, such as volatility and value at risk. Because of their practical importance, however, it is worth discussing some techniques for predicting and controlling them.

ESTIMATING RISKS

Position-Based Measures

The simplest and perhaps most robust risk estimates for an alpha are based on its current positions. These are easy to compute and do not rely on any assumptions about the alpha's future behavior, but they tend to be brittle and measure only extreme risk. The extrinsic risks associated with concentration in a particular security, group of correlated securities, or factor quantiles can be measured by position concentrations. Excessive concentration is a risk, as the alpha can expect severe losses if its prediction for the returns of the highly concentrated position is wrong.

The risk associated with a factor, given in the form of an alpha vector, can be estimated by the orthogonal projection of the alpha onto that vector. If a news event is expected to affect a certain set of instruments, the event risk can be measured as the exposure to those instruments. Another position-based approach to factor risk is to run a regression of the historical returns of the given positions against the historical returns of the factors. The beta coefficients, or factor loadings, define the risk associated with those positions.

The intrinsic value at risk of a given set of positions is simply the p percentile loss in the returns distribution of the given set of positions (usually $p = 5\%$ or 10%), and the expected tail loss is the average loss, conditional on being below the p percentile. It is possible to calculate the value at risk of each individual position (making no assumptions about the correlation between positions) and of the overall portfolio (making the implicit assumption that the correlation structure of the instruments is stable).

Historical PnL-Based Measures

A smoother risk estimate can often be obtained by looking at the performance of an alpha's historical positions rather than just its present set of positions. This makes the assumption that the alpha's positions are adapted to the current environment. Because the historical PnL series changes only slowly over time, these measures are smoother and can be more easily controlled without causing excessive churn, but they may be slow to detect changes in the alpha's risk profile or environment. One way to detect extrinsic risks is to consider the PnL concentration in certain sectors. Even if the positions do not appear to be concentrated, if the PnL is highly concentrated in certain sectors, the other sectors are not contributing to the diversification of the alpha. See Figure 14.1 for an example.

Though its overall in-sample performance may look very reasonable, this alpha's performance may degrade rapidly if there is a regime change in either of the two key sectors. A more robust alpha should have its performance equally distributed across as many sectors (and securities within those sectors) as possible, unless there is a good reason not to. If the nature of the data or the idea is such that it can be expected

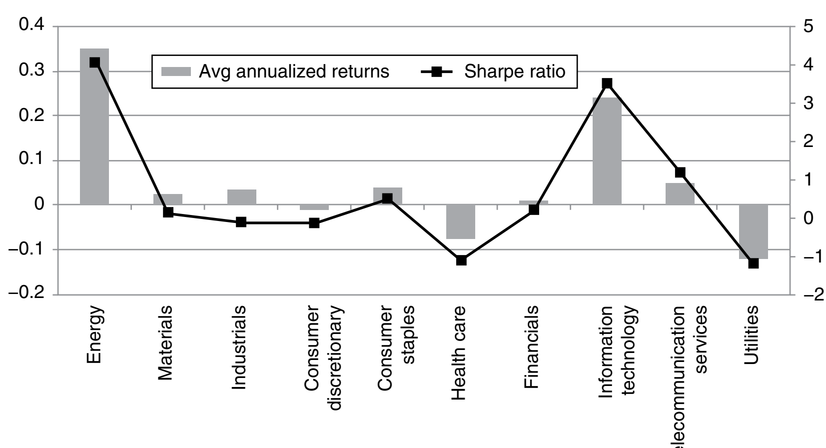

Figure 14.1 Example of an equities alpha whose performance is primarily driven only by the energy and information technology sectors

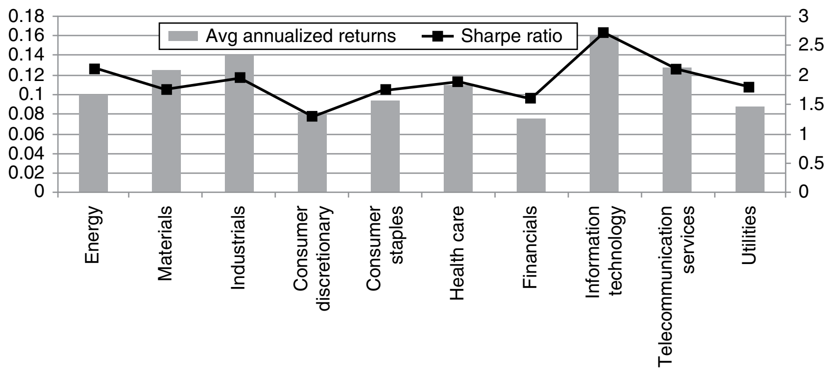

Figure 14.2 Example of an equities alpha whose performance is reasonably distributed across all sectors

to work on only a few sectors, it is generally better to restrict the alpha to these sectors in advance, before testing it, and to control the alpha's high risk by imposing sizing constraints according to the number of instruments. Assigning weight to groups of instruments that do not produce consistent returns is a waste of capital, but throwing them out after seeing their performance raises the risk of survivor bias.

Figure 14.2 shows a reasonable target distribution. Achieving perfect parity among sectors is unrealistic, but in this case the alpha is significantly positive on all sectors.

Similarly, a researcher should check the distribution of an alpha's performance relative to extreme alpha values. An easy way to test for this is to divide the alpha values into quintiles and find the mean (and standard deviation) or returns coming from each quintile. In an ideal alpha (Figure 14.3), the top quintile (highly positive alpha values, if the alpha is centered around 0) yields highly positive future returns and the bottom quintile (highly negative alpha values) yields highly negative future returns.

In practice, many alphas derive almost all of their performance from just the top or the bottom quintile, and quintiles 2 to 4 are simply noise, as in Figure 14.4.

Because such alphas have good predictive power only in tail cases, the actual breadth of performance decreases and the chances of a drawdown increase if the tail information is degraded in the future. Because there's no information in the central quintiles of such alphas, it makes sense to throw out those instruments where the absolute value is below some noise threshold. However, because the result is an alpha that trades a smaller

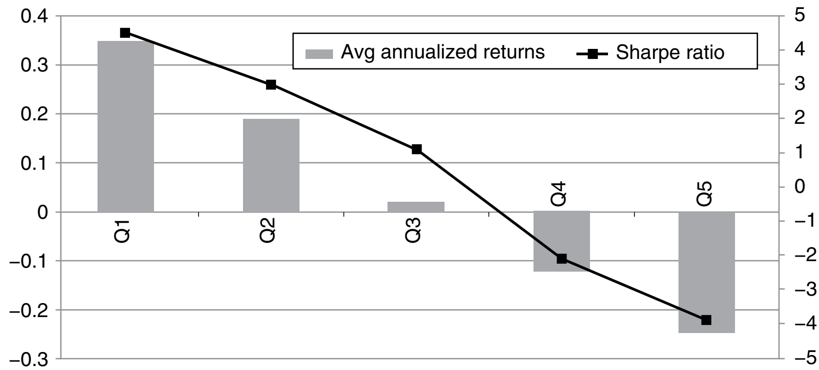

Figure 14.3 The desired quintile distribution of an alpha

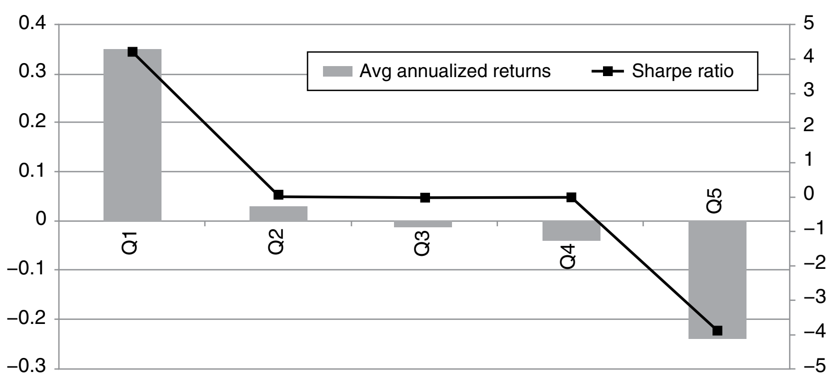

Figure 14.4 A quintile distribution where only the tails of the alpha have predictive power

number of instruments, we can expect it to have higher volatility and lower robustness than the ideal one in the event of a single-instrument shock.

In other cases (as in Figure 14.5), the strongest tail values do not work. The low predictive power of the strongest signals implies that the alpha may not be robust. The researcher should probably investigate the alpha further and either refine the hypothesis or throw it out.

PnL-based factor risks can be estimated by examining the distribution of returns over factor quantiles or by regressing the actual historical returns of the alpha against the historical returns of the chosen risk factors. An alpha's intrinsic risk can also be measured as the annualized volatility, value at risk, or maximum drawdown of the actual historical PnL series rather than the current position. It is important to consider

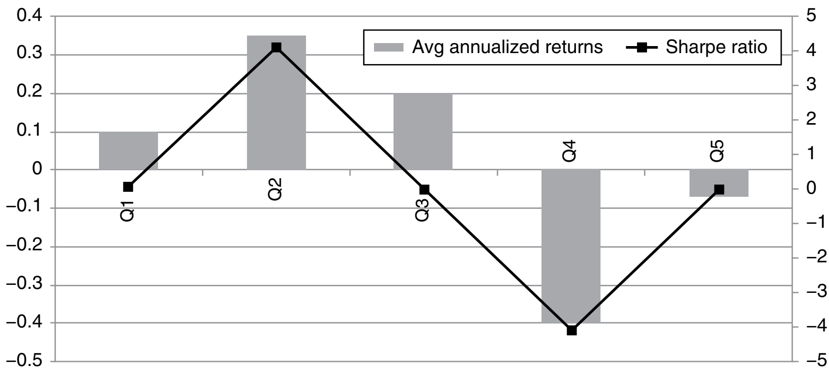

Figure 14.5 An alpha that is not robust

the time scales on which to measure both extrinsic and intrinsic risk measures. A narrower window or a faster decay factor makes the risk measure more responsive to regime changes at the cost of historical memory. It is also important to consider the time structure of the alpha when choosing these parameters. If the alpha changes its positions quickly, it is more likely changing its risk exposures quickly, so a narrower time window makes sense. If the alpha has a natural periodicity (e.g. seasonality for an agricultural commodities alpha), risk measures on fractions of that period will tend to be noisy, so all windows should be multiples of the period. It is generally worthwhile to combine estimates on shorter and longer time horizons for added robustness and as a safeguard in case the basic time structure of the alpha breaks down.

DRAWDOWNS

A drawdown is the percentage loss of an alpha from its previous high value. For example, if an alpha has made 20% returns since inception and then drops in the next few days (or weeks) to an 18% return, the drawdown is measured as 2%. Because no alpha makes money every day, every alpha has drawdowns.

Investors generally have to worry about two features of drawdowns:

- The largest drawdown the alpha has had throughout its history (and in each year of its history).
- The duration of the longest drawdown.

An excessively steep or long drawdown can bankrupt an individual investor or lead to capital flight from a fund, so it is very important to control drawdowns.

When investigating a backtest result, an alpha's drawdowns should be measured in relation to its other features – for example, its annualized return and information ratio. The annual returns should outweigh the drawdowns. Sometimes an otherwise solid alpha has a sudden sharp drawdown, then returns to its previously consistent performance. In other cases, drawdowns consist of slow and steady negative performance for many days before the alpha starts performing again. Of course, when performance turns negative in a real alpha deployment or an out-of-sample test, it is impossible to know in real time whether the alpha has stopped working altogether or just hit a temporary drawdown from which it should recover promptly. Hence, it is important to measure the depth and duration of the historical drawdowns in the in-sample period. This provides us with a benchmark against which we can measure the performance out of sample and in live trading.

Unfortunately, because they are rare, drawdowns are also easily overfit. It is easy to "fight the last battle" and come up with a clever idea that would have prevented the large drawdown seen in the backtest but do nothing to prevent the next drawdown in live trading. One useful tactic for measuring drawdown risk is bootstrapping. It works as follows:

1. Measure the autocorrelations of the alpha's PnL. Bootstrapping makes sense when there is only a finite set of significant autocorrelations.
2. Create 1,000 synthetic 10-year PnLs by randomly selecting PnL snippets of lengths equal to the autocorrelation periods (with replacement).
3. Plot the distribution of the max drawdowns of the synthetic PnLs. The 90th percentile is the bootstrapped drawdown.

Bootstrapping is useful because while it is easy to tell a plausible story about the particular market conditions that caused a drawdown and simply overfit to cut risk under those conditions, it is much harder to overfit the entire return distribution and autocorrelation structure. If the realized drawdown decreases but the bootstrapped drawdown does not, the risk has not been controlled, only masked. If the bootstrapped drawdown is controlled, it is safer to believe that the underlying distribution will not produce extreme drawdowns.

CONTROLLING RISKS

Diversify When Possible

Because different instruments are exposed to different types of risk and volatility scales like the square root of the number of independent variables, the extrinsic and intrinsic risks of an alpha or portfolio can generally be reduced by diversification, as long as the position concentrations are under control. For example, alphas constructed only on the FTSE 100 have lower diversification than alphas constructed on the entire set of UK and European stocks. Diversification can include new instruments, new regions or sectors, and new asset classes. The lower the correlations between the instruments, the better the risk approximates the ideal central limit theorem. However, there are limits to diversification. If the instruments are too diverse, the volatilities may be too heterogeneous to allow all the instruments to contribute meaningfully without excessive concentration risk, or the instruments may simply behave too differently for the same alpha ideas to be relevant. Moreover, as the underlying universe expands, other risks can come into play, such as country and currency exposure, political risk, and counterparty risk. These risks should be considered and mitigated.

Reducing Extrinsic Risks

Extrinsic risks can be controlled by neutralization or hedging. Hard neutralization consists of forcing the given risk to zero. In the case of position concentration, this can be easily achieved (assuming there are no constraints on short positions) by subtracting the group mean from the individual positions, by orthogonalizing the position vector to the factor vector, or by subtracting beta times the factor. Dollar-neutral or industry-neutral positions are achieved by hard neutralization. Soft neutralization consists of capping the exposure to the given risk, either by subtracting a portion of the exposure or by using a constrained optimization method to produce the positions.

Hedging consists of using one instrument or set of instruments as a hedge against the risk incurred by other instruments or sets of instruments. For instance, one can hedge the market beta of an equity portfolio via S&P 500 futures or exchange-traded funds, or the currency risk of a global bond portfolio via currency spots or futures. The resulting risk control is not perfect, as the hedge is imperfectly correlated with the underlying risk, but it is often useful in cases where neutralization is impractical, such as when shorting is impossible or excessively costly, or the risk is a short-term event risk and the hedge is more liquid than the underlying portfolio.

Reducing Intrinsic Risks

Intrinsic risks, as well as the extrinsic risks that remain after soft neutralization or hedging, should be controlled by dynamic position sizing. Most alphas benefit from broad caps on volatility, value at risk, expected tail loss, and position concentrations. When the risk goes up, the book size should scale down so that the alpha does not risk all of its long-term PnL on only a few high-risk days. Alphas with broad beta or risk-on/risk-off behavior can also use other relevant proxies, such as the CBOE Volatility Index, fund flows into risk-on/risk-off assets, or spikes in the correlation eigenvalues, as signals to scale their risk appetite to fit current market conditions. No single risk measure captures the full complexity of the risk profile, so it is useful to combine several relevant measures and use the most conservative one. Alphas that are highly vulnerable to certain event risks that can be known in advance (for example, central bank meetings and numbers announcements) should scale down or exit their positions in advance of the event or hedge with more-liquid instruments if they are unable to scale down in time. Stop-loss and take-profit thresholds can also be seen as examples of very short-term position-sizing constraints that cut positions after a trade has reached the expected level of risk and prevent excessive drawdowns.

Just Get Out

Not all risks can be measured or controlled. If the underlying assumptions of an alpha appear to be at risk of breaking down, the alpha cannot reasonably be expected to react. Examples of such cases include news events such as extreme natural disasters (beyond what the alpha would have seen in its backtesting period, unless the alpha is a news- or sentiment-based alpha that can be expected to exploit the event), sudden changes in the correlation structure of the underlying assets (such as the pegging or depegging of a currency), or evidence of counterparty credit risk (assuming the alpha had previously taken its counterparties for granted) – but the most important cases are the ones that nobody expected. It is the responsibility of the investor to be thoughtful in considering the alphas' failure modes and not trade them when they are likely taking unanticipated risks.

CONCLUSION

Although not all risks are knowable, some common extrinsic and intrinsic risks are worth measuring and controlling. In-sample performance charts and summary statistics reveal only part of the story. An analysis of exposures to known alpha factors, concentrations of positions and PnL, and drawdown distributions can help researchers understand the sources of risk they are taking, mitigate them where appropriate, and size them safely.

15
Alphas from Automated Search

By Yu Huang and Varat Intaraprasonk

"Change is the only constant in life," the Greek philosopher Heraclitus wrote some 2,500 years ago. His words are especially relevant to today's financial markets.

We live in an age of information explosion. With the exponential growth in new sources of data, it is becoming impractical to test all data manually. To tackle this problem, computer algorithms can be used to facilitate the search for alpha signals within the huge data cloud. This computer-aided method, called automated alpha search, can significantly boost the efficiency of the search for signals, producing thousands of alphas in a single day. This comes at a price: not all of the signals found are real alphas. Many of the seemingly great alpha signals discovered by automated searches are noise fitted to the in-sample historical data and have no predictive power. Thus, the focus of any automated alpha search is avoiding overfitting to improve the quality of the output signal. This chapter reviews the process of building an automated alpha search system.

EFFICIENCY AND SCALE

The main focus of an automated search is to find a large number of alpha signals from an exponentially larger number of combinations of inputs and functions. These combinations can also be recursive; combinations of combinations can generate novel alpha signals. Such complexity makes efficiency one of the foremost concerns in an automated search. This chapter presents the problems that are unique to automated alpha searches, decomposes the search process into tangible components that are similar to those in a manual alpha search, and shows how the search for efficiency governs different treatments in each area.

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An automated search is subject to three problems resulting from its large scale: computational load, the inability to manually inspect every component, and lower confidence in each alpha. An automated search usually involves combining different data with different functions by trial and error. As a result, a high level of computational power is usually needed. Optimizations that reduce memory usage and improve speed can result in finding more and better alphas. The large number of combinations also means that it is impossible to inspect each of the resulting formulas by hand. Even if one wants to investigate a sample manually, the alpha expression can be very complicated and without obvious financial significance. Moreover, the sheer number of trials means that it is common for combinations that make no mathematical and economic sense to be erroneously recognized as alphas through survival bias. A good search process should reject such noise from the output or – better – should prevent it from happening in the first place. Last, the impossibility of inspecting every single alpha reduces the researcher's confidence in each alpha compared with his confidence in alphas made by hand. Therefore, new kinds of testing are required for an automated search to maintain the quality of the alphas.

To address these three concerns, researchers can investigate three main components of any alpha search (manual or automated): input data, search algorithm, and signal testing (see Figure 15.1). Input data are meaningful financial variables, such as price, earnings, and news.

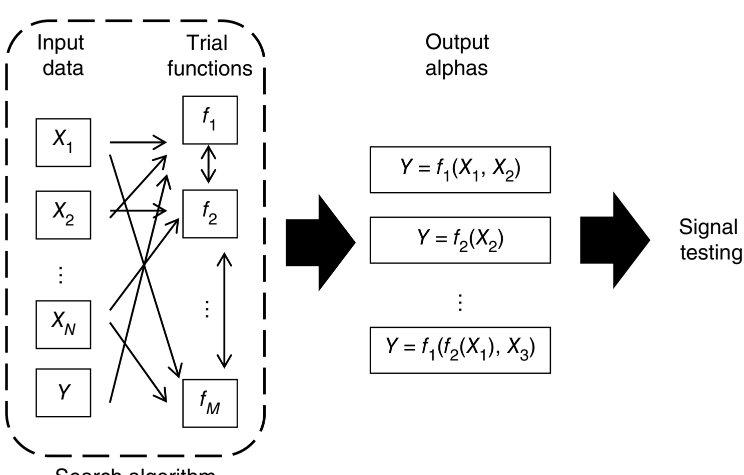

Figure 15.1 The automated search process

The goal of any signal search is to use these data to predict a target function Y, which can be the future stock returns or variants thereof. To find the relationship between the input data and the target function, a fitting algorithm is used to determine the parameters of a preselected family of trial functions f (the simplest example being the linear functions). Once the alpha is found, it is tested for robustness.

INPUT DATA SHOULD NOT COME FROM TOO MANY CATEGORIES

Feeding too many input variables into the fitting algorithm will lead to better in-sample fit but usually will result in worse predictive power because of overfitting. Beyond this point, one often-overlooked issue is the number of data categories. Here the category refers to the type and source of data. Some commonly explored categories include, but are not limited to, price volume, analyst ratings, fundamental data, news, and insider trading. Trying to accommodate too many variables will likely lead to an overfitted result, but fitting variables from many different categories is often worse. Data from each category has its own characteristic frequency. For example, fundamental data usually exhibits clear quarterly cycles, price–volume data is generally uniform, and insider trading filings are typically randomly spaced. If the model contains data from many different categories, it generally is more complex and more susceptible to noise in the data.

INPUT DATA AND UNITLESS RATIOS

Good stock return predictors should be homogeneous and comparable across stocks. As a result, raw financial data such as price and earnings generally are not good predictors because they are not comparable across different stocks. For example, the value of earnings is not cross-sectionally comparable, but earnings divided by revenue is. The reason is that dollar earnings depend on the size of the company. Larger companies usually have higher dollar earnings, but larger companies do not necessarily have higher stock returns. Similarly, earnings per share depend on the share size, so they also are not comparable across stocks. Earnings divided by revenue, however, show the profit margin as a percentage, so they can be compared across stocks.

Ratios of variables in the same category that are measured in the same units generally are comparable indicators. Another method is to compare the current value of a given bit of data with its historical value. For example, the current price divided by the average price over the past quarter is a unitless variable that can be compared across stocks. Note that some widely used ratios may not be good candidates for an automated search. For example, the famous P/E (share price divided by earnings per share) is not suitable for an automated search because the ratio can diverge if the value of earnings is near zero. The E/P ratio would be more suitable, as the price is never close to zero. Similarly, current earnings divided by the earnings of the previous period also can diverge.

These techniques to make comparable variables are essential in an automated search because of the researcher's inability to inspect every alpha. By using only comparable variables as inputs to the search process, it is possible to reduce the number of meaningless formulas created in the system – for example, price minus volume. This lessens the computational load by reducing irrelevant parts of the search space and improves the alpha confidence because the alphas have a higher probability of making economical and mathematical sense.

UNNECESSARY SEARCH SPACE

In a manual alpha search, it may be possible to fit a small number of parameters and trial functions by exhaustive search because the manual search space is small. This is not feasible in an automated alpha search; the computational resources required to survey the whole space would be too great in practice. Therefore, it is important to narrow down the search space as much as possible.

One possible way is to screen out combinations of functions and data that do not make sense. For example, functions such as log that cannot take a negative input value should not be matched with stock returns. Human knowledge can be used to identify and drop some less useful input data. For example, if the aim of the search is to find short-term signals, the change in slowly varying data, such as industry classification, can be omitted from the search space. Examining the coverage in time (how often the data change or become unavailable) and the coverage across stocks (how many stocks have the data available at a given time) also can help weed out less useful data. Last, an iterative search uses an initial search across a coarse grid on the parameter space to find an area with possible alphas, and follows by placing a finer grid around the area. For example, in the first round of an iterative search, a momentum formula may be fitted to the timescale of both two months and six months. If the two-month period works better, one- and three-month periods can be used in the next round. Such a method breaks the process down into smaller and faster steps. It also yields intermediate results that can be used to evolve the search process on the fly. Iterative search also can be applied to the trial functions by searching for functions of functions that create good results.

INTERMEDIATE VARIABLES

Performing a manual alpha search often reveals that an intermediate variable involving a simple function of more than one piece of basic input data can make a strong alpha. One example is the aforementioned P/E ratio, which is a composite of the price and the earnings data. An automated search also may find such useful intermediate variables, which appear in many alphas. It is possible to reduce the computational load if the search system can record these variables and reuse them in other searches. Similarly, the combinations of the trial functions can be recorded and reused. This reuse of prevalent intermediate variables is one of the bases for genetic algorithms (GAs), a full discussion of which is beyond the scope of this chapter.

SEAS OF ALPHAS, NOT SINGLE ALPHAS

In addition to the input data, the search algorithm itself can be optimized. Unlike a manual alpha search, in which the goal is usually to find the single best alpha in a small parameter space, an automated search looks for a number of good alphas in a large search space. Therefore, the algorithm should not try to find the global optimum in the search space but to find as many local optima over as large an area as possible. The ability to find a diversified set of alphas depends not only on the search algorithm but on how the search space is defined. As mentioned earlier, a researcher should filter out irrational combinations of functions and data beforehand so as to traverse only the sensible search areas. Further, by recording the most productive search areas, the researcher can concentrate the next search run on such areas to find more alphas and increase confidence, or avoid such areas to seek other undiscovered signals. The ability to find diverse alphas across the search space is one measure of how well the search algorithm and the search space are constructed.

SIMPLE ALPHAS

Because an automated search can yield a large number of alphas, a researcher may be tempted to keep increasing the complexity of the function space to obtain more alphas. Because good alphas are usually simple, this depth-based approach of making complex alphas is prone to generating a lot of noise functions that look like alphas in sample but perform badly out of sample. Therefore, the researcher should limit the depth of the search and focus more on a breadth-based approach by expanding the search space – the input data and trial functions. The quantity of the alphas found will generally grow more slowly, but the quality should be significantly higher.

LONGER BACKTESTING PERIODS

Increasing the backtesting period raises the available number of data points and increases the statistical significance of the result, but only under the assumption that the dynamics beneath the data are the same. This is not always true for financial markets. The market players and their behaviors change rapidly and in turn change the financial market dynamics. Therefore, it is a compromise when choosing the length of input data: if the period is too short, there will be less data and less confidence in the result, but if the period is too long, the shifting underlying dynamics may make the result less reliable.

In a manual search, one generally has an idea of what market dynamics are being captured and how long they are expected to persist. An automated system lacks this advantage, so one may want to consider quantitative methods for detecting when the backtesting period is too long, such as splitting the backtest and checking consistency across periods. At the cost of a modest increase in computational complexity, it may be possible to update certain parameters dynamically within the alphas rather than fitting them as part of the search, so that a longer backtesting period remains relevant.

Another concern with a longer backtesting period, especially in a large-scale search, is the higher computational load. In an iterative search, an incremental backtest period is a useful trick to take advantage of a longer backtest period without using excessive resources. For example, one starts the first round of the search with a backtest period from date M to date N. In the next round, traversing the finer grid of a smaller search space, the period of M–0.5year to N+0.5year is used. In the third round, the period of M−1year to N+1year is used, and so on. This way, the first rounds, where only a preliminary result is expected, are much faster to run, while the later rounds, where the fine-tuning occurs, use more data points for greater robustness. Extending the backtest period to each consecutive round also adds a quasi out-of-sample test at every round, allowing us to measure the yield and gain confidence in the alphas if the yield is high or abort the search if the yield is low and survivor bias is a concern.

ALPHA BATCH, NOT SINGLE ALPHA PERFORMANCE

In human research, each alpha usually is supported by economic or financial reasoning; the quality of alphas largely depends on the robustness of the parameter fitting, which is independent from one alpha to another. Therefore, the confidence of each manual alpha can be measured separately. For example, the quality can be inferred from the backtest performance or the parameter sensitivity test. By contrast, in an automated search each alpha does not have a predetermined explanation behind it, so the confidence in the alpha depends not only on the fitting algorithm but also on the search space. Therefore, it is less meaningful to ask about the quality of individual alphas than about the quality of the search as a whole. The aggregated performance of alphas made from the same search space and search algorithm is called the batch performance. This is analogous to an orchestra, whose quality is measured based on the whole ensemble, not on the music of individual performers.

Selection bias is a common pitfall, arising from an excessive focus on single alphas. After completing an automated search, it is tempting to test the out-of-sample performance of each output alpha and select only those that perform well. This practice, however, can introduce a selection bias into the alpha batch because the out-of-sample performance has been used in the alpha selection. As a result, it no longer can be considered out of sample. To alleviate this bias, consider the statistical significance of the average performance of all the alphas in the batch and decide whether to accept or reject the whole batch. For example, suppose a batch of 100 alphas is produced with a cutoff in-sample information ratio $(\text{IR}) > 0.15$. The alphas are tested and found to have an average out-of-sample $\text{IR} = 0.01$, with standard deviation of $\text{IR} = 0.12$. Sixty alphas have out-of-sample $\text{IR} > 0$ and the rest < 0. In this case, the average out-of-sample IR is too low, so all 100 alphas should be rejected, including the 60 with positive out-of-sample performance.

Studying batch statistics can help spot errors in the system that otherwise can be very hard to identify. For example, a system is set up to find low-turnover alphas using data that is updated quarterly, but the turnover of the output alpha batch is unusually high. This can point to a possible error in parameter fitting. Batch statistics also can yield useful information about the input data and trial functions; for example, the data or functions that show up many times in the alpha batch may have higher predicting power. Such insights can be used to further optimize the search space for subsequent runs.

Another application of alpha batch statistics is a technique called a yield test. If a researcher uses a set of search space (input data and functions) that makes economic or financial sense, she can expect the number of alphas found in this space to be higher than those found from a set of noisy data input or functions; that is, the good search space should have higher yield than the noisy search space. Therefore, the researcher can try feeding noise inputs into the automated search system and compare the yield and quality of the output alpha batch. The batch based on noise inputs should be worse than the batch from the supposedly good search space. If the number and quality of the alphas do not differ much regardless of whether a good or a noisy input is used, this can indicate a bad overall process, suggesting that the resulting alpha batches, even those from the clean space, are likely to be noisy.

DIVERSIFY THE ALPHA BATCH

A diversified portfolio has lower risk. This principle also can be applied to batches of alphas from different automated searches. Each alpha batch already possesses some diversification because it contains many single alphas. However, a researcher can increase diversification at the batch level by varying the set of input data (for example, fundamentals, price–volume), trial functions (linear combination, time-series regression), performance testing (maximizing returns, minimizing risk), or even the search process itself (different iterative processes). Combining alphas from many batches may further reduce the correlations among the alphas and the overall portfolio risk.

SENSITIVITY TESTS AND SIGNIFICANCE TESTS

A good alpha signal should be insensitive to noise. Cross-validation of data from different periods, from different durations, on random subsets of data, on each sector of stocks, and so forth can be a good way to mitigate the risks of overfitting, as well as the risks of noise data: we have more confidence in the signals that are less sensitive to these input changes. On the other hand, each input data field should make a significant contribution to the result. The simplest way to test significance is to remove one input variable or replace it with noise and check whether the result changes significantly. We trust the signal more if each input variable makes a significant contribution.

MANUAL ALPHA SEARCH

A high-quality alpha search requires careful handling of the input data, trial functions, search algorithm, and performance testing. It is initially difficult to pinpoint the proper choices for each of these, especially when working with a new set of input data or objective functions. Therefore, before venturing into an automated search, it is imperative to start with a manual search on the same input, because the complexity is lower and it is easier to understand all aspects of each alpha. Once the inputs are clearly understood, a researcher can generalize the process and make it suitable for an automated search.

CONCLUSION

An automated alpha search offers many advantages over a conventional manual alpha search – in particular, significant increases in efficiency and volume. The downside is that it requires caution in several areas. Automated search may exacerbate the extent of overfitting, which can be countered by careful and meaningful variable selection, input data category restriction, selection of testing periods, and sensitivity tests. These are all critical steps to avoid overfitting and generate genuine alphas. Last, by considering batch performance, improvements and diversification can be applied to the batch level; this is difficult to do with alphas obtained by manual search because of the low numbers of similar alphas and the difficulty of clustering different alphas together. With advances in the field of artificial intelligence, we expect automated alpha search to continue to grow in interest and importance.

16
Machine Learning in Alpha Research

By Michael Kozlov

INTRODUCTION

Over the past several decades, machine learning has become a common tool for almost any task that requires information extraction from large datasets. In alpha research, several common problems can be solved using a machine learning methodology:

- **Regression problems**, in which Y and X are quantitative variables and Y is inferred by a function $\mathrm{Y} = \mathrm{F}(\mathrm{X})$.
- **Classification problems**, in which Y is a qualitative variable and inferred from a quantitative variable X.
- **Cauterization problems**, in which a quantitative variable X is observed and classified into groups with similar features.

In this chapter, we will introduce the most common techniques used to address these problems.

In alpha research, it is not important to describe perfectly what has happened in the past, but it is important to be as precise as possible in predicting the future. Therefore, we are faced with the following dilemma: an overly complex model may enable perfect calibration but lead to overfitting and a poor quality of prediction, whereas an overly simplistic model that fits the sample data very poorly has no chance of predicting future behavior more accurately.

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WorldQuant Virtual Research Center.

MACHINE LEARNING METHODS

Historically, the field of machine learning received a boost after World War II, when humanity faced a pressing need to analyze a lot of information and make a lot of correct decisions quickly, beyond what would have been possible by relying solely on human common sense and computational abilities. In 1957, Frank Rosenblatt of Cornell Aeronautical Laboratory invented what he called the perceptron, in what is commonly referred to as the beginning of machine learning as a science. The idea was obvious and promising: if the human brain is nothing but an assembly of neurons, we can create an artificial neuron; just like a natural neuron, it would be pretty simple.

The artificial neuron was implemented as the simplest linear classifier of input signals. Each artificial neuron has parameters that can be fit on a set of training examples. A perceptron is an assembly of neurons that may represent a stronger and more complex classifier. The disadvantage of perceptrons is that having too many parameters may lead to overfitting, when positive training results do not have strong predictive power for the new data.

In the 1960s, Soviet scientists Vladimir Vapnik and Alexey Chervonenkis invented the generalized portrait algorithm, which later developed into the family of classification algorithms known as support vector machines (SVMs). The generalized portrait and SVMs were new steps in machine learning. In contrast to the perceptron, with SVMs the solution presumes that the accuracy achieved during training is preserved out of sample and hence prevents overfitting.

Let's now briefly review the most important directions and methods in machine learning (see Figure 16.1).

Supervised and Unsupervised Learning Algorithms

The term "supervised algorithm" means that we expect the machine to train itself from a set of ground-truth examples we provide. For instance, we prepare a set of pictures with the correct labels "cat" and "dog" and expect the machine to train itself to distinguish between them. Another example would be the set of correct results (selected from the past) for a prediction task.

The term "unsupervised algorithm" refers also to cauterization tasks, where we don't know the correct answers in advance. In this case, the machine search is directed only by some predefined quality criterion.

For example, in alpha research the task of predicting stock prices can be a good application of supervised learning, and the task of selecting stocks for inclusion in a portfolio is an application of unsupervised learning.

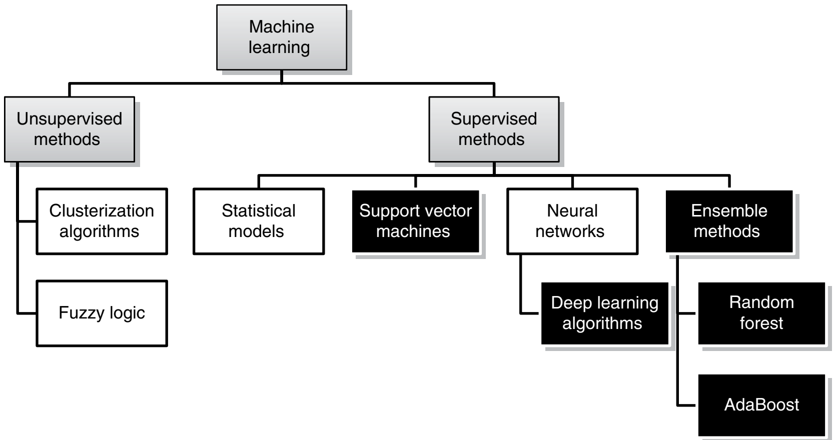

Figure 16.1 The most developed directions of machine learning. The most popular are in black

Statistical Models

Models like naive Bayes, linear discriminant analysis, the hidden Markov model, and logistic regression are good for solving relatively simple problems that do not need high precision of classification or prediction. These methods are easy to implement and not too sensitive to missing data. The disadvantage is that each of these approaches presumes some specific data model.

Trend analysis is an example of applications of statistical models in alpha research. In particular, a hidden Markov model is frequently utilized for that purpose, based on the belief that price movements of the stock market are not totally random. In a statistics framework, the hidden Markov model is a composition of two or more stochastic processes: a hidden Markov chain, which accounts for the temporal variability, and an observable process, which accounts for the spectral variability. In this approach, the pattern of the stock market behavior is determined based on these probability values at a particular time. The goal is to figure out the hidden state sequence given the observation sequence, extract the long-term probability distribution, and identify the current trend relative to that distribution.

Support Vector Machines

A support vector machine is a machine learning algorithm with a strong theoretical basis. It is very robust and has several modifications for various types of problems, but it usually requires a lot of training time and is not the best technique for parallel computations; this is a disadvantage for modern algorithms.

The main idea of SVMs is that, given a set of data points in a vector space classified into two nonoverlapping groups (categories), an SVM algorithm partitions the space into two subsets to maximize the distance between the training points and the boundary. New instances are then mapped into the same space and assigned to the category.

SVMs can be a very useful method for the analysis and prediction of financial time series because they can be formulated in terms of a risk function consisting of the empirical error and a regularized term that is derived from the structural risk minimization principle. A common approach is to use a vector regression (SVR) to solve regression and prediction problems. By varying the margins of the SVR, you can simulate changes in the volatility of the financial data. Furthermore, in an SVR the effects of asymmetrical margins can be taken into account, reducing the downside risk of the model.

Neural Networks

Neural networks (NNs) grew out of the idea to represent the structure of the human brain with artificial neurons very similar to natural ones. It was quickly observed that the key point is not the neuron structure itself but how neurons are connected to one another and how they are trained. So far, there is no theory of how to build an NN for any specific task. In fact, an NN is not a specific algorithm but a specific way to represent algorithms. There is a well-known backpropagation algorithm for training NNs. Neural networks are very efficient, given sufficient computing power. Today they have many applications and play an important role in a number of artificial intelligence systems, including machines that beat human players in chess and Go, determine credit ratings, and detect fraudulent activity on the internet. However, the lack of theory and lack of internal transparency of NNs (whose internal logic is hard to interpret) have somewhat hampered their development.

Ensemble Methods

Ensemble methods, like random forest and AdaBoost, aggregate the solutions of multiple "weak" classifiers or predictors with poor individual accuracy to obtain a stronger classification or a more precise prediction. The random forest algorithm constructs a set of simple decision trees relying on training examples, then makes these trees "vote" to produce the final decision for new cases. AdaBoost (for "adaptive boosting" algorithm) aggregates various "weak" classifiers (albeit with higher than 50% accuracy each) to obtain the final decision as a weighted sum of "weak" decisions. These algorithms are very scalable and good for parallel computations.

Because the main idea of random forest and AdaBoost is to combine rough and moderately inaccurate weak hypotheses to form a very accurate strong one, they frequently are used for portfolio optimization. For example, we can start with a set of relatively weak alphas and construct a stable and well-performing strategy using the random forest and AdaBoost methodologies.

However, strong classifiers learned by random forest and AdaBoost tend to have high error rates. Some improved variants of these algorithms have been proposed recently to reduce the rate of false positives. For example, AsymBoost balances the asymmetric costs of false negatives and false positives somewhat by reweighting the positive and negative samples at each training round. Another alternative is FloatBoost, which incorporates the backtracking mechanism of floating search and repeatedly performs a backtracking to remove unfavorable weak classifiers after a new weak classifier is added by AdaBoost; this ensures a lower error rate and reduced feature set at the cost of about five times longer training time.

Deep Learning

Deep learning (DL) is a popular topic today – and a term that is used to discuss a number of rather distinct things. Some data scientists think DL is just a buzz word or a rebranding of neural networks. The name comes from Canadian scientist Geoffrey Hinton, who created an unsupervised method known as the restricted Boltzmann machine (RBM) for pretraining NNs with a large number of neuron layers. That was meant to improve on the backpropagation training method, but there is no strong evidence that it really was an improvement. Another direction in deep learning is recurrent neural networks (RNNs) and natural language processing. One problem that arises in calibrating RNNs is that the changes in the weights from step to step can become too small or too large. This is called the vanishing gradient problem.

These days, the words "deep learning" more often refer to convolutional neural networks (CNNs). The architecture of CNNs was introduced by computer scientists Kunihiko Fukushima, who developed the neocognitron model (feed-forward NN), and Yann LeCun, who modified the backpropagation algorithm for neocognitron training. CNNs require a lot of resources for training, but they can be easily parallelized and therefore are a good candidate for parallel computations.

When applying deep learning, we seek to stack several independent neural network layers that by working together produce better results than the shallow individual structures. There is some evidence that employing deep learning to time-series analysis and forecasting has better results when compared with previously existing techniques. The most popular architecture for time series and forecasting was the deep belief network proposed by Kuremoto et al. (2014).

Fuzzy Logic Methods

In classical logic, every statement is true or false. In real life and human logic, however, this is not always enough; some statements are "likely true," "indefinite," "unlikely," and so forth. In other words, there is a grayscale between yes and no. By allowing machines to operate with such underdefined statements, we can produce what's known as fuzzy logic, which has imprecise inference rules and provides mechanisms to make decisions under a lack of information.

Financial analysts are showing an increasing interest in using expert systems and neural networks to model financial processes and market performance. But it's also important to recognize that fuzzy logic methods are gaining popularity in the development of hybridized expert and neural network software systems. In fuzzy expert systems, we attempt to specify fuzzy rules, which allows greater variety in response, depending on the degree of belief built into the decision rules.

CONCLUSION

Certainly, data is one of the most valuable resources in the modern digital world. Machine learning has become a common tool to extract information from large datasets. While science is leaping forward to novel data management frameworks, software solutions, and algorithms to facilitate the usage of this resource, the world itself is exponentially increasing in volume and complexity. Therefore, it is impossible to utilize the entire set of available data for alpha construction purposes without machine learning techniques.

17
Thinking in Algorithms

By Sunny Mahajan

A good quant should be a jack of all trades and, with time and experience, a master of some. Effectively navigating various unexplored landscapes requires skill, care, and the right set of tools to get you to your destination in one piece. With the passage of time and technological progress, we have discovered many new ways of making this journey more quickly and more safely. Manipulating huge swaths of structured as well as unstructured datasets in the hope of making it to that ever-lucrative alpha is no less than an expedition, and algorithms serve as our trusted advisers on these exciting adventures.

To stay competitive, you need to be well equipped and, more importantly, you need to choose the right tool for the job. Even with the right tool, you have to make a decision between finesse and brute force. In predictive modeling, knowing how to walk this fine line makes all the difference. That said, let's take a look at some of the mathematical techniques and algorithms that should be part of your quant tool kit. We will go through the underlying intuition and the practical use cases for these algorithms.

DIGITAL FILTERS

Digital filters perform mathematical operations on discrete time signals to attenuate or amplify certain frequencies. These mathematical transforms are characterized by transfer functions that describe how they respond to various inputs. As such, digital filter design involves expressing performance specifications in the form of a suitable transfer function.

Two classes of digital filters are finite impulse response (FIR) and infinite impulse response (IIR). The key difference between them is that

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IIR uses feedback and FIR does not. In terms of the type of filtering involved, basic filter types are low-pass filters (which attenuate higher frequencies), high-pass filters (which attenuate lower frequencies), band-pass filters (which keep only a certain band of frequencies), and band-stop filters (which attenuate a band of frequencies). The amplification or attenuation introduced by a filter is called its gain and is a function of signal frequency. By combining the basic filter types, you can end up with the desired transfer function.

One of the most popular applications of digital filters is to smooth time-series data – simple and exponential moving averages are essentially low-pass filters. In addition, the lag introduced by digital filters depends on the transfer function characteristics. As such, with the right digital filter design, it is possible to achieve equivalent or better smoothing with reduced lag, and lower lag is preferable.

Another popular use of digital filters is in time-series decomposition. With a suitable combination of low-pass, band-pass, and high-pass filters, you can effectively decompose the raw time series into its trend and cycle components. With these extracted components, we can design better indicators and trading signals. Once you understand the basics of transfer function modeling, it is easy to design and test custom filters.

In addition to the simple moving average and exponential moving average, it's good to have in your tool kit an effective low-pass filter known as a Butterworth filter. For high-pass filtering, you can just subtract the low-pass filter output from the original time series.

OPTIMIZATION AND LOSS FUNCTION DESIGN

The heart of any optimization problem is selecting an optimal solution from a set of feasible solutions. Feasibility is usually defined by design specifications, production requirements, and manufacturing-process limits. The optimality of a solution is quantified in terms of minimizing a loss function (or a cost function).

The choice of a good loss function differentiates an effective optimization algorithm from an ineffective one and depends on the nature of the problem, as well as the dataset. To illustrate our point, consider the differences between the L1 norm and the L2 norm. The L2 norm squares the individual error terms and heavily penalizes the optimizer for larger error terms. Although this can be desirable when we'd like our solution to have a good performance across the dataset, it can end up being nonrobust in the presence of outliers. On the other hand, the L1 norm formulation is quite robust and generates sparse solutions, but it can be unstable. In practice, this means that many of the error terms end up being zero, while some can be quite large; this does not bode well for our worst-case performance.

Also employed in the form of regularization, the L1 norm and L2 norm have been used successfully to improve performance over ordinary least squares regression. In the classical form, standard regression penalizes the error terms with an L2 norm. However, this often suffers from the problem of unreasonably large and unstable model coefficients, especially in the presence of highly correlated predictors. This can be dealt with by adding an L2 norm penalty on the model coefficients, which penalizes the optimizer for large coefficients (also known as ridge regression or Tikhonov regularization). Additionally, if we know that only a subset of the predictors are actually useful, we can embed that sparsity structure in the learning problem by including an L1 norm penalty on the model coefficients (i.e. a Lasso regression). The Lasso technique has been successfully used as a feature selection strategy in several real-world applications. It's not uncommon to encounter both the problems described above in the same application; this is easily solved by including both the L1 norm and the L2 norm penalties on the model coefficients (i.e. elastic net). This gives us a nice trade-off among performance, robustness, sparsity, and stability.

It is also worth noting that there exists an interesting function called the Huber loss, which uses L2 norm for smaller values of error and switches to L1 norm for error terms exceeding a user-specified threshold. This loss function has the robustness of L1 norm and the stability of L2 norm, and often performs better than either in real-world problems.

Once you understand the basic properties of various loss functions, it is possible to get creative and devise effective solutions for everyday quant problems using optimization.

THE BIAS–VARIANCE TRADE-OFF

In an ideal setup, we would have the perfect learning algorithm trained on sufficient and complete data to build our predictive models. Unfortunately, real-life problems are not so manageable.

The curse of dimensionality implies that with an increasing number of features, we need exponentially more data for our results to be meaningful. To make matters worse, we are faced with the trade-off between information decay and statistical significance. We want to use a large enough data sample to obtain statistically significant results. However, the further we go back in history, the less relevant our data points become, because most real-life problems involve moving targets. The structure and parameters of the model are evolving continuously, and we have only a limited amount of representative data samples from recent history.

To give our learning algorithms a fighting chance, we need to reduce the dimensionality of the problem or embed some prior knowledge of the problem structure in the learning process.

Models with high variance tend to overfit on training data, exhibit high variability in their predictions, and fail to generalize on test data. By reducing the dimensionality of our problem, we limit the degrees of freedom in the learning process.

Models with high bias tend to oversimplify the problem. Although they do not tend to overfit, they suffer from underfitting and have poor performance on both training and test datasets. However, when used in moderation, some relevant assumptions or prior knowledge of the problem structure can help the learning algorithm counter the overfitting problem described above and generate better predictive models.

With awareness of the two extreme ends of this spectrum, let's now discuss the use of dimensionality reduction and shrinkage to effectively manage the bias–variance trade-off.

DIMENSIONALITY REDUCTION

Also commonly referred to as feature extraction, dimensionality reduction deals with the problem of extracting the underlying structure of a dataset by expressing it in terms of a few features that explain most of the variation in the underlying data. As mentioned earlier, this is immensely useful in predictive modeling to counter the effects of the curse of dimensionality.

One of the most commonly used nonparametric dimensionality reduction algorithms in quantitative finance is principal component analysis (PCA). It has been used successfully for building statistical risk models, developing asset allocation algorithms for portfolio construction (principal portfolios), and clustering.

An extension of PCA, sparse principal component analysis (sPCA), adds a sparsity constraint on input variables. In ordinary PCA, the components are usually linear combinations of all input variables; sPCA overcomes this limitation by finding components that contain just a few independent variables. As such, sPCA is often more effective at noise removal than PCA and is useful for feature selection thanks to the baked-in sparsity constraint.

SHRINKAGE ESTIMATORS

When dealing with datasets of high dimensionality and limited data samples, we can often improve upon naive or raw estimators by combining them with some additional information about the problem, usually in the form of a structural estimator. Essentially, shrinkage converts an unbiased raw estimator into an improved biased one.

A very popular and successful application of shrinkage is in improving the estimates of the covariance matrix for asset allocation and risk management. Ledoit and Wolf (2004) demonstrate that by shrinking the sample estimator of the covariance matrix toward a structural estimator (based on the constant correlation model), they are able to construct portfolios that outperform those based on the naive sample estimator of the covariance matrix. The usefulness of shrinkage in improving statistical estimates has stood the test of time.

PARAMETER OPTIMIZATION

The choice of parameters is very important in the out-of-sample performance of quant models. Static parameters do not account for the fact that most problems in finance involve moving targets, and the optimal parameter set is a function of problem characteristics that need not necessarily be static or uniform in the cross section of our trading universe. In many cases, you can do better by using dynamic parameters, which change with time as well as the characteristics of the cross section. For example, you could improve a simple news trading strategy by accounting for the efficiency of stocks as a function of their market caps. Large caps attract more attention and are therefore more information efficient than their small-cap counterparts. As such, you can potentially improve the performance by modulating the holding period of such a strategy as a function of the market capitalization. This involves dynamic parameterization, which changes with the characteristics of the entity being modeled.

Static and dynamic algorithms do not exploit any information gained from the performance of the algorithm out of sample. By closing the feedback loop and using this information, it is possible to fine-tune the algorithm parameterization based on realized performance. Going one step further, we have self-adaptive algorithms, in which the parameter tuning logic is embedded in the primary algorithm and takes place automatically as the program runs.

CONCLUSION

Thinking in algorithms allows us to build simpler, more efficient solutions to everyday quant problems. It enables us to conduct research in a disciplined fashion, uncover new insights, and confidently apply predictive models. Algorithm research is a discipline in itself, and it is important to keep abreast of the latest innovations to maintain our mathematical and technological edge in the pursuit of alphas.

PART III
Extended Topics

18
Equity Price and Volume

By Cong Li and Huaiyu Zhou

INTRODUCTION

In finance, the efficient market hypothesis (EMH) asserts that financial markets are "information efficient." That is, with the information available at the time that the investment is made, one cannot consistently achieve returns in excess of average market returns on a risk-adjusted basis.

There are three major versions of the EMH: the weak, the semistrong, and the strong. The weak hypothesis states that the prices of traded assets (for example, stocks, bonds, or property) already reflect all past available public information. The semistrong hypothesis argues that all past publicly available information and current public information already has been priced into securities. The strong hypothesis declares that all public and private information is reflected in a security's price. Thus, given only the current and historical price-volume data, the EMH implies that it is impossible to make a profit in an efficient market and that there are no such things as price-volume alphas.

Is this true? No, it is not. Although the development of information technology, information processing, and automatic trading, in addition to other advances have brought the market closer to full efficiency, full efficiency has not, and may never be, attained. Quantitative traders seek to profit from remaining inefficiencies. Price–volume alphas, relying only on the market data, continue to refute the EMH every day.

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SEEKING PROFITS THROUGH PRICE AND VOLUME

Trading Frequencies

Price–volume alphas can seek profits from trading at different rebalancing frequencies. Unlike some long-term investors who balance their positions once a quarter, active portfolio managers typically trade more frequently. They may rebalance their portfolios daily – and sometimes multiple times a day. The more often they trade, the more likely their performance will be statistically significant. The mean of N random variables drawn from independent and identical Gaussian, or normal, distributions has the same mean but 1/sqrt(N) of the standard deviation of the original distribution. Given the same information coefficient, traded four times more often, we can expect an information ratio (IR) that is two times better. Also, more-frequent trading allows active portfolio managers to target short-lived trading opportunities that will vanish if the portfolio is balanced only monthly or quarterly. In some cases, a specific event will drive the price and volume to abnormally high or low values, causing price–volume anomalies. Only fast-moving traders can react to such anomalies, trade accordingly, and seek to profit when the price reverts to its usual level.

Once costs are taken into account, however, potential profits from such anomalies decrease, and many become nonexistent. Trading costs are highly related to trading frequencies. According to a study by researchers at the University of Rochester (Novy-Marx and Velikov 2015), strategies that turn over their portfolios more than five times per year may lose more than 1% per month on trading costs. There generally is a trade-off between higher IRs and lower trading costs.

Momentum-Reversion

Traders can profit by looking at price and volume in different ways. Instead of considering only individual instruments, it is possible to treat the entire pool of tradable assets as a whole. Looking at a single instrument, we can see technical indicators like the moving average convergence–divergence (MACD), which measures momentum by subtracting the longer-term moving average of prices from the shorter-term one, or the average true range (ATR), a moving average-based measure of volatility (generally over a 14-day horizon). When we look at a portfolio, we see different things, such as the interrelationships of the instruments, their co-movement as a group, and instruments that appear temporarily or permanently as outliers compared with the others. It is possible to apply global optimization and group risk neutralization across the whole group.

One interesting phenomenon is the momentum-reversion effect. Single instruments usually exhibit momentum. Assets tend to follow their historical trends – stronger or weaker assets tend to continue being stronger or weaker for a certain time period – so an investor can attempt to profit by following the trend. However, within a sufficiently correlated group of stocks, the picture is quite different. For example, within an industry or subindustry, stronger stocks usually will revert to being weaker in the near future.

Furthermore, the presence of a momentum-reversion effect depends on the time horizon. In general, prices tend to revert to the mean over short periods, such as intraday or daily horizons, but they tend to follow the trend over longer horizons of weeks or months. Here are two different strategies based on the S&P 500 index.

The first is an intraday mean-reversion strategy based on the previous day's high and low levels. When the previous day's price is down and the range (high–low) exceeds a given threshold, the strategy will buy the previous day's low and sell at the end of the day, with no stop-loss or profit target. The rationale is that days with higher intraday volatility will see stronger mean reversion and volatility is usually higher in bear markets.

Trend-following, or momentum, strategies work on a longer horizon. Here are some sample strategies (Clare et al. 2013):

- Strategy 1 (simple daily moving averages): a buy signal occurs when the S&P 500's value moves above the average price of a reasonable time window (250 days or 500 days).
- Strategy 2 (moving average crossovers): a buy signal occurs when the shorter-duration average of the S&P 500's value moves above the longer-duration average.
- Strategy 3 (breakout rules): a buy signal occurs when the S&P 500's value trades at an "*x*-day" high.

Simulating the strategies above using data from July 1988 to June 2011 shows that they outperform the market, with annualized returns ranging from 10.5% to 11.6% and Sharpe ratios ranging from 0.54 to 0.62.

Integer Effect

Psychological factors also can be sources of price–volume alphas. When human traders (as opposed to computers) plan to buy Apple (AAPL) shares, they tend to issue orders like "BUY *N* shares with limit price of 100 USD." Humans are less likely to input orders like "SELL AAPL with limit price of 155.29 USD." Round numbers (integers, tens, or hundreds) attract a lot more attention from human traders, and this can be targeted in designing alphas. Another example is that people look at price movements asymmetrically: most people care less about a 1% rise in their holdings than a corresponding 1% loss. Furthermore, people tend to hold their losing positions too long and sell their winning positions too soon. By studying such psychological factors, quant researchers can find price trading signals.

Price–Volume with Other Types of Data

Price–volume data has great predictive power when combined with other types of data, especially firmwide events. A particularly significant price or volume movement often is a reflection of a known or unknown market event that likely will have a further impact on market sentiment over time. For example, an empirical study shows that predictable increases in volume lead to predictable increases in prices when quarterly earnings announcements generate substantial volume shocks, which leads to predictable subsequent returns (Frazzini and Lamont 2007). A strategy of buying the stock of every company expected to announce earnings over the next month and shorting stocks not expected to make an announcement generates in testing excess average annual returns of 7–18%. The effect is especially strong for large-cap securities. The study has a relatively long in-sample period, from 1927–2004, showing that the result is robust over different market regimes.

CONCLUSION

The simple examples discussed in this chapter show that price–volume strategies can be viable. Many other types of signals can be extracted from price–volume data, such as market sentiment and the average buy price of different investors. Technical indicators are designed to describe these kinds of information and may help investors better understand and predict stock price movements.

In the finance industry, it is important to trade unique models that have not already been arbitraged away by other market participants. Each trader cherishes his or her models and keeps them well hidden. A model is valuable only when it has limited exposure. Once it becomes public, its predictive power diminishes and soon disappears (occasionally reappearing years later, after it has been forgotten). The market is also evolving; old models decay as new ones emerge. The constant search for new models is the key to why some firms can survive in this business. There are almost unlimited ways to use simple equity price and volume data in quantitative finance.

19
Financial Statement Analysis

By Paul A. Griffin and Sunny Mahajan

Financial statements are formal records of a company's financial health for a given period of time or at a given point in time. Security analysis, popularized by Benjamin Graham and David Dodd in their 1934 classic investing tome (2009), is the in-depth study of these statements on a per company basis to gauge the potential for excess returns based on a company's underlying qualities. This analysis is used by fundamental value investors, Warren Buffett being the most famous practitioner. It contrasts with studying the movements and order flow of stock prices, as discussed by Edwin Lefèvre in *Reminiscences of a Stock Operator* (2006), or other technical analysis approaches, such as momentum-based strategies, which make bets based on an expectation that price trends will continue into the future (see Chan et al. 1996 and references therein).

Financial statement analysis attempts to systematically measure the effect of factors computed using these statements and to determine their ability to predict future returns; investors can use it to rank, sort, and filter companies to seek to create a portfolio with improved financial strength. The opinion that financial statement analysis can be leveraged to generate excess returns was initially received with skepticism because of the prevailing orthodoxy of the efficient market hypothesis (EMH), which postulates that in an efficient market, current prices reflect all available information. However, subsequent works on multiple factors constructed from a diverse and logical selection of earnings information demonstrated violations of the EMH over long periods of time (see, for example, Abarbanell and Bushee 1997; Bartov and Mohanram 2004; Beneish and Nichols 2009; Chan et al. 2001; and Piotroski 2000).

Finding Alphas: A Quantitative Approach to Building Trading Strategies, Second Edition. Edited by Igor Tulchinsky et al. an
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Traditional financial statement analysis typically results in a stock screen generating a long-only, low-turnover portfolio with a reduced investment universe selected on the basis of companies' fundamental characteristics. Modern analysis, however, uses financial statements to derive quantitative portfolios with stock exposures based on fundamental ratios and derived metrics – and possibly subject to other constraints without specifically reducing the investment universe. Under these more contemporary terms, investors try to use fundamental factors as predictors in a multifactor regression or features in a machine learning algorithm. Financial statement analysis, along with additional data sources associated with market performance, analyst recommendations, and earnings surprises, can be combined to identify alphas.

This chapter is not designed to cover the entire subject of fundamental analysis; a more comprehensive overview of the subject is provided in the next chapter. This chapter is intended to serve as a basic introduction to the subject and may, we hope, provide some inspiration for future research.

BASICS

Companies release financial statements on a quarterly and annual basis. There are four main statements: balance sheets, income statements, cash flow statements, and statements of shareholders' equity.

Balance sheets are a snapshot at a single point in time of a company's assets, liabilities, and shareholders' equity. Unlike the balance sheet, which pertains to a given moment, income statements provide information about a company's financial performance over a specific accounting period. The cash flow statement provides data on the cash inflows and outflows from a company's operations and external investment sources for a given period. The statement of shareholders' equity shows changes in the interests of the company's shareholders over time.

Investors use these statements to evaluate a company's risks, performance, financial health, and prospects. Note that in this context, preliminary quarterly announcements and the subsequently filed statements can differ; the audited annual financial statements are generally considered to be the most authoritative.

THE BALANCE SHEET

The basic equation of accounting, also called the balance sheet equation, is represented by the balance sheet in Table 19.1 and is expressed as follows:

$$\text{Assets} = \text{Liabilities} + \text{Equity}$$

Note that this balance sheet is for a given date and provides a snapshot of the company's well-being. By comparing snapshots, investors can find changes that could cause a repricing of the company's outstanding equity. Total assets are typically used as a normalizing factor to make the values of other factors comparable among different companies or to compare snapshots of the same company at different times. For US companies, the value of total assets includes the intangible asset known as goodwill, defined as what a company pays for another company above book value. Though goodwill contains items such as branding, investors should generally consider whether to discount the goodwill included in the total assets as a normalizing factor.

The following well-known factors constructed from the balance sheet were positively correlated with future returns from 1976 to 1996, as observed by Piotroski (2000):

- Increased liquidity (current assets over current liabilities)
- Improved sales over total assets
- No equity issuance
- Less long-term debt

Table 19.1 The balance sheet equation

Balance sheet YYYYMMDD	
Assets	Liabilities + Equity
Current assets	Current liabilities
Other assets	Long-term debt
Intangible assets (goodwill, etc.)	
Total assets	Shareholders' equity

Table 19.2 The income statement

Income statement YYYMMDD	
Net sales (sales)	A
Interest income	B
Cost of goods	C
Operating expenses	D
Income taxes	E
Gross margin	A – C
Income from operations	A – C – D
Gross income	A + B
Net income	A + B – C – D – E

THE INCOME STATEMENT

The income statement reflects changes in the balance sheet from one time period to the next, as shown in Table 19.2. Most companies use accrual-based accounting, so the income statement does not reflect the movement of cash but, rather, the accrual of obligations to be paid. For example, if a company signs a multiyear contract to supply products, it recognizes the revenue when it fulfills each obligation in the contract, not when the other party transfers cash to an account.

The following factors based on the income statement were positively correlated with future returns in the US from 1976 to 1996, according to Piotroski (2000):

- Net income > 0
- Improved net income over total assets
- Improved gross margin

THE CASH FLOW STATEMENT

The cash flow statement, as shown in Table 19.3, describes the sources of the change in a company's cash balance from one period to the next.

Table 19.3 The cash flow statement

Cash flow statement YYYMMDD	
Cash balance	A
Cash from operations	B
Borrowings	C
Stock sale	D
Purchases	E
Taxes	F
Cash flow	B + C + D – E – F
Cash balance	A + B + C + D – E – F

The following factors were positively correlated with future returns in the US from 1976 to 1996, according to Piotroski (2000):

- Cash from operations > 0
- Cash from operations > net income

GROWTH

The factors above are focused on finding quality in company performance. However, investors may also be interested in growth prospects.

A similar regression analysis for growth stocks was performed by Chan et al. (2001) and Bartov and Mohanram (2004); they found signals that correlated with future returns specifically for growth stocks (stocks with low book-to-market ratios) from 1979 to 1999:

- Net income/total assets > industry median
- Cash flow/total assets > industry median
- Net income variance < industry median
- Gross income variance < industry median
- R&D expenses/total assets > industry median
- Capital expenditure/total assets > industry median
- Advertising expenses/total assets > industry median

R&D, capital, and advertising expenses are separate items inside the operating expenses line item of the income statement, as indicated in Table 19.4. Growing companies will build out these areas with expectations of improved future sales.

Table 19.4 The income statement: operating expenses

R&D expenses	D1
Capital expenses	D2
Advertising expenses	D3
Other operating expenses	D4
Operating expenses	D = D1 + D2 + D3 + D4

CORPORATE GOVERNANCE

Management monitors and seeks to improve company performance using metrics, and market participants will tend to reward the stock price when they observe improvements in some of these. Metrics positively correlated with future returns, according to Abarbanell and Bushee (1997), are:

- Reduced inventory per unit sales
- Improved accounts receivable per unit sales
- Improved sales minus change in gross margin
- Reduced administrative expenses per unit sales
- Improved tax rate
- Earnings quality – change to the use of FIFO versus LIFO
- Audit qualification – change to qualified auditing
- Sales per employee

NEGATIVE FACTORS

Some factors are specifically useful for isolating a short portfolio. Beneish and Nichols (2009) suggest searching for earnings manipulation, a history of mergers, equity issuance, and other forms of management efforts to improve the reported earnings or cash flow without actually improving the core business. Factors negatively correlated with future returns include:

- Higher net sales than free cash flow
- Low book to price
- High sales growth
- Low cash flow from operations to price

- Acquisition in past five years
- Equity issuance > industry average over two years

Nissim and Penman (2003) show that high financial leverage, defined as net financing debt over common equity, is negatively correlated with operating profitability; the definition of financial leverage excludes operating liabilities. High long-term financial leverage can be a signal of pending liquidity issues or even insolvency. A well-known case study of the misguided application of financial leverage is the history of the hedge fund firm Long-Term Capital Management. Also, the Enron Corporation accounting scandal was based on the use of special-purpose vehicles to keep long-term debt off the balance sheet, and the corrected accounting of debt led to the company's insolvency. Generally, additional leverage adds risk that can lead to either higher profits or the risk of ruin. Therefore, it is wise to analyze leverage and debt in conjunction with other factors to find the combinations that indicate meaningful positive or negative correlations with future returns.

SPECIAL CONSIDERATIONS

When analyzing financial statements, investors must factor in the industry of the company being studied. In commodity-based industries, for example, the underlying commodity price contributes significantly to sales, so sales increases are not necessarily a measure of improved company performance. Banks have different reporting requirements and should be given special treatment. The phase of the economic cycle may affect the correlation of debt with price appreciation and significantly impact factors closely associated with growth.

FACTORS AS SCREENS

In the investment literature, the most common use of factors is to construct a universe screen, particularly by the mechanism of assigning a score of +1 to a company when it passes a particular test, then combining the scores over all factors and taking a long position on the highest-rated companies. This is generally a reasonable fusion method in the absence of a more significant statistical analysis, according to Kahneman (2011).

CONVERTING FACTORS TO ALPHAS

Note that most of the scores are based on the rate of change, which generally subtracts the latest statement data from the previous year(s); otherwise, seasonality will contaminate direct quarter-over-quarter comparisons. Statement data may be delayed for alpha analysis, and investors should be careful to note the time delays in the data used for alpha generation. Point-in-time financial data provides significantly more-realistic results (and worse backtesting results) because it removes the forward bias associated with statement refilings.

More sophisticated statistical analyses, such as regressions and factor correlation analysis, may produce better alphas. Investors can also employ machine learning techniques such as genetic algorithms to find good factor combinations; this may be particularly successful if the inputs are based on a thorough understanding of the factors' meanings. The market rewards strategies based on new meaningful factor combinations, so researchers should think creatively and continually scan the literature for the latest ideas.

CONCLUSION

Financial statement analysis allows analysts to identify trends and discern investment opportunities by comparing key performance metrics over multiple time periods and statement types. Many financial signals have been observed to be correlated to excess returns and can be effectively leveraged in an investment process.

Though financial statements do not directly reflect all the information that indicates a company's potential, they do contribute a key piece of the investment puzzle. In the pursuit of alphas, the meaningful interpretation and analysis of financial statements can be a solid basis for informed investment decisions.

20
Fundamental Analysis and Alpha Research

By Xinye Tang and Kailin Qi

Along with techniques such as pairs trading, momentum investing, event-driven investing, and news sentiment analysis, fundamental analysis is an important tool used in designing quantitative alphas. By examining relevant economic and financial factors, fundamental analysts attempt to reveal a security's value and determine whether it is undervalued or overvalued. A potentially profitable portfolio can then be constructed by going long the relatively undervalued securities and/or going short the overvalued ones. This chapter introduces the key ideas and data sources used in fundamental analysis, as well as the applications of fundamental analysis in quantitative alpha research.

Fundamental analysis can be applied to a range of financial securities. In the context of stocks, fundamental analysis is defined as techniques to determine a company's intrinsic value by analyzing underlying factors that affect its business and its prospects. Fundamental analysts seek to answer such questions as: is the company's revenue steadily growing? What is the company's ability to pay its debt? Does the company have good profitability as well as high earnings quality? Does the company have enough liquid assets compared with liabilities?

On a broader scale, fundamental analysis refers to the analysis of the economic well-being of a financial entity, not just its price movements. Fundamental analysis can be applied not only to single stocks but to sectors and industries as aggregates or even to the market as a whole. In contrast, technical analysis – another major form of security analysis and an important direction in alpha research – focuses solely on the price and volume movements of securities without concerning itself with the fundamentals of the underlying factors.

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Fundamental factors can be either qualitative or quantitative. In alpha research, we primarily look at quantitative factors, which can be measured or expressed in numerical terms. Because financial statements are the standard medium by which a company discloses information regarding its financial performance, the quantitative information extracted from them is often used to design alpha signals. Much empirical accounting research has attempted to discover value-relevant attributes from financial statements in order to enhance fundamental analysis.

FINANCIAL STATEMENTS

As described in the previous chapter, the four main financial statements are the balance sheet, the income statement, the cash flow statement, and the statement of shareholders' equity. The balance sheet provides a financial snapshot of an organization at a particular point in time. It lists a company's assets and liabilities. Investors can use the balance sheet to derive the company's debt level and relevant financial measures, such as the debt-to-equity ratio, quick ratio, and current ratio, which help them understand the company's debt interest payments, credit rating, and performance compared with the industry average. Red flags, such as a large decrease in reserve accounts or a large increase in inventory or accounts receivable, are also exposed on the balance sheet.

The income statement provides a measure of a company's profitability over a period of time, including earnings or profits and expenses or costs. Earnings before interest can be used as a measure of operational profitability, ignoring any interest burden attributable to debt financing. Because of conservatism in accounting, expense items also might include some costs that are not directly related to goods sold during the current period, while some research and development expenditures might not be shown.

The cash flow statement is an important measure of a company's financial well-being because it shows the change in cash over the year. If the statement shows that the enterprise is not able to generate enough cash to pay its dividends but is keeping the productivity of its capital stock out of cash flow from operations, or that the amount of cash flow from operations is lower than that from investing, it may be an early warning sign of potentially serious debt and future cash flow problems.

Shareholders' equity is the difference between the assets and the liabilities of a company (also known as its net worth) and is listed on the balance sheet. The statement of shareholders' equity shows the change in the equity section of the balance sheet during the given period. Companies typically break out common shares, preferred stock, treasury stock, and retained earnings on the statement of shareholders' equity. Investors often follow business metrics such as paid-in capital, the capital invested in the company when it issued its shares, and retained earnings – the portion of earnings that the corporation has chosen to reinvest in the business – on the shareholders' equity statement. When a company chooses to reinvest in the business rather than pay out dividends, it signals that management believes the stock is undervalued and expects it to grow. However, this signal is easily manipulated because it is under management control.

FINANCIAL STATEMENT ANALYSIS

In-depth analysis of financial statements gives investors insight into a company's current and likely future performance. For example, earnings accruals may be biased by management manipulation. Management may assume that investors see high earnings today as a sign of high earnings coming in the future. In fact, earnings consist of two parts: actual cash flow, which is generated by operations, and accruals, which are calculated and decided by accountants, thus leaving room for manipulation. To analyze the quality of accruals, it is worth looking at a case study conducted by Sloan et al. (2011).

1. Sloan scaled earnings, accruals, and cash flow by total assets to compare companies of different sizes.
2. He then analyzed the relationship between earnings and the quality of accruals. He amassed data on accruals, earnings, and cash flows from sample companies, and ranked them by earnings. Sloan assigned company-years into deciles based on the rank of earnings and calculated the average value of earnings in each decile. Then he tracked the results of earnings for the previous and following five years around the calculated year.
3. Last, he compared the results with a ranked version based on the values of the accruals part of earnings.

Sloan's analysis shows that, based on earnings alone, a company that has high performance this year is expected to continue to have high earnings for several years into the future. After ranking the accruals component, however, the predictability of earnings is worse. The cash flow component is a much more powerful predictor than the accruals component. In other words, when analyzing the future level of earnings, it is better to rely on earnings generated from cash flows than on the accruals.

To gain some understanding of a company's value and financial performance, you can analyze the valuation ratios, which are mathematical calculations using figures mainly from the financial statements. Some of the most well-known valuation ratios are price-to-earnings and price-to-book. Some empirical research indicates that factors related to contemporaneous changes in many financial statement ratios can yield significant abnormal returns.

Relevant information outside the standard format of financial statements is submitted in the form of footnotes. Footnotes disclose critical content to help investors get a better view of a company and make informed decisions. Details on matters such as accounting policy, changes in accounting methods, long-term purchase commitments, pending or imminent litigation, and executives' stock options can be found there. Companies hardly ever expose their mistakes or difficulties in headlines or tables, so reading between the lines of these disclosures can give diligent investors an advantage. In some cases, companies use financial disclosures to hide the fact and the effect of changing accounting rules, which might hurt stock prices. Empirically, when there are many new footnotes in financial reports, some red flags may be buried in the long paragraphs. If the footnotes do not appear meaningful, chances are the company is being intentionally obscure. The ability to detect early warning signs in the footnotes of financial reports sets elite investors apart from average ones. Because the footnotes appear as unstructured text, the advanced alpha researcher must find or develop appropriate text-mining systems to convert them to usable signals. Though this step adds to the difficulty of utilizing such data, it provides an opportunity to extract uncorrelated signals.

Alpha researchers also see quarterly conference calls as a tool for corporate disclosure. While financial statements give insight into a company's past performance, conference calls give investors both an idea of the current situation and management's expectations for future performance. Some commentators would say that investors can gather critical information for long-term models, as well as technical indicators, from the tone and manner of the CEO and CFO, especially in the question-and-answer part of the conference call – when, say, they are explaining significant deviations in performance from previous estimates. Empirical evidence shows that the sentiment of the conference call can predict earnings surprises in the following 60 trading days. Analyst interest – those researchers who participate in the call but do not cover the company – is an early indicator of the company's future fundamentals and is positively correlated with stock returns over the next three months (Jung et al. 2015). Investors respond strongly to extreme words and phrases in the earnings call, with significantly higher abnormal trading volume and stock returns after the call (Bochkay et al. 2016). When the number of questions asked during the Q&A section is far below expectations, the next-day abnormal return is lower (Chen et al. 2016). Surprises in the linguistic tone (the relative frequency of negative and positive words) tend to move stock prices (Druz et al. 2016).

Macroeconomic variables can also be used as powerful and fundamental stock price indicators for particular industries – for example, the correlation between oil prices and stock prices in the transportation industry or interest rates in financial services.

Analyst reports produced by investment banks and brokerage firms – the sell side – are another potentially useful information source for investors. These reports analyze business prospects and build valuation models using past and present fundamental information on a specific company and its relevant industry; their price and earnings targets, comments, ratings, and recommendations can be meaningful components of alphas. Because large institutional investors often refer to sell-side reports and can move markets thanks to the volume of assets they manage, analysts' views can be self-fulfilling in the short term even if they are not accurate in the long term. Analyst research also serves as context for any subsequent fundamental announcements because the market has already priced in sell-side expectations; the "surprise" difference between the consensus prediction and the actual announcement is often more meaningful than the fundamentals themselves.

Because of the infrequency with which fundamental data is updated, fundamental alpha signals have lower trading turnover and lower stock coverage than other signals, such as price–volume-based alphas. On the other hand, fundamental information tends to be reflected in stock prices over a longer period of time. The cumulative returns to the fundamental signals usually concentrate around the subsequent earnings announcement and level off one year after the signal's disclosure, indicating that a large percentage of abnormal returns can be attributed to previous years' earnings changes.

Fundamental analysis can give researchers ideas on alternative stock classifications. For example, stocks can be labeled as either value or growth, based on the company's financial performance. Value stocks refer to those at relatively low prices, as indicated by low price-to-earnings, price-to-book, and price-to-sales ratios, and high dividend yields. Growth stocks refer to just the opposite: high price-to-earnings, price-to-book, and price-to-sales ratios, and low dividend yields. Similarly, investors can generate classifications by using other fundamental factors differentiating one type of stock from another. These kinds of classifications allow investors to more accurately observe the market behavior of different groups of stocks and thus design better alpha signals.

CONCLUSION

Growing evidence in both academic and industrial research shows that the application of fundamental analysis can potentially yield significant excess returns. Information extracted from the data sources mentioned in this chapter, such as financial statements, conference calls, and sell-side analyst reports, has historically displayed strong power to predict future stock returns. Quantitative alpha researchers utilize this information to build their fundamental alphas and seek to create portfolios with low turnover and stable profits.

21
Introduction to Momentum Alphas

By Zhiyu Ma, Arpit Agarwal, and Laszlo Borda

In financial markets, "momentum" refers to the empirical observation that asset prices that have been rising are likely to rise further, and vice versa. Within the framework of the efficient market hypothesis, momentum is one of the market anomalies (along with reversion, seasonality, and momentum reversal) that originate from the fact that investors' immediate reactions may be improper and will tend to adjust over time.

In a seminal 1993 paper, Jegadeesh and Titman found that the winners and losers in the past 3–12 months are likely to continue to win and lose. The same phenomenon has been extensively studied, and it has been confirmed that momentum works for most asset classes and financial markets around the world (Chan et al. 2000; Hong and Stein 1999; Hong et al. 2000; Jegadeesh and Titman 2001, 2011; Rouwenhorst 1998). The observed profitability of momentum alphas, however, has shrunk a great deal in recent years, and they suffered a large drawdown during and around the financial crisis of 2008 (Barroso and Santa-Clara 2015). Since then, many research papers have suggested modifying the rule to enhance the potential profit and reduce the potential drawdown while keeping the spirit of a momentum alpha (Antonacci 2014). This continues to be an active field of research within the academic community.

Researchers have attempted to explain through behavioral models why momentum alphas work. According to a well-accepted theory of conservatism bias, investors tend to underreact to new information (Barberis et al. 1998; Chan et al. 1996; Daniel et al. 1998; Edwards 1968; Zhang 2006). In an imperfectly efficient market, it takes time to resolve and price new information. This explanation seems to hold water when we investigate the impact of events on the markets.

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The stock price gains momentum when public information is announced (for example, earnings announcements); the more powerful the information, the stronger the momentum effect. An interesting observation is that stock momentum actually starts to build up before the announcement is made (that is, when the public information was private information), indicating that investors' expectations, guided by analysts' recommendations and forecasts, also play a role in the momentum effect. Another class of momentum alphas may be based on identifying events using news, earning announcements, or any other quantitative formulation and then defining alphas based on the stock returns preceding the event.

Not only do investors underreact to new information – stock analysts do, too. Under peer pressure, analysts are reluctant to make outstanding (but possibly correct) forecasts; instead, they tend to gradually adjust their forecasts on future earnings and target prices. Consequently, when investors in the market make investment decisions based on analysts' recommendations, the overall decision itself is an underreaction; this provides a supplementary explanation of the price momentum effect. As per a contrarian theory of delayed overreaction, abnormal momentum returns in the holding period are expected to be followed by negative returns because of the subsequent reversal when the stock prices eventually return to their fundamental values. Daniel et al. (1998) and Hong and Stein (1999) have proposed alternative models that are consistent with short-term momentum and long-term reversals.

An alternative (or supplementary) hypothesis assumes that momentum investors bear significant risk for betting on the strategy and that the higher returns they accrue are a compensation for the risk (Li et al. 2008). Momentum strategies implemented on stocks with high bid–ask spreads (thereby exhibiting exposure to illiquidity risk) provide strong returns (Lesmond et al. 2004). It is therefore crucial to take transaction costs into account when evaluating the potential profitability of a momentum strategy. The returns associated with a momentum strategy implemented on stocks with relatively low analyst coverage are very strong, as the slower dissemination of public information increases the momentum profits (Hong and Stein 1999; Hong et al. 2000). Momentum profits have been observed to be significantly higher when the strategies are implemented on growth stocks (low book-to-market) compared with value stocks (high book-to-market), most likely because growth stocks are harder to evaluate than value stocks (Daniel and Titman 1999). A somewhat contrarian and surprising finding suggests that momentum profits are higher for stocks with higher volumes (Lee and Swaminathan 2000). High-volume stocks typically generate more public information and can be traded more easily with lower transaction costs; a potential explanation is that the large difference in opinion about higher turnover may arise from difficulties in evaluating the fundamental values of these stocks.

It is important to mention here that other alpha signals in their most basic form may contain significant exposure to the price momentum factor. In some of these cases, momentum represents an unintended source of risk, which can be minimized by neutralizing the basic signal to the momentum factor. In other cases – seasonality, for example – momentum contributes significantly to the strategy's return, so momentum neutralization is not an option. For more details on momentum as a risk factor, see Chapter 13.

Seasonal effects potentially impact the performance of the momentum strategy: the average monthly returns to the momentum strategy corresponding to quarter-ending months have been found to be significantly higher than the returns corresponding to non-quarter-ending months. This pattern is stronger for stocks with high levels of institutional trading, suggesting that "window dressing" (selling recent losers and buying recent winners at the end of the reporting period) by institutional investors and tax-loss selling contribute to stock return momentum (Gray 2015).

Another approach to developing momentum alphas is based on the momentum exhibited by macroeconomic factors. In arbitrage pricing theory, the returns of a stock or other financial asset can be modeled as a linear function by a much smaller set of macroeconomic factors or theoretical market indexes. The exposures of stocks to the various factors are dynamic and constantly changing. Yet when compared with single-stock returns, single-factor returns are much more stable and exhibit stronger momentum characteristics (at least, over a given period of time or market state). Alphas based on factor regressions therefore assume that the factors' returns have a momentum effect. Another application of factor momentum is to trade the factors that the market currently favors by reverse-engineering the factors in which mutual fund managers are currently investing.

Another approach for developing momentum alphas is based on group momentum, which often is associated with a phenomenon called co-movement. Related stocks – stocks of companies that are in comparable areas of business or share similar exposures to a common factor that significantly explains their returns – tend to move together.

Moskowitz and Grinblatt (1999) evaluated momentum in industry returns by forming industry portfolios with stocks ranked based on their industry returns. They found that stocks with high industry returns outperformed the low-industry-return stocks in the six-month period following portfolio formation. The extent to which industry momentum contributes to momentum profits was re-examined by Grundy and Martin (2001). Momentum profits also can arise from lead–lag effects because the stocks in the group do not move by exactly the same amount at the same time. Usually, a few leaders in the group move first (possibly driven by new information or by reacting to the common factors early), then other stocks in the group follow the leaders. The lagged stocks enjoy the momentum profits, as investors can seek to anticipate their future price movements based on the movement of the leaders and the common factor realizations. In addition to directly related stocks, there are related groups (for example, industries on a common supply chain), which transfer returns from one leading group to the others.

CONCLUSION

When any predictable patterns in returns are identified, investors act quickly to exploit them until the predictability is eliminated. However, based on the observed positive returns that momentum alphas have generated across major markets around the world, it can be argued that momentum effects represent the strongest evidence against the efficient market hypothesis. For the same reasons, momentum has attracted and will continue to attract substantial research; financial economists have not yet reached a consensus on what generates momentum profits. Indeed, as momentum effects are evidence of market inefficiency, attempts have been made to provide behavioral explanations for the phenomenon. Developing momentum alphas on liquid universes (sets of more efficient stocks) is a particular challenge, which requires deeper exploration.

22
The Impact of News and Social Media on Stock Returns

By Wancheng Zhang

INTRODUCTION

Stock prices naturally respond to news. But in recent years, news and sentiment seen on social media have grown increasingly significant as potential predictors of stock prices. However, it is challenging to make alphas using news. As unstructured data that often includes text and multimedia content, news cannot be understood directly by a computer. We can use natural language processing (NLP) and machine learning methods to classify and score raw news content, and we can measure additional properties of the news, such as novelty, relevance, and category, to better describe the sentiment of the news. Similar techniques can be applied to social media data to generate alphas, though we should bear in mind that social media has much more volume and is much noisier than conventional news media. This chapter gives an overview of ways to find alphas using news and social media.

NEWS IN ALPHAS

It is not easy for machines to accurately parse and interpret the meaning of news. As in other areas in statistical arbitrage, an algorithm has the advantages of fast response time and broad coverage, but at the expense of weaker accuracy than a human analyst. Nowadays, trading firms can analyze news within 1 millisecond and make trading decisions instantly. Big news usually causes large price movements instantly, often with a subsequent overshoot and reversal.

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Since 2007, the application of sophisticated linguistic analysis of news and social media has grown from a highly speculative area of research into mature product solutions. Professional data vendors use sophisticated algorithms to analyze news and deliver the results in real time. News analytics and news sentiment are widely used by both buy-side and sell-side institutions in alpha generation, trading, and risk management. Increasingly, Big Data vendors offer packages, services, or data sources to help firms use news in the investment process.

ACADEMIC RESEARCH

Since 2000, news on stock returns has become a popular topic. Some of the key research areas include the aggregation and dispersion of sentiment; beta calculations using news; leading news stocks; weighting schemes in textual analysis; news confirmation by day-return earnings announcements; the idea that no news is good news; the notion that stocks that are sensitive to news outperform the broader market; confirmation of news by trading volume; bias in the news coverage on stocks; momentum, overshoot, and reversal after news; and the relationship of news to analyst revisions. Related papers can be found by searching for "news" and "stock return" on the Social Science Research Network (SSRN).

The first research paper on using social media for stock prediction was "Twitter Mood Predicts the Stock Market," published by Johan Bollen, Huina Mao, and Xiao-Jun Zeng in *The Journal of Computational Science* in 2011. The paper argues that by analyzing Twitter texts the authors gained an accuracy of 87.6% in predicting daily up and down changes in the closing values of the Dow Jones Industrial Average (DJIA). Since then, key research areas include the prediction power of various forms of social media; social media applied to individual stocks; the discussion of noise in social media; finding valuable tweets by observing retweets and tweets from celebrities; and social media sentiment with long-term firm value.

SENTIMENT

Simply speaking, sentiment measures the quality of news. The most basic definition of sentiment is the polarity of the news: good, bad, or neutral. Advanced sentiment analysis can express more sophisticated emotional details, such as "anger," "surprise," or "beyond expectations."

The construction of news sentiment usually involves natural language processing and statistical/machine learning algorithms (for example, naive Bayes and support vector machines). The recent explosion of deep learning techniques has enabled rapid progress in understanding news. Novel techniques like word2vec have achieved higher accuracy compared with classical NLP methods.

Sentiment is usually normalized into scores (for example, in the range 0–100) that are cross-sectionally comparable across assets. By convention, a higher score means the news is good, a lower score means the news is bad, and a score near 50 means the news is neutral.

Individual news sentiment may have exposure to market aggregate sentiment, seasonality, and other timing factors (for example, before or after the earning season). For a relative-value strategy, it is useful to compare the relative sentiment among similar stocks.

Sentiment is also useful in risk management. For example, a portfolio manager may cut the size of a stock holding because of unexpected news, or estimate the portfolio covariance matrix taking into account the news sentiment score or news frequency.

Example

A simple alpha could be to follow the sentiment directly:

If (stock A sentiment > 70) long stock A;
if (stock B sentiment < 30) short stock B;
use the no-news stocks in the same industry for neutralization.

NOVELTY

Novelty measures whether the news is a brand-new story or an update to an old story. Vendors may split one long report into several parts. Sometimes a story is a follow-up report on previous news. In other cases, news may be revised several times after the initial report. Less novel news usually has less impact on the market because the information delivered in the previous news may already be reflected in the market. If we view news as events in a time series, novelty usually is inversely proportional to the time between the events.

Example

We could enhance the previous simple alpha by using novelty:

Score novelty from 0 to 1.

If $(\text{sentiment} > 70)\ \text{alpha} = +\ \text{novelty};$
if $(\text{sentiment} < 30)\ \text{alpha} = -\ \text{novelty};$
use the no-news stocks in the same industry for neutralization.

RELEVANCE

News can have an impact on multiple stocks. Relevance measures the focus of news on specific stocks. Some news, such as earnings or corporate actions, is company specific. The relevance of such news is usually high. One news story could talk about multiple companies in the supply chain of a product; in this case, the relevance of the news could be the highest for the company manufacturing the product and lower for other companies along the supply chain.

Industry or general macroeconomic news usually has lower relevance to individual stocks. A general news item about the banking industry may affect lots of banking stocks; a news story about Apple's new products may affect Apple and competitors like Samsung, with higher relevance to Apple and lower relevance to Samsung. In other words, relevance maps the news sentiment to individual stocks. It can be another factor to enhance news alphas.

Example

We could enhance the previous simple alpha by using relevance and ignore the news that affects too many stocks:

Score relevance from 0 to 1, get *ns* = number of stocks impacted by one news item.

If $(\text{sentiment} > 70 \text{ and ns} < 100)\ \text{alpha} = +\ \text{novelty} * \text{relevance};$
if $(\text{sentiment} < 30 \text{ and ns} < 100)\ \text{alpha} = -\ \text{novelty} * \text{relevance};$
use the no-news stocks in the same industry for neutralization.

NEWS CATEGORIES

Besides the simplistic classification of news into "good" or "bad," further classification into more detailed categories can enhance the analysis and use of news. A category can be as broad as "earnings," which may include all earnings-related reports, like earnings announcements, earnings forecasts, earnings revisions, earnings guidelines, earnings conference calls, and earnings calendars. Or it can be more specific, like "corporate legal issues."

There are several important aspects to consider when using news categories. First, different categories of news may have different response times in the market. Some categories have longer-term effects on company valuations; other categories can cause short-term price fluctuations. Second, markets have different flavors of news at different times. A category-rotation strategy can take advantage of these flavors of news styles. Third, some news categories are specific to certain industries and sectors, and may affect only those industries or sectors. Last, categories make different types of news easier to combine with other types of information to create alphas. For example, one can use earnings news together with analyst earnings revisions. News vendors like Bloomberg provide tags and categories for raw news, and automatic categorizations by advanced machine learning methods are becoming more common.

Example

Consider the earnings news example. We can drop "market reports" categories and use a simple "learning" method to further weight the news:

Ignore all news from the categories "market imbalance" and "market movements."

For each news category,

Category_score = the average of relative stock returns after the news happened in the past two years

$$\text{If}\left(\text{sentiment} > 70\ \text{and ns} < 100\right)\text{alpha}$$

$$= +\ \text{novelty} * \text{relevance} * \text{category\_score};$$

$$\text{if}\left(\text{sentiment} < 30\ \text{and ns} < 100\right)\text{alpha}$$

$$= -\ \text{novelty} * \text{relevance} * \text{category\_score};$$

use the no-news stocks in the same industry for neutralization.

EXPECTED AND UNEXPECTED NEWS

A seemingly good piece of news, if the information already is expected by the market and thus reflected in the price, will not cause a positive price movement. For example, a piece of news reads, "Earnings have large growth – 150% compared with last year." Analyzing this news usually gives positive sentiment. However, if the previous market consensus was that the company would grow 200%, the value in the news is below expectations and will cause the price to go down. Therefore, it can be helpful to use news data together with market consensus and market expectations. Textual analysis and calendar analysis can be useful in determining whether the news is a routine update or something different. Surprises and unexpected news and events usually result in larger price movements.

HEADLINES AND FULL TEXT

Headlines usually contain the most important information and are well formatted, so they are easier to parse and analyze. Full text provides more detailed information, but it is harder to work with. One academic research paper shows an interesting result: most of the information in a paragraph is included in the first and last sentences. Similarly, we can focus more on the first and last paragraphs of an article, or the first and last few words. The paragraph structure and sentence structure also can contain valuable information.

NO NEWS IS GOOD NEWS?

There is an old saying: "No news is good news." This is true to some extent; news means change, events or something unusual happening, and markets hate uncertainty. News is also usually associated with higher volatility, higher volume, analyst revisions, and the expectation of more news. These aspects imply potential risks to the company. Because more and more firms are using news in their risk management models, institutional investors may reduce their holdings of companies that are frequently affected by news reports or even remove them from their portfolios. Because institutional investment flow tends to be positive for stock returns, this can lower returns.

Example

When there is an abnormal amount of news for a company, short the company.

NEWS MOMENTUM

If the impact of news on a stock is not immediately and fully priced in by the market, the stock price may exhibit drift or momentum as the news becomes more widely known and understood. This effect is much stronger for smaller stocks because they are less closely observed, and for unexpected news. For large stocks and expected news, the price generally exhibits a reversal after an initial overshoot.

Example

For the first three days after the news release, hold a position in the same direction as the two-day stock returns for the two days prior to the news release; for the following five days, reverse the trade to capture the reversal.

SOCIAL MEDIA

In April 2013, a Twitter post by the Associated Press claimed there had been an explosion at the White House that injured President Obama. The tweet was false, but it caused a huge instant reaction in the market. From 1:08 p.m. to 1:10 p.m., the DJIA dropped more than 140 points. Though the index rebounded just as quickly, one fake Twitter event caused market losses of $136 billion. This case clearly shows the significant potential value of social media in algorithmic trading. Many data vendors are capturing this opportunity. Companies like Dataminr and PsychSignal provide millions of social data feeds on a daily basis. They also provide data to third-party vendors that create sentiment products used by many hedge funds.

The most popular social media platform for generating alphas is Twitter because it can be easily mapped to stocks (by checking the @ ticker symbol) and people (such as the CEOs of public companies). There is also increasing research based on online forums like Yahoo Finance message boards and StockTwits, blogs by professional investors and traders, Facebook, Glassdoor, and even Wikipedia.

Social media currently is a hot area in quant research. Essentially, social media can be viewed as news, but with much more volume and much more noise. Many of the ideas that work for news also can work for social media, but there are several challenges in applying sentiment analysis to the contents of social media. First, social media has a larger number of records and updates more quickly. Second, social media content usually is casual in format – a Twitter post, for instance, can contain a lot of abbreviations and poorly formatted words. This increases the difficulty of language processing. Third, how do we find original and important records? A lot of social media content is in response to news and has a smaller impact than more original social media content. Hence, there are many fake signals in social media, and that is why it is difficult to use social media for predictions.

Example

Use the frequency of tweets and the number of retweets to short companies being mentioned with increasing frequency (tweets about companies are mostly negative).

For each company, calculate the number of tweets that mentioned the ticker symbol or company name on a particular day. Get the number of retweets for each tweet and set it as t. Set $\textit{frequency} = \text{sum of } \log(t+1)$.

$$\text{Alpha} = \text{time\_series\_rank}(\text{frequency}, 1\,\text{month}) - 0.5$$

CONCLUSION

The quantity of news, social media content, and companies processing Big Data is increasing rapidly. More and more market participants are using automatic methods to analyze and trade this information. Therefore, the average impact of each piece of information on stock returns will likely decrease over time. To continue to find alphas in news, one will need to parse more news, find the most impactful news, filter noise, and adopt more advanced machine learning methods to learn and classify the news.

23
Stock Returns Information from the Stock Options Market

By Swastik Tiwari and Hardik Agarwal

INTRODUCTION

In finance, an option is a financial derivative that represents a contract sold by one party (the option writer) to another party (the option holder), giving the buyer the right, but not the obligation, to buy or sell an underlying asset or instrument at a specified "strike price" on or before a certain date. The seller has the corresponding obligation to fulfill the transaction – that is, to sell or buy – if the option holder exercises the option. The buyer pays a premium to the seller for this right. Because call options give the option to buy at a certain price, the buyer wants the underlying asset or instrument to go up in price. And because put options give the option to sell at a certain price, the buyer wants the underlying asset or instrument to go down in price. Speculators use options to make leveraged bets on the underlying assets, while hedgers use options to reduce the risk of holding them.

The equity options market provides a lot of useful information for seeking to predict stock returns. Equity options contribute to price discovery because they allow traders to align their strategies more precisely with the sign and magnitude of their information. The leverage in equity options, combined with this alignment, creates an additional incentive for traders to invest time and money in research to generate private information. In this way, trades in equity options may provide more refined and precise signals of an underlying asset's value than trades in the asset itself. Understanding how and why equity options affect price discovery is therefore vital to understanding how information is incorporated in asset prices.

Finding Alphas: A Quantitative Approach to Building Trading Strategies, Second Edition. Edited by Igor Tulchinsky et al. an
WorldQuant Virtual Research Center.

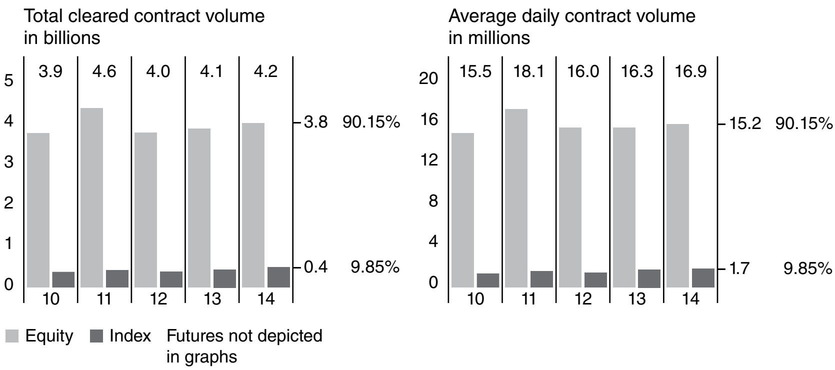

Figure 23.1 Options cleared and daily contract volumes 2010–2014
Source: © 2018, The Options Clearing Corporation. Used with permission. All rights reserved.

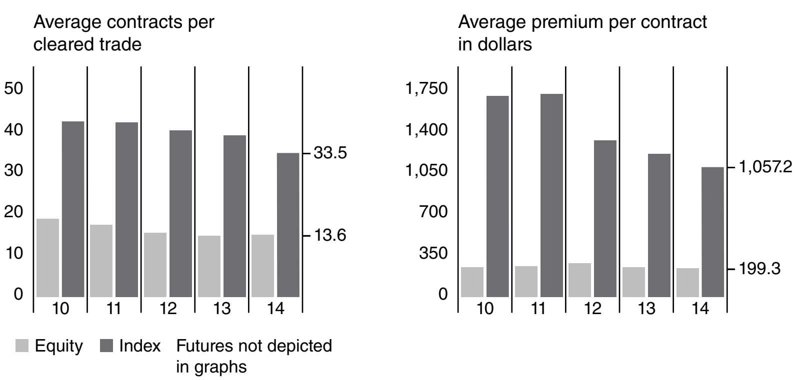

Figure 23.2 Options daily call and put volumes 2010–2014
Source: © 2018, The Options Clearing Corporation. Used with permission. All rights reserved.

Equity options are becoming increasingly popular with both retail and institutional investors. There are currently 15 options markets in the US, run by BOX Holdings Group, Cboe Group, Miami International Holdings, Nasdaq, and the Intercontinental Exchange's NYSE.

In its 2014 annual report, Options Clearing Corp. (OCC) presented the statistics and charts shown in Figures 23.1–23.3.[1]

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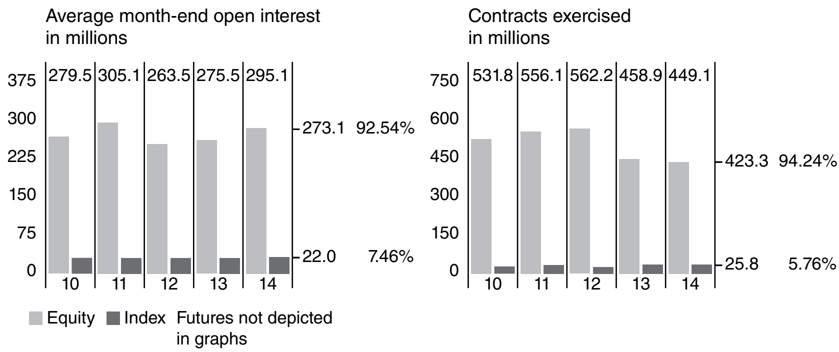

Figure 23.3 Options open interest and contracts exercised 2010–2014
Source: © 2018, The Options Clearing Corporation. Used with permission. All rights reserved.

VOLATILITY SKEW

A useful source of information on the direction of the options market is the implied volatility of stock options. This is the value for the volatility of the underlying instrument such that, when the value is input in an option pricing model (such as Black–Scholes), the model will return a theoretical value equal to the current market price of the option. In the case of equity options, a plot of the implied volatility against the strike price gives a skewed surface. The volatility skew is the difference in implied volatility between out-of-the-money, at-the-money, and in-the-money options. The volatility skew is affected by sentiment and supply–demand relationships, and provides information on whether fund managers prefer to write calls or puts. In equity options markets, a skew generally occurs because money managers, on the whole, would rather write call options than put options, as can be seen in Figure 23.4.

In their paper "Option Prices Leading Equity Prices: Do Option Traders Have an Information Advantage?" Jin et al. (2012) survey the existing literature on the information advantage, including Bollen and Whaley (2004), Bradshaw et al. (2010), Gârleanu et al. (2009), Van Buskirk (2011), and Xing et al. (2010). Bollen and Whaley and Gârleanu et al. attribute the "shape of observed volatility skew and its predictive ability to the buying pressure due to the information possessed by option traders." Bollen and Whaley find that "contemporaneous changes in daily implied volatilities are driven by changes in net buying pressure." Options traders with expectations of positive news create an excess of buy-call trades and/or sell-put trades, which causes

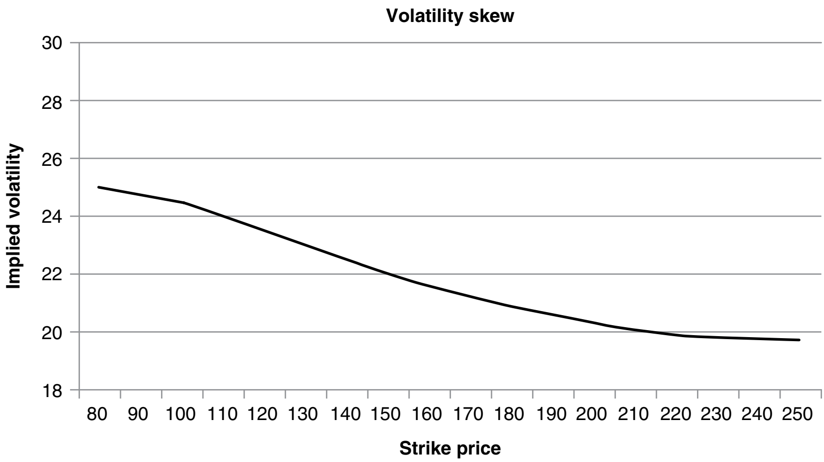

Figure 23.4 Sample volatility skew in equity options markets

prices and implied volatilities of call options, relative to put options, to rise. Similarly, options traders with expectations of negative news create an excess of sell-call trades and/or buy-put trades, which causes the prices and implied volatilities of put options, relative to call options, to rise. Thus, when options traders expect information about the probability of a negative event, the demand for out-of-the-money put options increases relative to the demand for at-the-money call options, thereby increasing the volatility skew.

Researchers have shown that there is a negative association between volatility skews and individual stock returns at the company level. This finding is consistent with the hypothesis that volatility skews reflect negative information. Xing et al. (2010) state that the "greater the volatility skew in the traded options of the stock, [the] higher the underperformance." They calculate the underperformance of the underlying stocks of options with higher skews relative to the underlying stocks of options with lower skews as 10.9% per year on a risk-adjusted basis. In a long–short equity alpha, this implies taking a long position on stocks whose options have lower volatility skews and a short position on stocks whose options have higher volatility skews. A few recent studies have examined the predictive ability of volatility skews for extreme negative events. Van Buskirk (2011) finds that high volatility skews predict negative jumps over short windows containing earnings announcements and over longer windows containing no earnings announcements, but

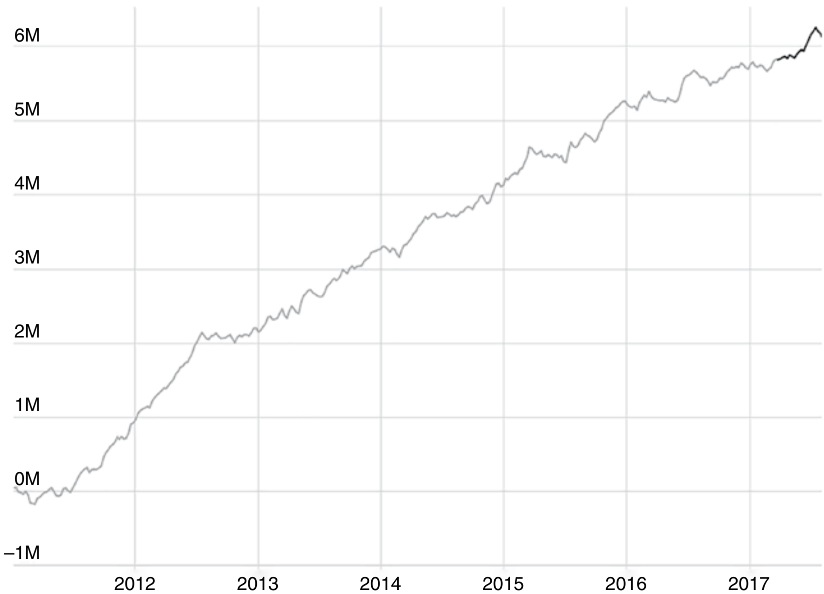

Figure 23.5 Performance of alpha on the Russell 1000 stock universe using volatility skew[2]

do not predict negative jumps around management earnings forecasts or dividend declarations. Bradshaw et al. (2010) show that the "predictive abilities of volatility skews and accounting opacity for crash risks are incremental to each other." According to the authors, although the information advantage as reflected in the predictive ability of volatility skews is greater for negative news than for positive news, the predictive ability of the options market applies to news surprises of a range of magnitudes. This phenomenon can be used to find stocks to short long–short equity alphas on longer and shorter time scales.

Figure 23.5 shows the performance of an alpha on the Russell 1000 universe of stocks. The alpha uses the slope of the implied volatility curve to measure the skew. The idea is to buy stocks that have shown a decrease in the slope of the implied volatility curve (or decrease in volatility skew), and vice versa.

[2] Alpha = −(change in slope of the implied volatility curve).

VOLATILITY SPREAD

The put-call parity relation states that in perfect markets, the following equality holds for European options on non-dividend-paying stocks:

$$C - P = S - D.K$$

where C and P are the current call and put prices, respectively; D is the discount factor; K is the strike price; and S is the spot price. For US options, which allow early exercise, the equation takes the form of an inequality: $S \geq D.K + C - P$. From these relations, it can be shown that European call and put options with the same strike price and maturity date should have the same implied volatilities, while the US call and put options should have a spread in the implied volatilities ("volatility spread") attributable to the early-exercise premium (Hull 2008).

However, Ofek et al. (2004) show that the volatility spread cannot be entirely explained by the early-exercise premium. Ofek et al. and Cremers and Weinbaum (2010) demonstrate that this volatility spread implies future stock returns. For example, Cremers and Weinbaum find that stocks with high volatility spreads outperform those with low volatility spreads by 50 basis points per week, on average. Bollen and Whaley (2004) and Gârleanu et al. (2009) attribute the "predictive ability of volatility spreads to the demand-based option models." Higher volatility spreads indicate greater excess demand for call options than for put options, suggesting that options traders may possess expectations about positive news. Thus, the volatility spread can be considered as indicative of the nature (positive or negative) and potential impact of the news expected by the options traders, by measuring the overall net buying pressure in the options market. This phenomenon can be used in an equity alpha to go long stocks with high volatility spreads and short those with low volatility spreads.

Figure 23.6 shows the performance of an alpha on the Russell 3000 universe of stocks. The alpha uses implied volatility information of at-the-money call and put options. The idea is to buy stocks with higher call-implied volatility than put-implied volatility, and vice versa.

OPTIONS TRADING VOLUME

The trading volumes of stock options can also carry useful information about future stock returns. In their paper "The Option to Stock Volume Ratio and Future Returns" Johnson and So (2011) focus on the inferences

Figure 23.6 Performance of an alpha on the Russell 3000 stock universe using volatility spread[3]

that can be drawn from the trading volumes of options and their underlying stocks. The authors provide theoretical and empirical evidence that O/S – the ratio of the total option market volume (aggregated across calls and puts) to the total equity market volume – is indicative of the private information available to informed traders. The O/S measure was first coined and studied by Roll et al. (2009), whose findings state that "cross-sectional and time-series variation in O/S may be driven by the trades of informed traders in possession of private information." As an extension of these findings, Johnson and So examine the relationship between O/S and future returns, and find outperformance of low O/S companies over high O/S companies. Their methodology involves sorting companies by O/S at the end of each month and computing the average return of a portfolio consisting of a short position in high O/S stocks and a long position in low O/S stocks, holding this portfolio for one month. This portfolio provides an average risk-adjusted monthly hedged return of 1.47%. The authors attribute the negative relationship

[3] Alpha = implied volatility of at-the-money (call options – put options).

between O/S and future equity returns to short-sale costs in the underlying equity markets: because of capital constraints and equity short-sale costs, informed traders prefer to trade options more frequently when they expect negative news than when they expect positive news.

According to Johnson and So (2011), "O/S predicts earnings surprises, standardized unexplained earnings, and abnormal returns at quarterly earnings announcements in the following month." The same O/S-measure-based portfolio construction methodology also contains information about future earnings announcements that occur in the month subsequent to the "holding month." They contend that this is consistent with the hypothesis that O/S reflects private information that is incorporated into equity prices when the news becomes public. Furthermore, they state that their model "also predicts that O/S is a stronger signal when short-sale costs are high or option leverage is low" and confirm this in the data. These ideas can be used to go long low O/S companies and short high O/S companies in a long–short equity alpha.

Figure 23.7 shows the performance of an alpha on the Russell 1000 universe of stocks. The alpha uses option volume information from the

Figure 23.7 Performance of an alpha on Russell 1000 stock universe using option-to-stock-volume ratio[4]

[4] Alpha = stock trading volume/(call + put option trading volume).

Nasdaq OMX PHLX and compares it with average daily stock volume. The idea is to buy stocks that have a high ratio of stock volume to option volume, and vice versa.

OPTION OPEN INTEREST

Open interest is the number of outstanding options contracts on a given underlying asset. In their paper "Do Option Open-Interest Changes Foreshadow Future Equity Returns?" Fodor et al. (2010) examine the relationship between option open-interest changes and future returns. They show that options traders buy relatively more (fewer) call (put) options when they are near-term bullish on the underlying asset. Similarly, options traders buy relatively more (fewer) put (call) options when they are near-term bearish on the underlying asset. Because of this behavior, changes in aggregate open interest contain information about future equity returns. The authors assert that informed investors leverage their bullish (bearish) views through increased long call (put) positions.

In their empirical investigation, the authors demonstrate a strong negative relationship between recent changes in aggregate put open-interest levels and future underlying equity returns. Companies with increases in recent put open interest significantly underperformed companies with decreases in put open interest. The authors find that an opposite but much weaker relationship exists for the call open-interest changes. They note that the ratio of the recent changes in call open interest to put open interest is the most effective predictor of future equity returns and that this relationship is positive in the sense that large increases in the ratio tend to be followed by relatively strong future equity returns.

Fodor et al. demonstrate the documented preference of informed traders, as first discussed by Black (1975), to leverage their views through options (bullish views through long call positions and bearish views through long put positions) because of the relatively small initial outlay requirements. Fodor et al. present further evidence that real-world informational differences between the options and equity markets result in differences in the rates at which information gets incorporated into prices in the respective markets. The open interest in equity call and put options can thus be used to select long and short stocks in a long–short equity alpha.

Figure 23.8 shows the performance of an alpha on the Russell 3000 universe of stocks. The alpha uses call and put option open-interest information from PHLX. The idea is to buy stocks with higher call open interest compared with put open interest, and vice versa.

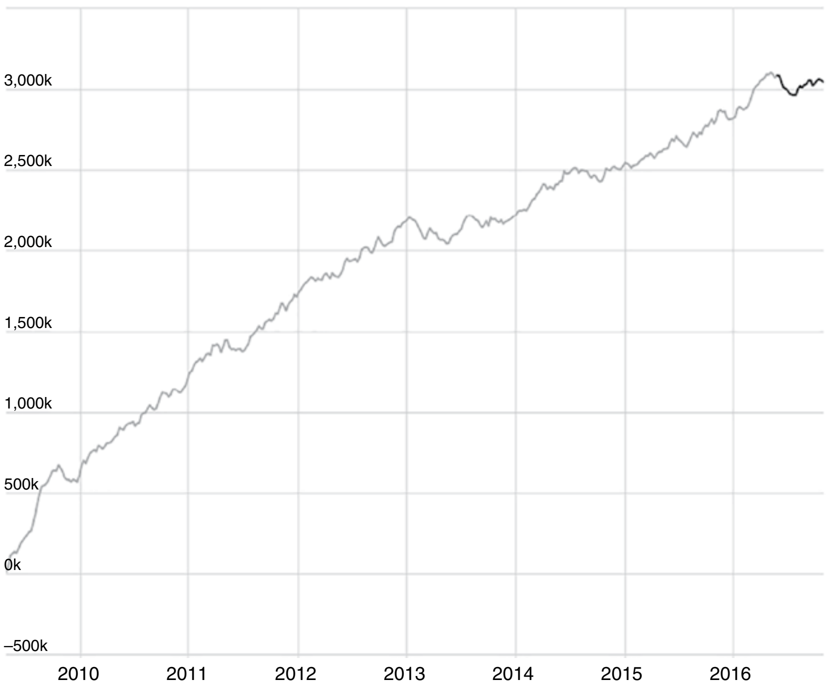

Figure 23.8 Performance of alpha on the Russell 3000 stock universe using call and put open interest[5]

CONCLUSION

As shown in the extensive research literature, equity options markets contain useful information to seek to predict stock movements. The shape of the volatility skew, the volatility spread, the options trading volume, and the options open interest are all useful tools for predicting near-term performance of the underlying stock.

[5] Alpha = open interest of call options/open interest of put options.

24
Institutional Research 101: Analyst Reports

By Benjamin Ee, Hardik Agarwal, Shubham Goyal, Abhishek Panigrahy, and Anant Pushkar

This chapter is a general overview of analyst research reports and stock recommendations that alpha researchers may encounter in financial media sources. We will discuss the best ways to access analyst recommendations, and address the all-important question of how these reports can help inspire systematic trading ideas.

Sell-side analysts' recommendations, ratings, and price-target changes – on companies and entire industries – are featured prominently in financial newspapers, conferences, blogs, and databases, which often cite these reports to explain major stock price movements. Indeed, numerous studies by industry associations and academics have found that analyst research contains valuable information.

Nevertheless, the phrase "stock analyst" conjures up images of sophisticated researchers from Goldman Sachs or J.P. Morgan who conduct high-powered earnings calls with Fortune 500 CEOs to gather information and present their findings to multibillion-dollar institutional funds. How can you, a new alpha researcher (with something less than a few billion dollars at your disposal), access this valuable body of analysis? Just as important, why should an alpha researcher, who is interested in constructing systematic market strategies, pay attention to what are typically company-specific analyses?

Finding Alphas: A Quantitative Approach to Building Trading Strategies, Second Edition. Edited by Igor Tulchinsky et al. an
WorldQuant Virtual Research Center.

ACCESSING ANALYST RESEARCH (FOR FREE, OF COURSE)

An analyst report generally contains the following:

- A detailed description of a company and its industry.
- Estimates for relevant financial numbers, such as earnings and revenue.
- A price target.
- A buy, hold, or sell recommendation based on the analyst's research.
- A thesis explaining the recommendation.

Sell-side analysts often perform research that is costly, sophisticated, and time consuming; naturally, they want to provide first access to their valued clients. To be sure, you will not be able to access all (or even most) analyst research on a company via public sources. Nevertheless, the portion of analyst research that finds its way to publicly accessible media can be a valuable learning tool for new alpha researchers.

In fact, some analyst research is surprisingly accessible, with the financial media acting as an intermediary. In this case, the term "financial media" includes not only traditional sources like *The Wall Street Journal* and Bloomberg, but also aggregator websites such as Yahoo Finance and Google Finance. The latter are particularly useful sources of analyst analysis, estimates, and questions posed to corporate management during earnings calls. Pulling up mentions of analyst research on a company is often as easy as entering that company's stock ticker into your favorite finance portal. For instance, typing Apple's stock ticker (AAPL) into Yahoo Finance's portal turns up the headlines in Figure 24.1, from November 2018.

The left-hand side of the screenshot shows headlines and links to articles that sometimes draw upon analyst research. On the right side, Yahoo Finance has helpfully summarized the analyst recommendations (strong buy, sell, and so forth), price targets, upgrades, and downgrades. Clicking on Upgrades & Downgrades will lead to a detailed table with earnings and revenue estimates for AAPL, as well as EPS trend and revisions for the company.

You may wish to try out this process on other portals, such as Google Finance or Bloomberg.com, before picking the one that works

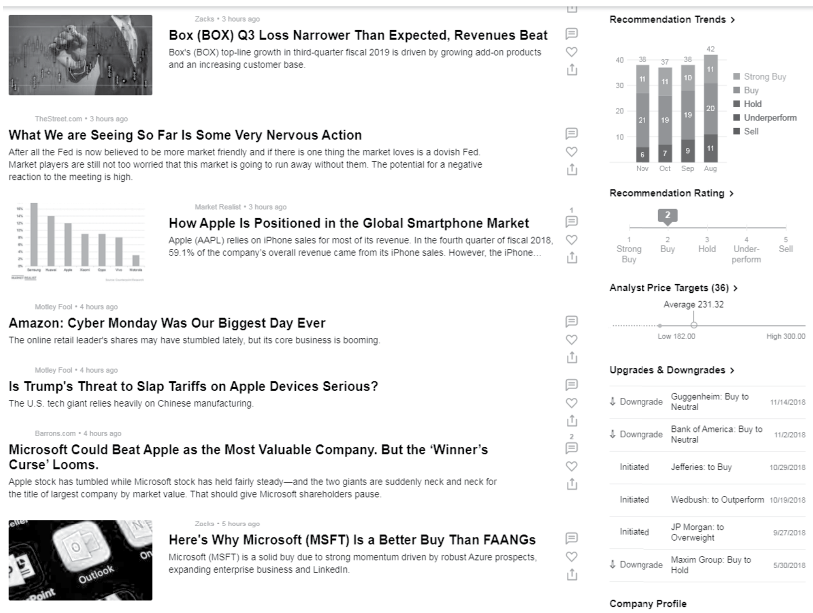

Figure 24.1 Screenshot of search result for "AAPL" on Yahoo Finance
Source: Yahoo Finance © 2019. All rights reserved. https://finance.yahoo.com/.

best for you. If these don't provide what you're looking for, try using search engines directly (Google "AAPL analyst reports," for instance).

As with analyst research, finance portals often provide transcripts of companies' earning calls, as well as stock analysts' questions during the calls and managements' responses. In the next example, we use another finance portal, Seeking Alpha (https://seekingalpha.com). There are many places on the internet where you can find such information. Other examples: the Motley Fool website (www.fool.com), stock exchange websites (such as www.nasdaq.com), and the investor relations section of company websites. Some of these sources also contain a fair amount of discussion by nonbank market commentators on specific industries as well as individual stocks. The discussion on these sites can be similar to research from stock analysts, touching on points such as firm-specific fundamentals, macroeconomics, geopolitics, and market conditions. Table 24.1 provides additional examples of such market commentary sites and finance blogs.

Table 24.1 Market commentary sites and finance blogs

Market commentary sites	**Link**
Bloomberg	http://www.bloomberg.com
The Wall Street Journal	http://www.wsj.com
Seeking Alpha	http://www.seekingalpha.com
Morningstar	http://www.morningstar.com
TheStreet	http://www.thestreet.com
Finance blogs	**Link**
Econbrowser	http://econbrowser.com/
Free Exchange	http://www.economist.com/blogs/freeexchange
ZeroHedge	http://www.zerohedge.com/
CXO Advisory Group	http://www.cxoadvisory.com/blog/
Freakonomics	http://freakonomics.com/
Marginal Revolution	http://marginalrevolution.com/

Note: In many places, our listing coincides with a ranking compiled by *Time* magazine. The URL is http://content.time.com/time/specials/packages/completelist/0,29569,2057116,00.html.

See if you can find Apple's third-quarter 2018 earnings-call transcript and analyst Q&A on the Seeking Alpha website (Figure 24.2).

SO FAR, SO GOOD. BUT WHY SHOULD YOU CARE?

Good question. Most analyst reports (and market commentaries) focus on a single stock or industry, whereas you, as an alpha researcher, are looking for systematic market strategies that trade tens of thousands of stocks each day. *So what* if some analyst from Bank XYZ likes a particular company? How do we go from this to trading thousands of companies on 20 different stock exchanges around the world?

You can combine information from analyst reports for various stocks to construct an alpha that trades a more diversified set of stocks.

1. **Recommendations**
   Useful information from analyst reports includes buy and sell recommendations. We can use the average recommendation rating for stocks to make an alpha. Figure 24.3 shows the performance of an

Transcripts | Technology

Apple (AAPL) Q3 2018 Results - Earnings Call Transcript

Jul. 31, 2018 8:39 PM ET | 16 Likes | About: Apple Inc. (AAPL)

Q3: 07-19-18 Earnings Summary

Press Release | 10-Q | Analysis | News

EPS of $2.34 beats by $0.16 | Revenue of $53.3B (+ 17.4% Y/Y) beats by $870M

Apple, Inc. (NASDAQ:AAPL) Q3 2018 Earnings Call July 31, 2018 5:00 PM ET

Executives

Nancy Paxton - Apple, Inc.

Timothy Donald Cook - Apple, Inc.

Luca Maestri - Apple, Inc.

Analysts

Kathryn Lynn Huberty - Morgan Stanley & Co. LLC

Shannon S. Cross - Cross Research LLC

Brian White - Monness, Crespi, Hardt & Co., Inc.

Antonio M. Sacconaghi - Sanford C. Bernstein & Co. LLC

Laura Martin - Needham & Co. LLC

Operator

Good day and welcome to the Apple Incorporated Third Quarter Fiscal Year 2018 Earnings Conference Call. Today's call is being recorded. At this time for opening remarks and introductions I'd like to turn the call over to Nancy Paxton, Senior Director of Investor Relations. Please go ahead.

Figure 24.2 Screenshot of Apple Q3 2018 earnings call transcript on Seeking Alpha

Source: Seeking Alpha. http://seekingalpha.com.

alpha that uses buy and sell recommendations from analyst reports for the Russell 3000 universe of stocks. The idea is to go long stocks with buy recommendations and short stocks with sell recommendations.

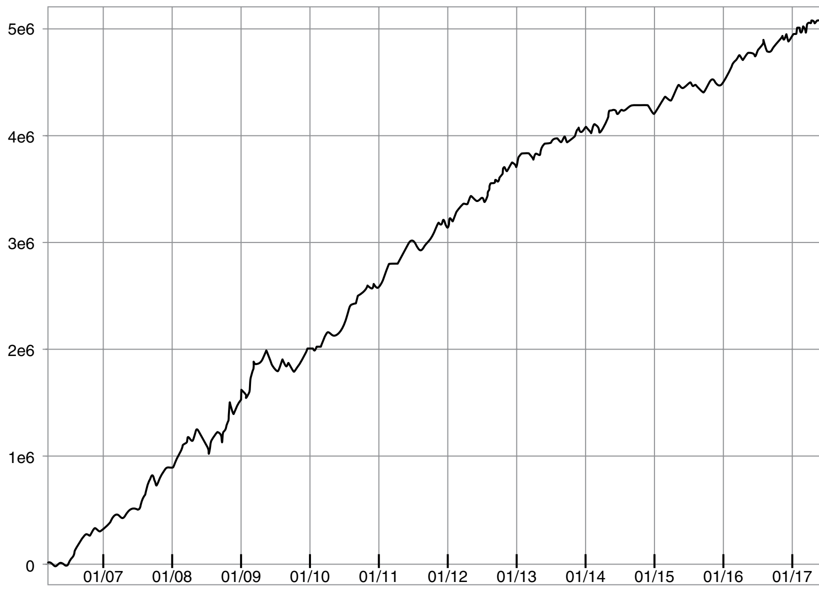

Figure 24.3 Performance of alpha using buy and sell recommendations[1]

2. **Price targets**
   Analysts calculate the projected price levels of stocks. Figure 24.4 shows the performance of an alpha using the Russell 3000 universe that compares the analyst price target with the present stock price. The idea is to buy the stock if the projected price target is above the current stock price and sell it short if the price target is below the current price.
3. **Earnings estimates**
   Analysts provide estimates for various fundamentals of a company, such as earnings, dividends, and cash flow. Figure 24.5 is a snapshot of summarized statistics for earnings estimates of AAPL from Yahoo Finance.

   Figure 24.6 shows the performance of an alpha based on the Russell 3000 universe of stocks, using the growth in earnings estimates. The alpha buys stocks with positive growth and sells short stocks with negative growth.

[1] Alpha = average buy recommendation – average sell recommendation.

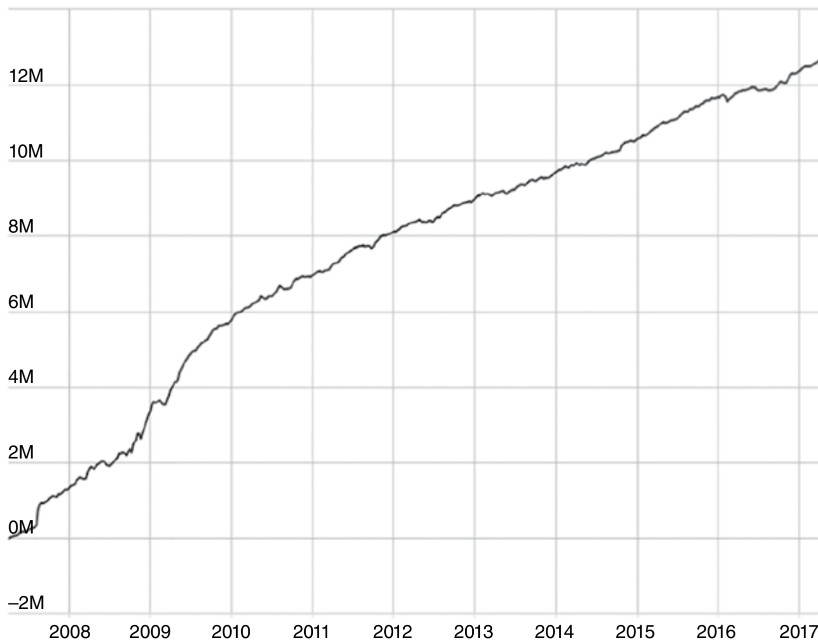

Figure 24.4 Performance of alpha using price target[2]

Currency in USD

Earnings Estimate	Current Qtr. (Dec 2018)	Next Qtr. (Mar 2019)	Current Year (2019)	Next Year (2020)
No. of Analysts	34	33	40	34
Avg. Estimate	4.72	3.04	13.45	14.83
Low Estimate	4.51	2.41	11.54	10.98
High Estimate	5.59	3.39	15.4	18.5
Year Ago EPS	3.89	2.73	11.91	13.45

Figure 24.5 Screenshot of earnings estimates results for AAPL on Yahoo Finance

Source: Yahoo Finance © 2019. All rights reserved. https://finance.yahoo.com.

4. **Earnings surprises**
   When a company releases its earnings for the quarter or year, the actual earnings number can be compared with the earnings estimated by analysts for that period. A higher than expected earnings number is generally taken as a positive indicator, and vice versa.

[2] Alpha = analyst price target – stock price.

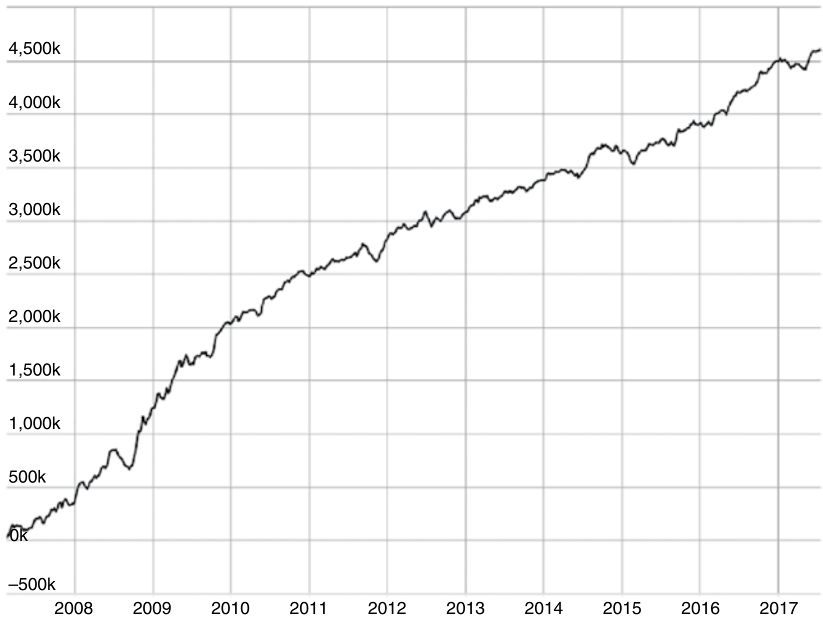

Figure 24.6 Performance of alpha using earnings estimates[3]

> Figure 24.7 shows the performance of an alpha, based on the Russell 3000 universe of stocks, that uses the earnings surprise. The idea is to buy the stock if the company's earnings consistently outperform analyst estimates and sell it short if the earnings underperform estimates.

Researchers looking for systematic market strategies can develop unique or less-known alpha ideas from reading stock analyst reports. The following points may be worth considering:

- **The analyst's thought process is far more important than any specific buy or sell recommendation.** Did she decide to upgrade AAPL for industry-specific reasons (the market for smartphones has been growing at double-digit rates), for company-specific reasons (net margins have been increasing over the past four quarters), or for a more general reason, such as AAPL's low price-earnings ratio compared with the rest of the industry? Regardless of the reason,

[3] Alpha = change in analyst's earnings estimate for next fiscal period.

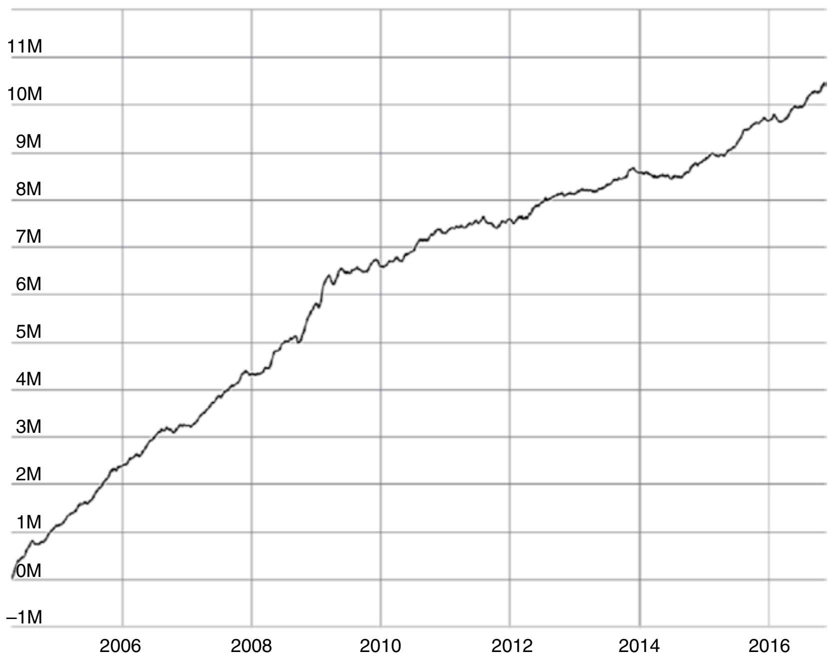

Figure 24.7 Performance of alpha using earnings surprise[4]

an interesting question is: can I apply this to other companies? For instance, if the analyst says she likes AAPL because the CEO has been buying stock in the company, should this logic be applied only to AAPL or to publicly listed companies in general? This line of reasoning has been known to yield new strategy ideas.

Figure 24.8 shows an alpha developed using this hypothesis (go long if there is a share buyback and short otherwise) for the Russell 3000 universe of stocks.

- **Analysts usually ask good questions during earnings calls.** They should, because they are highly paid to do so. And for a new researcher trying to figure out how to make sense of the dense numbers that are a modern corporation's financials, these questions can be a lifesaver. More information is not always better, especially if you have 20 pages of numbers per company and need to separate signal from noise. How can you understand which accounting item is important? One clue is to think about the numbers or trends analysts focus on and the logic

[4] Alpha = actual earnings reported − analyst earnings estimate.

Figure 24.8 Performance of an alpha using share buybacks[5]

that motivates their questions. Are they puzzled by an extremely large and unseasonal change in inventory from one quarter to the next? Why is this important? As always, we should ask if it is something that is generally important beyond the company under discussion.

One way to extract trading signals from earnings calls is to focus on the collective sentiment of the company's management and the analysts and reporters present during such calls. The questions of analysts and the answers provided by management can be a measure of overall market sentiment about a company's quality of earnings and hence the future price of its stock.

Text-parsing algorithms can use this information to derive a net sentiment score (positive or negative) for the stock and decide to buy or sell accordingly. Figure 24.9 shows an alpha using this idea on the Russell 3000 universe.

- **Analysts have detailed industry knowledge**. As Larrabee (2014) points out, industry-specific expertise has been cited as one of the most important attributes (and competitive advantages) of stock analysts. The best sell-side analysts are able to move stock prices with

[5] Alpha = if shares bought back by company's board executive then buy; otherwise sell.

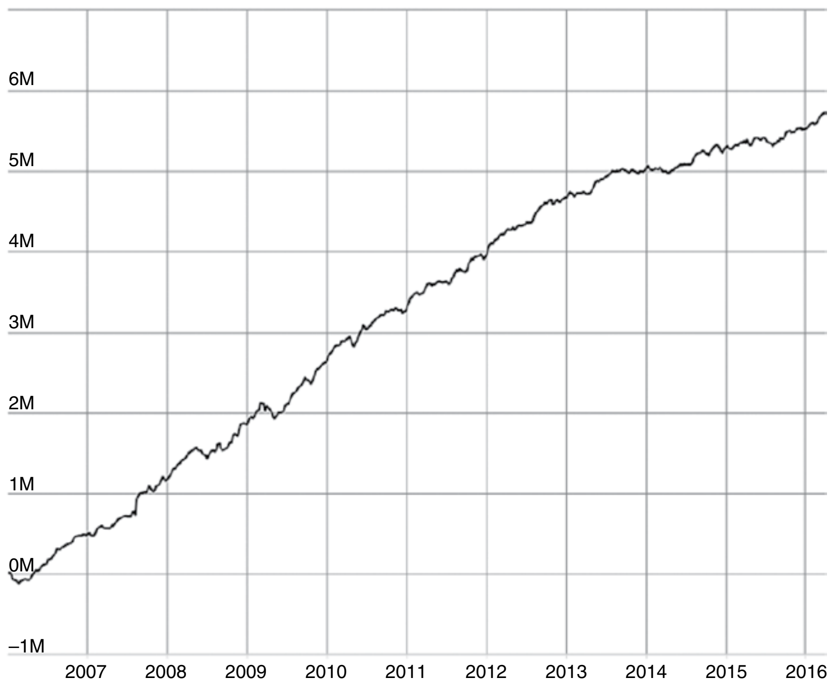

Figure 24.9 Performance of alpha using earnings-call data[6]

their ratings and forecasts, and this effect is stronger for analysts with industry experience. Alpha researchers can learn a lot about methodology from analysts' work. For instance:

- Valuation methodologies vary across industries. Constructing a discounted cash flow model may be very different for the manufacturing sector compared with consumer cyclical firms, noncyclicals, and other sectors. Analysts may focus on different valuation metrics, such as the price–earnings ratio for one industry and the price–book ratio for another. For the alpha researcher, it is important to understand the underlying reasons for these differences in order to normalize and compare data appropriately for the universe of tradable stocks.
- Each industry may have its own unique driver or measure of operational performance, which usually features prominently in analyst reports. Dot-coms used to look at "eyeballs" back in the late 1990s

[6] Alpha = average positive sentiment – average negative sentiment.

(perhaps they still do), and airlines think about "passenger miles," whereas biotech companies may focus on drug trials or drugs in the pipeline. Understanding the key drivers of operational performance in each industry may help the alpha researcher figure out interindustry variations in her strategy's performance.

- **Analyst research can provide valid trading signals.** On occasion, analyst research can directly move stock prices. You may have seen headlines attributing a large price bump or fall for a specific ticker to an analyst upgrade or downgrade, or to an increase in price targets. An extensive body of academic research shows a link between analyst research and stock returns; you can find it on Google Scholar under "stock analyst research." A better understanding of analyst recommendations may help you make better use of this information in constructing strategies.

THINGS TO WATCH OUT FOR IN READING ANALYST REPORTS

Whether you are reading analyst research to look for inspiration on new market strategies or want to use its recommendations and targets directly in strategy construction, it may help to keep in mind some of the pros, cons, and idiosyncrasies of this research.

- **Positive bias.** While different banks have different approaches, academic researchers contend that stock analysts as a group exhibit positive bias. One implication is that the distribution of analyst recommendations is skewed. For example, if we are counting buy, hold, and sell recommendations, there are far more buy than sell recommendations. Academic researchers have debated the reasons for this; Michaely and Womack (1999) and Lin and McNichols (1998) have questioned whether banks are inclined to issue optimistic recommendations for companies with which they have relationships.
- **Herding.** Herding refers to the theory that analysts try not to be too different from one another in their public recommendations and targets. Part of the reason for this may be behavioral: making public stock price predictions (or "targets," in analyst-speak) is a risky endeavor with career implications. All else being equal, there may be some safety in numbers from going with the crowd. A corollary

to this is that analysts who are more confident or have established reputations are usually willing to deviate more from the consensus.

Behavioral reasons aside, there may be sound reasons for analysts to arrive at similar conclusions – for example, most might be working off the same sources of information. Hence, it might be interesting to understand major analyst deviations from the consensus, what is unique about their methods or data source, and whether this can be systematized.

- **Coverage drop.** Analysts have a greater tendency to issue buy (or at least slightly positive) ratings than sell ratings. The reason for this is ingrained in how the financial industry works. The desire of analysts to please their potential investment banking clients can create a conflict of interest. Issuing negative research on the stocks of their own corporate clients (or potential clients) may cost brokerages profitable business. In other words, a brokerage firm would rather be wrong on any buy or sell recommendation than be right and lose a corporate client.

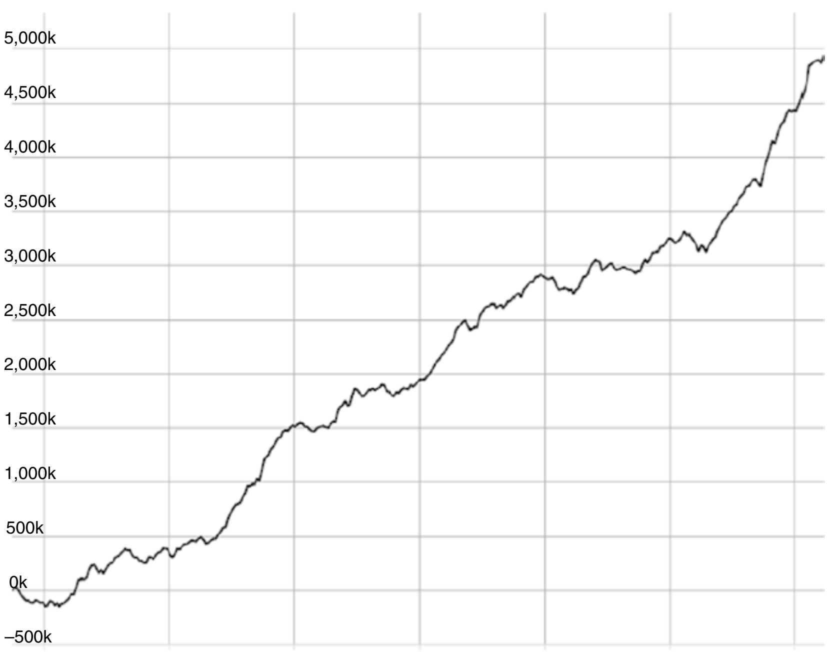

Figure 24.10 Performance of an alpha using coverage drop[7]

[7] Alpha = short-term analyst coverage/long-term analyst coverage.

In some cases – especially large-cap stocks – an analyst may rather drop coverage of the stock than give a sell signal on it and be proved wrong later. Therefore, a drop in coverage of a stock, especially a large cap, may be a red flag. Issuing a sell rating on a small company may have fewer repercussions for an analyst than issuing a sell rating on a big company.

Figure 24.10 shows the performance of an alpha that compares short-term and long-term analyst coverage. The idea is that if the number of analysts covering the stock has decreased significantly with respect to its long-term coverage, then we short the stock; we go long the stock if the short-term analyst coverage has increased.

WHY DO STOCK ANALYSTS TALK TO THE FINANCIAL MEDIA?

If you were to invest significant time and energy in detailed analysis that produced wonderful trading ideas, your first impulse might not be to pick up the phone and tell a bunch of reporters about it. After all, many ideas are capacity limited – only so many people can trade them before the price starts to move significantly and the chance for profit disappears.

Yet we find mentions of analyst research in media reports all the time. In fact, we may even rely on this because it allows us to peek into the world of analyst research at little or no cost. What explains this accessibility? Some possible reasons:

- Many meetings between stock analysts and the companies they cover are open to members of the public and therefore to the financial press. One example of this is earnings calls, which are available through publicly accessible transcripts. In the US, the Securities and Exchange Commission's Regulation Fair Disclosure, known as Reg FD, mandates that nonpublic information disclosed by issuers to investment professionals must also be made available to all market participants. This includes both analysts working for multibillion-dollar banks and members of the investing public.
- A certain amount of publicity probably doesn't hurt a stock analyst's career. Media mentions and interviews may increase demand for an analyst's research among investor clients, and high-profile recommendations that are proved right (such as calling the market bottom in 2009) may fast-track an analyst's career. These benefits are possible only if analysts go public with some of their research.

CONCLUSION

- Analyst research may be accessible via the financial media.
- Analyst recommendations and price targets may be trading signals in their own right.
- Fundamental estimates provided by analysts provide an outlook for a company and can be used to make alphas.
- Stock prices may respond to surprises resulting from a difference between reported fundamentals and their corresponding consensus values.
- The methodologies and reasoning processes analysts use to arrive at their recommendations may be a source of ideas for alpha researchers.
- Earnings-call transcripts can be analyzed to gain insight into the collective sentiment of a company's management, stock analysts, and reporters.
- Watch out for caveats, such as positive bias, analyst herding, and coverage drops.

25
Event-Driven Investing

By Prateek Srivastava

Joseph Nicholas defines event-driven strategies in his book *Hedge Fund of Funds Investing* (2004) as "strategies that are based on investments in opportunities created by significant transactional events, such as spin-offs, mergers and acquisitions, industry consolidations, liquidations, reorganizations, bankruptcies, recapitalizations, share buybacks, and other extraordinary corporate transactions. The uncertainty about the outcome of these events creates investment opportunities for managers who can correctly anticipate them and the success or failure usually depends on whether the manager accurately predicts the outcome and timing of a concrete event."

INTRODUCTION

Event-driven investment strategies attempt to take advantage of price inefficiencies around company-specific (and sometimes marketwide) events. The most popular event-driven strategies include actions taken in response to corporate actions:

- Mergers and acquisitions, which give rise to a trading strategy known as merger arbitrage or risk arbitrage.
- Spin-offs, split-offs, and carve-outs.
- Distressed securities.
- Index rebalancing.
- Capital restructuring events, such as share buybacks, debt exchanges, and security issuances.

Event-driven strategies are important because their distribution of returns is significantly different from that of the market, providing

Finding Alphas: A Quantitative Approach to Building Trading Strategies, Second Edition. Edited by Igor Tulchinsky et al. an
WorldQuant Virtual Research Center.

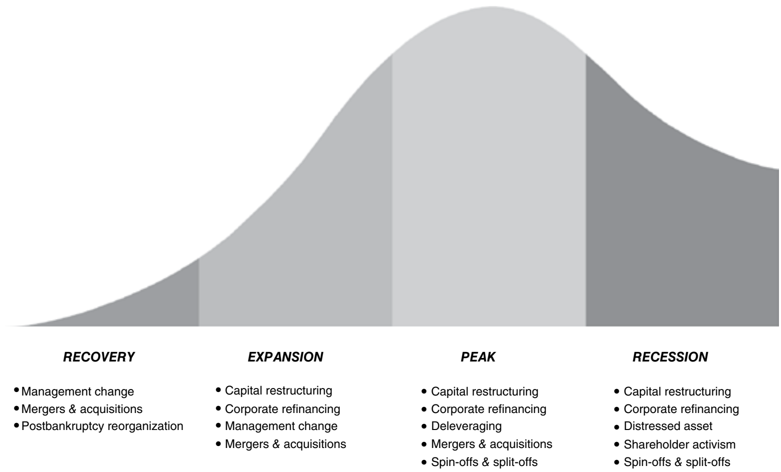

Figure 25.1 Corporate events during phases of the business cycle

diversification to a typical hedge fund's overall portfolio. A corporate event is generally unique to the specific organization and unrelated to broad market events, helping to reduce a portfolio's market dependency.

Another important advantage of an event-driven strategy is that it is an all-season strategy. In every phase of the business and economic cycle, companies are pursuing ways to unlock shareholder value, so there is always some type of corporate event happening. Merger arbitrage events are quite frequent when the economy expands, for example, and distressed-strategy events are more common when the economy contracts. Figure 25.1 lists corporate events that are more frequent in various phases of the business cycle.

MERGER ARBITRAGE

Merger, or risk, arbitrage is probably the best-known event-driven investment strategy. In a merger, two companies mutually agree to join together, which often involves an exchange of shares. In an acquisition, there is a clear-cut buyer (the acquirer) and seller (the target). Often, M&A begins as an acquisition, perhaps unfriendly, but eventually the target succumbs and agrees to a merger. Merger arbitrage is a bet that the deal will or will not close. Some of the major reasons companies make acquisitions are listed in Table 25.1.

Table 25.1 Common reasons for mergers and acquisitions

Synergy	Diversification	Growth	Increased supply-chain pricing power	Reduced competition
Merging with a company that has complementary strengths and weaknesses	Acquiring an unrelated business to reduce the impact of a particular industry's performance on the company's profitability ("conglomeration")	Acquiring a competitor company to increase market share inorganically ("horizontal merger")	Acquiring a supplier or distributor to eliminate one level of cost and save on the margins charged by the supplier or distributor ("vertical merger")	Acquiring a competitor company to lessen future competition

Since hedge funds began to proliferate in the 1990s, merger arbitrage has been a classic market-neutral strategy. However, the activity goes back to the 1940s, when Gustave Levy created the first arbitrage desk on Wall Street at investment bank Goldman, Sachs & Co. Goldman has been a valuable training ground for hedge fund managers, including Daniel Och, Richard Perry, and Tom Steyer, who came out of its risk arbitrage group in the 1980s to start their own firms. In fact, merger arbitrage was never more powerful than during the buyout boom of the 1980s, when arbitrageurs provided the leverage in many of that era's hostile deals.

The merger arbitrage process typically begins when the acquirer approaches the target company with the proposal of a merger or acquisition. This discussion happens at the board of directors level and is kept confidential. If the companies agree on a deal, a press release discloses the important terms of the merger, such as the offer price for the target company (or the exchange ratio of the shares in the case of a merger) and whether the deal will be paid for in cash or in stock. As its name implies, a cash merger is paid for in cash; in an all-stock deal, the merger is paid for in shares of the acquiring company at a certain exchange ratio. (Many deals involve a combination of cash and shares.) Following the news of the merger, the stock price of the target company typically jumps, but it generally does not reach the merger price because the deal carries the risk of not being completed. This is the point where the merger arbitrageur steps in. The difference between the target company's stock price and the merger price is known as the deal spread:

$$\text{Deal spread} = \frac{\text{offer price} - \text{target stock price}}{\text{target stock price}}$$

This is the return (excluding dividend payments before the merger date and transaction costs) that the merger arbitrageur will earn if the deal goes through.

Within a few days of the official deal announcement, the full merger agreement is released by the two companies. The agreement contains all the details of the merger, including the conditions necessary for the deal to close, the required government approvals, and, most important, the material adverse change (MAC) clause. The MAC clause lists the conditions, mostly financial, under which either party can walk away from the deal.

An M&A fund manager will thoroughly analyze the deal agreement, conduct a detailed financial analysis of the transaction, participate in management conference calls, and check filings of both companies with the Securities and Exchange Commission to predict the likelihood of the merger's completion and whether the expected returns from the deal are high enough to justify the risk involved. If he likes the trade, the fund manager will decide on the position size and hedge the risks. For example, in the case of an all-stock merger, the fund manager will buy stock in the target company and short the stock in the acquirer to hedge the risk that the latter's stock price will drop before the deal concludes.

The fund manager would diversify across many deals to ensure that no single failed merger causes an unacceptably large drawdown to the portfolio. Since 1985, more than 300,000 M&A deals, with an estimated combined value of $33.2 trillion, have been announced in the US alone, according to the Institute for Mergers, Acquisitions and Alliances. In terms of total transaction value, 2015 was historic: $2.4 trillion, from roughly 13,000 deals. The record number of deals took place in 2017, when there were 15,558 transactions. All this activity gives fund managers a sufficient breadth of events to diversify their portfolios.

Many conditions affect the completion of a merger. Friendly mergers, where the deal is backed by the target company's management, have a higher probability of completion than hostile takeovers. Some deals may not get the required approvals because of antitrust concerns or other regulatory issues. A deal also may fail because of overall market conditions. For example, if the plan is to use external financing to pay for the merger and a credit crunch hits the market, the acquirer may not be able to arrange financing. Likewise, if the target company's stock price falls below the merger offer price because of a market decline, the acquirer may believe it is overpaying for the stock and the deal may not go through at the original price.

Merger arbitrage strategies are generally uncorrelated to market movements, but they are not immune to market risk. The returns on M&A strategies are uncorrelated during bull and mild bear markets, but in significant downturns they show higher correlation to the market because factors like uncertainty of completion, regulatory problems, or inability to get financing increase the risk of deal failure.

SPIN-OFFS, SPLIT-OFFS, AND CARVE-OUTS

A spin-off is the opposite of a merger: a divestiture in which a company separates a portion of its business (a division or a subsidiary) and organizes it as an independent company that is often publicly traded. This generally is done to unlock overall shareholder value (Table 25.2). A company may want to sell its noncore or nonessential businesses to focus on its core operations and competencies. For instance, General Electric sold 15% of its noncore financing arm Synchrony Financial in a 2014 initial public offering and completed the separation the next year by offering GE shareholders the opportunity to exchange their shares for shares in the 85% of Synchrony GE still owned. (For more examples of spin-offs, see Table 25.3.)

Split-offs and carve-outs are similar to spin-offs. In a spin-off, shareholders of the parent company receive shares in the subsidiary on a pro rata basis. In the case of a split-off, shareholders of the parent company decide whether to tender shares in the parent in exchange for shares in the subsidiary. In an equity carve-out, the parent sells some shares of the subsidiary while retaining a fractional stake in the business.

Spin-offs are quite common; there typically are about 50 a year in the US alone. Many studies have found that both spun-off companies and their parents outperform the market in the years immediately after the split. Spin-offs generally outperform for a few reasons. Because the businesses are more focused on their core products, they run more efficiently and the profitability of each unit tends to grow. Also, the market starts valuing each business unit more accurately: analysts can assign each unit the price-earnings value of the individual industry to which it belongs rather than having to rely on a broader sector or on market values.

Even though these companies often outperform in the long run, they sometimes experience short-term price weakness. This may happen because shares of the spun-off unit may not fit the investment criteria of shareholders of the parent company. For instance, the spun-off company will have a smaller capitalization, and some shareholders might have limitations on their exposure to small-cap stocks, in their own right or because they typically have higher beta to the market. Generally, it is reasonable to invest in both the parent and the spun-off company, but it is important to carefully examine the particulars of any spin-off before making a decision on whether to keep, sell, or buy companies that are planning to spin off or already have done so.

Table 25.2 Reasons for spin-offs

Pure-play business	Efficient allocation of capital	Regulatory considerations	Higher valuation	Shareholder value
Splitting a company into components enables each component to become a pure play focusing on a particular product or industry.	Splitting allows more efficient capital allocation to each component business, especially if the components have varying capital needs.	Some divestments are made to avoid potential antitrust issues if several business units have in total gained an unduly large market share for a particular product or industry.	Individual business units may be better valued by the market than the combined business is ("conglomerate discount").	A company may choose to spin off a loss-making business unit to increase the value of its stock.

Table 25.3 Examples of notable spin-offs

Year	Spin-offs
2015	eBay spins off PayPal, an online payment platform.
2012	Kraft Foods splits off its snack business as Mondelez International.
2011	Travel website Expedia spins off its review site TripAdvisor.
2006	McDonald's spins off popular Mexican-food chain Chipotle.
1999	Hewlett-Packard spins off its measurement business as Agilent Technologies.

DISTRESSED-ASSET INVESTING

Distressed assets are the securities of companies or government entities that are experiencing financial or operational distress, default, or bankruptcy. Companies can become distressed for various reasons, including:

- Highly leveraged balance sheets
- Liquidity problems
- Credit downgrades
- Accounting irregularities
- Inadequate cash flows
- Poor operating performance

When an asset is distressed, it may trade far below its intrinsic value because of pessimistic investor sentiment. When this happens, investors whose mandates do not permit them to hold distressed securities, such as most mutual funds, are forced to sell them. This can cause huge differences between the assets' intrinsic value and the prevailing market price, and thus can present sizable potential profit opportunities. Investing in these assets to trade on the arbitrage between the intrinsic value and the prevailing market price of the security is known as distressed-asset investing. Warren Buffett fans might remember this strategy as the "cigar butt investing" approach:

> *"If you buy a stock at a sufficiently low price, there will usually be some hiccup in the fortunes of the business that gives you a chance to unload at a decent profit, even though the long-term performance of the business may be terrible. I call this the 'cigar butt' approach to investing. A cigar*

butt found on the street that has only one puff left in it may not offer much of a smoke, but the 'bargain purchase' will make that puff all profit."

— Warren Buffett, Berkshire Hathaway 1989 shareholder letter

The distressed-asset universe is huge and spans all kinds of below-investment-grade debt securities. These investments may include high-yield bonds, below-par distressed bank loans, debtor-in-possession loans, credit default swaps, preferred stock, common stock, warrants, and real estate assets. Distressed-asset investing tends to perform best during bull markets, when investors make money on the turnaround on investments made during the preceding economic downturn. A downturn provides a large number of opportunities for this form of investing. However, one can find good bargains even in a good economy: the US auto and airline sectors offered ample opportunities in the 2004–2006 period even though the economy was strong. The returns from distressed investing largely depend on company- and sector-specific factors rather than on overall business and credit cycles.

Hedge fund managers focusing on distressed securities can be categorized as active or passive. Active managers get involved in the daily business of the target company and work closely with its management to turn it around. Passive managers, meanwhile, are more oriented toward trading; they buy undervalued distressed securities and sell them when they revert to their fair value. Active managers who may have access to inside information are restricted in their trading until corporate information becomes public or immaterial. This is particularly a limitation in the event that a turnaround fails and the company files for bankruptcy. Active managers can sell their positions only after the bankruptcy process is complete, as opposed to passive managers, who, because they rely on public information, are not restricted.

INDEX-REBALANCING ARBITRAGE

In this investment strategy, the arbitrageur bets on which stocks will be included in or excluded from an index. Some of the most popular indices for rebalancing arbitrage are managed by the London Stock Exchange Group's FTSE Russell business. A big reason for this is that Russell indices are rebalanced once a year, in June, whereas other major indices, such as the S&P 500 and the Dow Jones Industrial Average, are adjusted on an irregular basis. Among the Russell family of indices, the Russell Microcap Index is the most popular among these arbitrageurs because the companies that constitute it are very small and may not be well known. After they join the index, these companies often see a jump in participation by funds benchmarked to it. Stocks that move from the Russell 2000 to the large-cap Russell 1000 Index do not see a comparable jump in interest because they were already within the broad universe of index investments and simply moved from one basket to another.

Index rebalancing (or index reconstitution) arbitrage is a play on identifying additions and deletions to the index before they actually are added and deleted. If an investor can buy and sell the stocks ahead of institutional investors, they can generate profits after the announcement as the institutions buy and sell them. Historically, added and deleted stocks have significantly outperformed and underperformed the index, respectively, in the 2–3 months after the announcements were made.

CAPITAL STRUCTURE ARBITRAGE

A company's capital structure comprises the shares, debts, and other financial instruments it uses to finance its operations. In capital structure arbitrage, one security of a company is traded against another security of the same company – for example, buying the company's bonds and shorting its stock, or trading its credit default swaps (CDSs) against its stock. Another play could be on the arbitrage between listings of the same security on different exchanges; such mispricings may happen because of liquidity or other factors. Another type of capital arbitrage is to trade on changes in the company's capital structure, such as share buybacks, share issuances, debt issuances, or debt exchanges. These trades do not express a view on the overall quality of the company but on relative mispricings or shifts in value among different forms of capital.

One of the most popular capital structure arbitrage plays is to profit from mispricings between a company's equity and its bonds or credit default swaps. This strategy has gained a lot of popularity with the growth of the CDS market. Consider, for example, what happens when extremely bad news hits a company. This will cause both its bonds and its stocks to fall, though the stock prices will likely decline further, for several reasons. Stockholders will absorb a greater loss than bondholders if the company is liquidated, because bondholders have a priority claim on the assets of the company; the dividend might be reduced or dropped altogether, whereas annual bond payments are fixed, and the stock market is usually more liquid and so reacts to news more dramatically. In the case of bad news, if a mispricing is detected, the fund manager can go long the equity and short the bond. Another way to play the same trade is to use CDSs instead of bonds: the fund manager can go long equity and buy undervalued CDS protection. There are many ways to construct the same trade, and it is up to the fund manager to conduct due diligence to find the one with the best risk-return profile.

A second type of capital structure arbitrage involves finding mispricings between different categories of debt (for example, senior versus junior, secured versus unsecured, and bank loans versus bonds). During periods of stress or financial distress for the issuer company, discrepancies will occur in the relative prices of these debt instruments. The fund manager can play on the convergence of the spread between these instruments to the equilibrium level. Another example of capital structure arbitrage is convertible bond arbitrage, based on bonds that can be exchanged for company stock. The spread between standard bonds and convertible bonds should be fairly consistent, but variances in the company's stock price and dividend levels can give rise to mispricings between these two categories of bonds.

CONCLUSION

Event-driven strategies capitalize on mispricings in securities linked to specific corporate events, such as mergers, acquisitions, spin-offs, bankruptcies, and restructurings. They have been among the best-performing hedge fund strategies historically and have gained a lot of traction over the past two decades. M&A strategies in particular have shown the best performance on a risk-adjusted basis, indicating why they are so popular among managers of event-driven funds. Those who incorporate multi-event strategies into a diversified hedge fund portfolio have the ability to potentially capture meaningful upside returns that are independent of broad market moves. Successful event-driven managers must possess vast deal experience, deep industry knowledge, and strong legal capabilities to assess the probable outcomes of a wide range of corporate events.

26
Intraday Data in Alpha Research

By Dusan Timotity

The dynamics of liquidity, transaction price uncertainty, the structure of the order book, and the formation of the bid–ask spread all contribute significantly to the performance of alphas. These patterns affect the realized return most trivially via the effects of trading turnover – the channel referred to as impact – but they also have indirect effects on alpha performance and can themselves be sources of alpha signals, through characteristics related to the intraday dynamics of the traded assets. Collectively, these properties of the asset market define the market microstructure.

Research in market microstructure, as its name suggests, aims to capture the structure of investors by separating distinct classes that differ in their behavior or motivation for trading. Since the milestone paper of Glosten and Milgrom (1985), a wide variety of microstructural patterns has been discovered and documented to significantly affect the expected returns of assets. In their pioneering results, the authors derived how bid–ask spreads are formed in equilibrium; this is highly important in the analysis of the after-cost performance of alphas. Before going into details, we first define the topic-specific terminology, such as liquidity, the bid–ask spread, and the order book, and clarify the differences between quote- and order-driven markets. Second, we discuss the notion of the illiquidity premium that stands for the positive relationship between expected returns and liquidity, with examples for potential alphas. Third, we present mainstream market microstructure models and their implications for asset prices.

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DATA IN MARKET MICROSTRUCTURE

Capital markets can be broadly classified as two types, based on their trading structure. In quote-driven markets, specialists – market participants, also known as market makers or dealers, who serve as counterparties for transactions at their quoted price – provide investors with the opportunity to trade and guarantee the execution at their unique bid and ask prices: the prices at which they are willing to buy and sell, respectively. This opportunity is also called liquidity, defined as the "degree to which an order can be executed within a short time frame at a price close to the security's consensus value" (Foucault et al. 2013). In contrast, in order-driven markets investors have access to the order book that collects various bid–ask price and quantity combinations from other counterparties and crosses them with one another. The latter market type has higher transparency; however, execution is guaranteed only up to the quantity offered at the particular price. Although both types are represented in capital markets – there are hybrid forms combining elements of both – alpha research is mainly focused on order-driven markets, especially in the case of equities.

Trade orders can be split into two groups, based on their motivation. Limit orders build up the order book by indicating willingness to buy or sell specific quantities at various prices, and therefore provide liquidity to the market. Market orders eat up liquidity by serving as counterparties to limit orders to a specific quantity at the lowest or highest ask or bid, respectively. Together these two types of trade orders drive the dynamics of liquidity and the depth of the order book, which refers to the price impact of a market order to trade a specific quantity. The shape of the order book is very important to the performance of alphas in live trading. As shown in Figure 26.1, the quantities of limit orders are aggregated at specific prices (upper left graph), which define the marginal and average execution prices (upper right and bottom left graphs respectively) and thus the cost (bottom left graph) of a market order with a specific size. Hence, through the analysis of the order book, investors can calculate how their alpha will perform after impact costs on a given asset.

THE ILLIQUIDITY PREMIUM IN ASSET PRICES

There is a positive relationship between the distance from the lowest ask to the highest bid price, also known as the bid–ask spread, and the

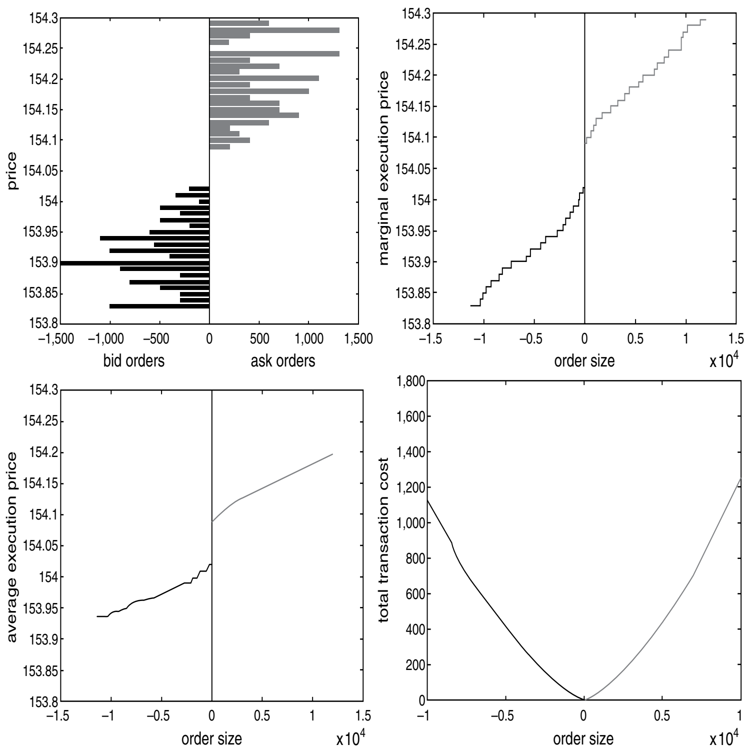

Figure 26.1 The limit-order book of IBM on January 28, 2015, at 09:55

Source: https://s100.copyright.com/AppDispatchServlet?publisherName=ELS&contentID=S0022053116300382&orderBeanReset=true. https://creativecommons.org/licenses/by/4.0/. https://doi.org/10.1016/j.jet.2016.06.001.

expected return. According to the illiquidity premium principle, because portfolio performance is measured after costs, investors require excess returns from illiquid assets to cover their losses from buying higher (at the ask price) and selling lower (at the bid price). The theory was first confirmed by Amihud and Mendelson (1986), showing that, on average, a 1% increase in the spread is associated with a 0.211% increase in monthly risk-adjusted returns. Hence, a strategy applied to assets with high spreads yields increased returns in exchange for a fixed cost: in line with the aforementioned results, a 1% extra fixed cost as a result of increased spread is counterbalanced by the elevated return over a period of $\frac{\text{excess spread}}{\text{monthly excess return}} = \frac{1}{0.211}$, or roughly five months. In other words, buy-and-hold investors with at least a five-month-long investment horizon, or investors trading daily alphas with turnover less than $\frac{\frac{\text{monthly excess return}}{\text{number of days in a month}}}{\text{excess spread}} = \frac{\frac{0.211}{21}}{1}$, or roughly 1%, seek a profit by investing in assets with a higher spread.

Liquidity can be measured in alternative ways. Researchers have shown that other proxies, such as the Amihud illiquidity (2002), can capture a significant proportion of the excess return. For example, this latter measure, calculated as the average daily ratio of the absolute stock return to dollar volume, ex ante predicts a monthly excess return of 0.163% in response to a 1 percentage point change.

It is important to note that liquidity is not constant over time. As shown in Figure 26.2, the spreads of equities vary significantly, both in time series and across assets. In fact, the recent financial crisis caused a large spike in the bid–ask spreads of equities (Pedersen 2009), which played a key role in the disappearing liquidity and falling stock prices. Investors also require a premium for the risk due to changing liquidity dynamics, on top of the premium related to the liquidity level. Pástor and Stambaugh (2003) created one of the best-known models to capture this type of exposure. In their model, the authors highlight that the increased sensitivity of an asset to market liquidity shocks comes with additional risk and therefore bears a significant risk premium. They measure that, on average, stocks with high sensitivities to liquidity provide an annual 7.5% return over those with low sensitivity. The cross-sectional differences among liquidity dynamics stress the importance of liquidity analysis in alpha research: small- and large-capitalization stocks might behave completely orthogonally to each other in their response to market liquidity shocks.

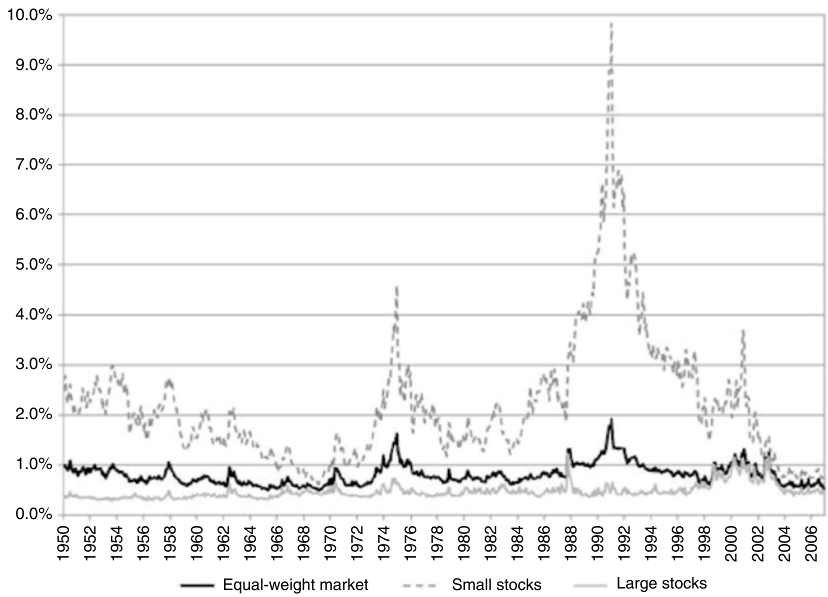

Figure 26.2 Bid–ask spread of NYSE stocks
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Changes in liquidity are relevant to intraday trading as well. Execution strategies and intraday alphas take advantage of the robust intraday patterns found in spread, volume, and return volatility; the best known of these are the U-shaped intraday pattern in volume (Jain and Joh 1988) and return volatility (Wood et al. 1985), and the reversed J-shape in bid–ask spreads (McInish and Wood 1992). Trivially, alphas whose trading is concentrated in periods when volume is high and spreads are low perform better after costs. The aforementioned empirical evidence for a positive intraday correlation between spreads and return volatility leads us to question its theoretical basis – that is, how spreads are determined and, in particular, how market microstructure is involved in these patterns.

MARKET MICROSTRUCTURE AND EXPECTED RETURNS

Apart from allowing us to model the dynamics of liquidity, intraday data enables analysis of the interaction among market participants. In fact, the goal of the latter research direction is often set to find theoretical explanations for empirical patterns documented by the former.

The theories of microstructure take into account the price discovery process and, in general, differentiate among informed traders, uninformed traders, and specialists. Informed traders are defined as rational entities that buy (or sell) if the "true value" of an asset is higher (or lower) than the bid (or ask) price. Uninformed traders, by contrast, act on no rational logic but trade purely for liquidity purposes. For example, they buy into equities in periods when they have excess income and sell when they are in need of cash. Specialists either control the quoted prices or submit limit orders to provide the market with liquidity, and aim to cover their eventual losses against informed traders by making a profit on the bid–ask spread.

According to Glosten and Milgrom (1985), conditional on the specialists being risk-neutral, there exists an equilibrium bid and ask price, and hence a spread. In their model, informed and uninformed traders submit market orders with probabilities π and $(1-\pi)$, respectively. The former know the exact value of assets that can be either high (v^H) or low (v^L). Specialists can only guess the expected value (v) using probabilities: They believe that $Pr(v = v^H) = \theta$ and $Pr(v = v^L) = 1-\theta$. Uninformed investors trade completely randomly on both sides; hence, the probability of a buy or sell trade coming from them is always 0.5. Then, if the specialists are competitive and risk-neutral, their expected profit is zero on both the bid (b) and the ask (a) sides. Therefore, if they lose against the informed traders (the first terms in equations 1 and 2 below) and win against the uninformed traders (the second terms in equations 1 and 2 below), their profits are

$$\theta\pi\left(a - v^H\right) + 0.5(1-\pi)(a - v) = 0, \tag{1}$$

$$\theta\pi\left(v^L - b\right) + 0.5(1-\pi)(v - b) = 0. \tag{2}$$

The difference between the ask and bid prices, or the spread (S), is then given by

$$S = \frac{\theta\pi(1-\theta)\left(v^H - v^L\right)}{\left(\theta\pi + 0.5(1-\pi)\right)\left((1-\theta)\pi + 0.5(1-\pi)\right)}. \tag{3}$$

Moreover, by further simplifying the model with the assumption that prices follow a random walk at the intraday level $(\theta = 0.5)$, the spread becomes a linear function of the probability of informed trading (π):

$$S = \pi\left(v^H - v^L\right). \tag{4}$$

The importance of Glosten and Milgrom's results lies in the illiquidity premium principle discussed above, stating that higher spreads increase the expected returns. One of the most detailed analyses of this indirect link between the probability of informed trading in a given stock and the stock's return was conducted by Easley et al. (2002). The authors measure the probability of informed trading (*PIN*) in individual New York Stock Exchange-listed stocks between 1983 and 1998 and show that after controlling for the Fama–French factors, a 10 percentage point change in *PIN* leads to an annual 2.5% premium in the expected return. Their model is logically fairly simple: an information event can occur each day with probability α that signals either good news with probability δ or bad news with probability $(1-\delta)$. Then, assuming that the expected number of trades from uninformed investors is constant, following a Poisson distribution with intensity μ, as shown in Figure 26.3, one can easily calculate the expected number of buy and sell trades conditional on the event occurrence. By defining the actual trades as buy or sell on a given day with the market order type, the authors use maximum-likelihood estimation to guess the underlying microstructure and, in particular, the probability of informed trading in any asset. The relationship between this estimated *PIN* and the expected return is trivial; replacing π in equation 4 above with *PIN* reveals the linear relationship with the spread and the return.

Various modifications of Glosten and Milgrom's model have been published subsequently. Some authors introduced other investor types

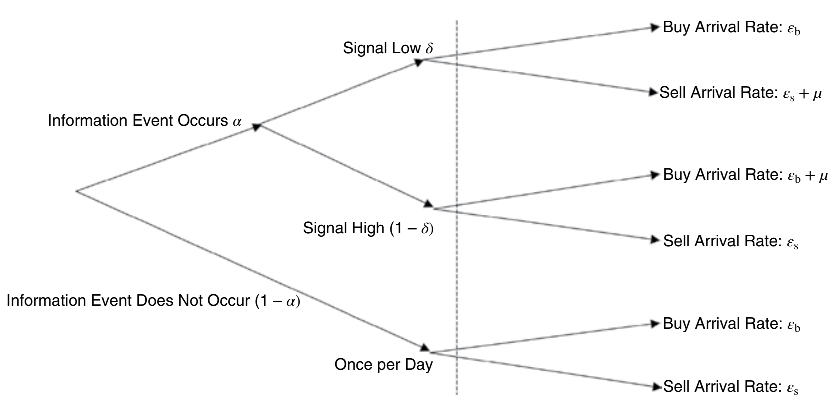

Figure 26.3 Tree diagram of the trading process in a given day
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in the microstructure and found evidence that these classes can significantly influence the expected return of assets. In Ormos and Timotity (2016a), a contrarian, heuristic-driven class is included in the model; by estimating the probability of heuristic-driven trading (*PH*), they showed that a 10 percentage point increase in *PH* yields an annual 4.5% excess return.

These measures, however, work only with a time-consuming maximum-likelihood estimation, and generally at low frequencies (quarterly or yearly). To avoid these disadvantages, alternative methods, such as the dynamic measure of the probability of informed trading (*DPIN*), have been introduced into market microstructure. According to Chang et al. (2014), *DPIN* succeeds at capturing a similar structure by using a much quicker method to calculate the probability of informed trading. The authors propose three slightly different methods based on trading data. The measure providing liquidity patterns that are the most similar to those documented in previous studies is the size-filtered probability of informed trading, calculated as:

$$DPIN_{SIZE} = \left[\frac{NB}{NT}(\varepsilon < 0) + \frac{NS}{NT}(\varepsilon > 0) \right] LT \tag{5}$$

where *NB*, *NS*, *NT*, ε, and *LT* stand for the number of buy trades, sell trades, and total trades; the autocorrelation-filtered return; and the large trade indicator (if the particular subperiod has greater trade size than median during the aggregating period). The idea behind their methodology is that informed trades tend to be large in magnitude and that informed traders buy or sell when prices go down or up. Their results provide further evidence for the significant relationship between informed trading and expected return at a daily level: the firm-specific return variation (*FSRV*), measured as a function of daily returns unexplained by market movements, $FSRV = \log \frac{1-R^2}{R^2}$ where R^2 is the coefficient of determination of the market model, is significantly and positively affected by *DPIN* measures, indicating a higher unexplained variance for stocks with a higher probability of informed trading.

In addition to highlighting cross-sectional effects in excess returns, market microstructure can contribute to alpha research through time-series analysis. As alpha quality is highly dependent on the magnitude of drawdowns, the ability to predict and avoid at least the largest negative shocks is essential. The predictive nature of the market microstructure dynamics often can be useful for this purpose. According to Easley et al. (2011), the "flash crash" of May 6, 2010, was a good example of such a drawdown: in their results, they use the volume-synchronized probability of informed trading (*VPIN*) and measure the ramp-up of informed trading that caused liquidity providers to leave the market; this was already noticeable at least a week before the flash crash and had reached its highest level in the history of the E-mini S&P 500 contract just before the collapse. Similarly, Yan and Zhang (2012) document the largest spike in *PIN* in a decade during the first quarter of 2000, when the dot-com bubble peaked. Another interesting pattern is shown by Ormos and Timotity (2016b): the authors reveal a plunge in the probability of informed trading subsequent to the Lehman Brothers collapse in 2008 when controlling for heuristic-driven traders.

These findings also highlight the importance of analyzing the dynamics of noise in alpha research. Alphas that are primarily based on technical analysis are likely to perform better for both periods and assets when the probability of informed trading is low compared with periods/assets with high *PIN*, for two reasons. First, assets with many informed traders are likely to revert more quickly to their fundamental values, so time-series patterns are not expected to last as long. Second, as noted above, higher *PIN* comes with lower explanatory power of market movements (Chang et al. 2014), and because technical analysis often relies on grouped patterns such as group momentum, its predictive ability is lower. However, because firm-specific attributes become more important at higher levels of *PIN*, alphas related to fundamental values, such as those based on balance-sheet items or insider trading, may have higher Sharpe ratios when applied to periods and assets with a higher probability of informed trading.

CONCLUSION

Intraday data can add significant value to alpha research in a variety of ways. Because of the illiquidity premium – the principle that investors require excess return for higher trading costs – the gap between the bid and ask prices (the spread) is an important factor in explaining the expected return. Together with the spread, the depth of the order book also affects the after-cost performance of a strategy, through the price impact on the average execution price of a transaction as a function of the traded volume. Because profits include liquidity, the riskiness of the latter also is included in the price: assets whose spread is highly sensitive to market liquidity shocks have higher risk and therefore yield an expected return premium over those with low sensitivity.

Intraday patterns also can be used to estimate the microstructure of assets. Separating the pool of investors into subclasses with different behaviors allows us to detect informed trades and estimate the probability of adverse selection. Liquidity providers lose against informed traders, on average, and therefore require a premium to cover their expenses, which they include in their bid–ask spread quotes. Again, in line with the illiquidity premium, this is reflected in the expected returns of assets; hence, higher levels of informed trading expect excess returns.

Last, the dynamics of the spread and microstructure can act as a time-series predictor of future drawdowns in the markets. Several studies have shown that changes in informed and heuristic-driven trading often precede negative market shocks and, in particular, meltdowns in which a key driving factor is disappearing liquidity. Therefore, it is essential to consider intraday patterns in alpha research, not only because these patterns can produce signals but also because they can significantly increase the performance and robustness of strategies based on alternative data.

27
Intraday Trading

By Rohit Kumar Jha

Intraday trading, also known as day trading, is speculation in securities – specifically, buying and selling financial instruments within the same trading day. Some of the more commonly day-traded financial instruments are stocks, options, currencies, and a host of futures contracts, such as equity index futures, interest rate futures, currency futures, and commodity futures. Strictly defined, all day-trading positions are closed before the market closes. Many traders, however, include day trading as one component of an overall strategy. Traders who trade intraday with the motive of profit are considered speculators rather than hedgers or liquidity traders. The methods of quick trading contrast with the long-term methods underlying buy-and-hold and value investing strategies.

It may seem quite unremarkable that a trader can buy and sell an instrument on the same day, but day trading is a relatively new concept. Although the practice can be traced back to 1867 and the creation of the first ticker tape, there were significant barriers to entry at that time, and as a result this type of trading was not popular among the general population. Day trading began to gain in popularity with the creation of electronic communication networks like Instinet in 1969 and the National Association of Securities Dealers Automated Quotation System, or Nasdaq, in 1971, as well as the abolishment of fixed commission rates in 1975.

An intraday alpha tries to time the entry and exit points of trades to make money on intraday price fluctuations. The switch from daily alpha research to intraday alpha research requires certain changes in style and approach. This chapter presents different styles of making intraday alphas, beginning with some fundamental differences in intraday alpha construction. Then we look into the pros and cons of day

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trading over daily trading. After that, we consider some different ways of making intraday alphas, followed by a few examples.

DAILY TRADING VERSUS INTRADAY TRADING

A wide variety of information is available for making daily alphas, from sources ranging from corporate balance sheets to social media to weather data. Most of the information sources used in making daily alphas are useless in intraday research because their horizons are too long to be helpful. However, other information sources, including bid-and-ask snapshot prices, detailed order-book data, and other microstructure data, have predictive power for much shorter time horizons and thus are much more helpful for intraday research.

In general, as the analyst inches toward higher-frequency research, he has less diverse sources of information and data at his disposal. When doing daily research, an analyst is not that concerned about the performance of individual alphas in relation to cost because it is possible to cross many different alphas. But in intraday research, cost becomes a concern at the alpha level, owing to the lack of sufficiently diverse sources of information and the lower ability to net out different alphas. This will be touched upon below when the process of making an intraday alpha is explained.

Intraday research offers some significant advantages over daily research. Because it is possible to trade at much finer timescales, the performance and returns of intraday alphas are generally much higher. The statistical significance of intraday alphas for even shorter backtesting periods is much higher for intraday alphas than for daily alphas. As a result, the out-of-sample performance of the alphas is very similar to the performance in the backtesting period.

When making daily alphas, the analyst tries to keep the alphas neutral to all possible overnight risks, like dollar delta exposure, sector exposure, and similar risk factors. When we are working on intraday alphas, however, most of these risk factors are acceptable beneath a certain threshold, as it is possible to get out of those positions immediately if they go against the alpha. This provides an opportunity to use these risk factors to try to improve returns.

Liquidity is defined as the availability of an asset to the market. At any particular time, there is only so much volume being traded. In other words, there is limited liquidity at any time. If someone trades a significant fraction of the volume being traded at a given time, she runs the risk of moving the price herself, making it more difficult to execute the trade. Most tradable instruments don't have sufficient liquidity during the day to trade them frequently throughout the day. This restricts intraday trading to the most-liquid instruments in any region. In the US, for example, it's difficult to trade anything except the top 200–500 most liquid instruments. This, in turn, leads to smaller possible capital allocations on intraday strategies.

DIFFERENT TYPES OF INTRADAY ALPHAS

There are different styles of intraday alphas. The classical definition of intraday alphas is that the alphas do not hold any overnight positions. Such alphas are called overnight-0 alphas. Similarly, overnight-1 alphas are those that hold positions overnight as well. In general, such alphas either hold unliquidated positions overnight or take the form of intraday overlays on overnight positions. In both overnight-0 and overnight-1 alphas, the alpha can either allocate positions continuously across different instruments or have a more discrete entry- or exit-based signal. In entry- or exit-based signals, the trade is entered based on an indicator or abnormal change in some derived statistics (called events) and the position is held until some exit triggers are met. These exit triggers can be a change in derived statistics or some stop-loss or profit-booking conditions.

When designing intraday alphas, an analyst needs to keep several constraints in mind. For one thing, liquidity is not the same throughout the day. It typically looks like Figure 27.1, with most trading happening at the start and the end of the day. Some stocks have very large slippage at the beginning of the trading day – for example, Microsoft Corp. (MSFT), as shown in Figure 27.2 – and in such cases it is generally a good idea to get into or out of positions in these securities when there is less slippage. Also, remember that not all financial instruments behave similarly, especially when we are working on intraday alphas for exchange-traded funds and futures. For many categories of ideas, the instruments need to be treated separately or in small groups of similar instruments.

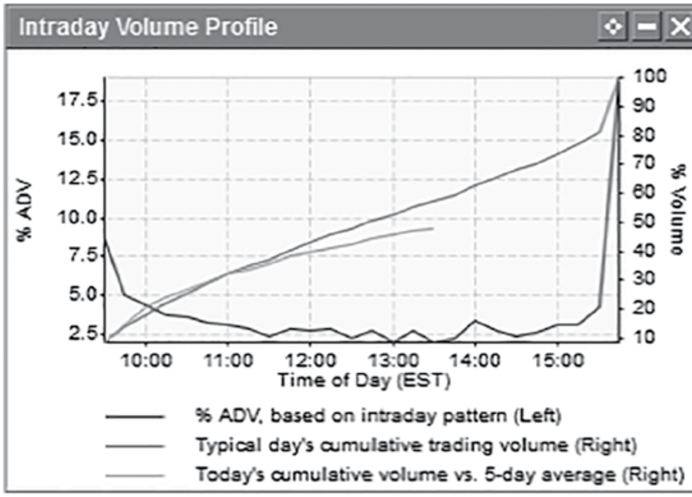

Figure 27.1 Daily trading volume for Microsoft Corp. (MSFT)

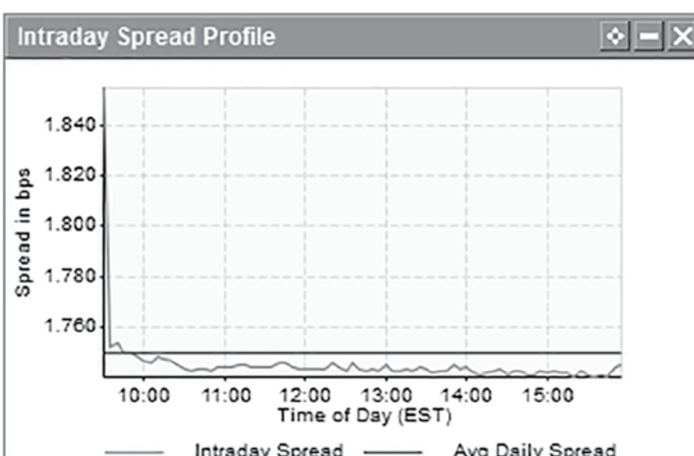

Figure 27.2 Intraday spread profile for Microsoft Corp. (MSFT)

MAKING AN INTRADAY ALPHA

The following is an example of a simple mean-reversion alpha. The analyst wants to capture the reverting nature of financial instruments. The alpha is defined as:

$$\text{alpha} = (\text{second\_last\_interval\_close} - \text{last\_interval\_close})$$

This is an overnight-0 continuous alpha on the top 500 liquid instruments. The positions are then neutralized by subtracting the cross-sectional mean, keeping each interval dollar neutral (equal long and short positions).

This idea can be improved by understanding it more deeply. This is a mean-reversion idea, and the analyst is trying to capture the tendency of instruments to revert to their mean positions. The instruments that are more volatile should have a higher tendency to revert. We can capture that in multiple ways. One way is presented below. Simply take the standard deviation of returns or price for the past 30–40 intervals and multiply the alpha value by the standard deviation:

$$\text{alpha} = (\text{second\_last\_interval\_close} - \text{last\_interval\_close}) * \text{std}(\text{close})$$

This improves the margins, but it decreases the Sharpe ratio. It is important to understand why. Introducing the multiplying factor increases both the returns and the volatility of the alpha, but the volatility is in the denominator of the Sharpe ratio, and the net effect of these opposite forces is to lower the overall Sharpe.

An analyst could try to lower the volatility of the alpha as a whole as follows:

$$\text{alpha} = (\text{second\_last\_interval\_close} - \text{last\_interval\_close}) / \text{std}(\text{close})$$

This lowers the volatility of the alpha and hence raises the Sharpe ratio, but it also significantly cuts the returns and margins.

The alpha design choices depend on the trader's requirements. The former version, with higher margins, would perform better after applying transaction costs. One can try variants of the same by using the cross-section rank of *std(close)* instead of the absolute values.

CONCLUSION

Intraday trading is significantly different from daily trading, in which an analyst can gather information from a wide variety of sources. At the same time, certain pieces of information with short-term predictive power, such as bid–ask and other order-book-level information, which are mostly useless in daily trading, have significant potential value in intraday trading.

Intraday trading is hampered by the limited liquidity of most financial instruments, which restricts day traders generally to the most liquid of instruments. But the limited trading-book size is compensated for by the higher potential returns generated in intraday trading. Intraday alphas can be of different types, varying from pure intraday alphas that hold no overnight positions to hybrid daily-intraday alphas that hold overnight positions but boost returns with an intraday overlay.

28
Finding an Index Alpha

By Glenn DeSouza

Alpha discovery is not limited to single-company equity instruments. With the dramatic rise of passive investing in the past two decades, exchange-traded funds (ETFs) and related index products have fostered the growth of various index-based alpha strategies. Historically based in large investment banks because of their reliance on technology investment, balance sheet usage, and cheap funding, these strategies have become more popular among buy-side firms in recent years, including large quant- and arbitrage-focused hedge funds and market-making firms.

INDEX ARBITRAGE IN PRACTICE

Index arbitrage is an alpha strategy that attempts to profit from differences between the actual and theoretical futures prices of a stock index, adjusted for the trader's unique costs, including cost of capital and borrowing costs (or stock rebate). The theoretical value, or the fair value in industry parlance, of an index futures contract can be described by the following top-down adjustment formula:

$$\text{Fair value of future} = \text{cash value of index} + \text{interest} - \text{dividends}$$

Holding a futures contract instead of directly investing in the underlying companies of a stock index frees up additional capital for investment (because futures have a much lower margin requirement than stock investments, particularly in the US), but it forces contract holders to forgo dividends, thus making interest rates and dividends the two primary differences affecting futures index arbitrage.

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How can such strategies prosper in an increasingly computerized and automated world? A practical example from investment bank trading desks in the past can be illuminating in this context. In the mid-2000s, some banks operated as follows:

- The bank's index arbitrage desk would calculate its own fair value using one or more of the following methods: top-down (by adjusting variables in the formula above based on macroeconomic forecasts), bottom-up (estimating and aggregating individual stock dividend forecasts), or option-implied information. The bottom-up method typically was the most reliable for generating profits, but it was also the most time consuming.
- After calculating the fair value and other product-specific costs, desks could compare multiple index-based products for arbitrage opportunities, in addition to the typical futures-versus-underlying-stocks arbitrage. These trades included arbitrage among futures, over-the-counter (OTC) index swaps, and index options.
- Some bank trading desks had a funding advantage – a lower cost of capital – which implied that the fair value of an index future was lower for them than for other firms. This offered more opportunities to short futures because the actual futures prices often appeared "rich" (expensive) compared with their own fair values. On the other side of these trades, typically, were institutional accounts that often paid a slight premium for the cheap access to leverage and liquidity afforded by futures.
- The desks would hedge their short futures exposure by simultaneously purchasing the underlying stocks. In effect, banks were sellers of balance sheet and institutional investors were buyers of it because of the banks' funding and balance sheet advantages.

Such a strategy at this stage might earn a small (less than 1%) return annually because the funding advantages typically were only a few basis points. So some banks became more creative in their inventory usage:

- Long positions from the acquired (and other bank) inventory could be converted into ETFs because many of the banks were ETF-authorized participants (APs), which allowed them to create and redeem ETF shares.

- For ETFs that were popular to short (and thus had higher than average borrowing costs), such as the Russell 2000 ETF (IWM), desks could now lend out their newly created ETFs and earn a higher stock-lending rate (sometimes 1% or more annually for certain highly sought-after funds).
- In other cases, inventory could be combined with options positions to create options reversals and conversions, which had their own OTC market and allowed inventory holders to provide liquidity in hard-to-borrow names to counterparties such as M&A arbitrageurs.
- Last, any remaining stock positions were examined for alpha-generating events such as tender offers or index changes. Stock risk could then be taken opportunistically in single names around those event dates.

In some cases, multiple overlays to a seemingly simple index arbitrage strategy could increase the overall returns of an index arbitrage desk from less than 1% to 5% or more.

How easy would this implementation be for buy-side firms? The answer depends partly on the size and pricing power of firms to lower trading and borrowing costs as much as possible to mimic the investment bank setup. Typically, only the largest hedge fund firms or active managers with related broker-dealer entities had the potential ability to negotiate such advantageous deals.

Some segments of the overall index arbitrage strategy, however, such as predicting market impact for certain indices, can be implemented by active managers without necessarily requiring a large balance sheet.

MARKET IMPACT FROM INDEX CHANGES

Besides being a popular ETF to short, the IWM fund is reconstituted annually, causing some market impact on its constituents and former constituents compared with other sought-after ETFs. FTSE Russell's published research has noted that the impact of buying newly added companies and selling deleted companies on the reconstitution date affected Russell 2000 index returns by an estimated 28 basis points (bps) a year for the period 2007–2015, although with large annual deviations (Figure 28.1).

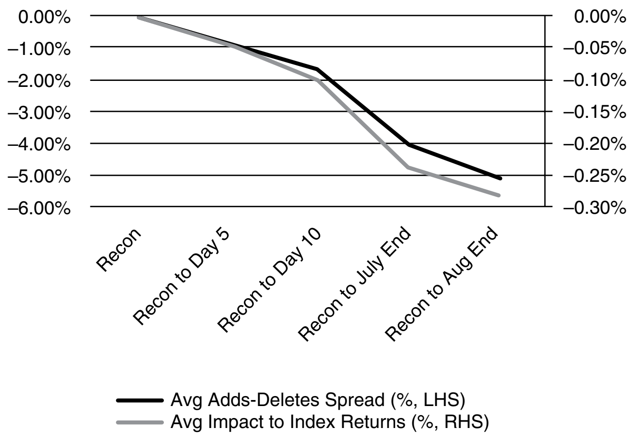

Figure 28.1 Average negative impact on Russell 2000 index returns from rebalancing (2007–2015)

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This would imply that arbitrageurs could short the added names and buy the deleted ones on the effective date of the reconstitution to earn a positive return. Such reversion could be expected to occur if the affected stocks had dislocated from fundamental and peer values in the months before the reconstitution and pairs- and sector-based relative-value traders were now pushing the stocks back toward their previous valuations. These large dislocations combine to imply that the true cost of owning the Russell 2000 IWM ETF is much higher than its 20 bps expense ratio would suggest.

In contrast to the Russell 2000, large-cap and total-market-tracking products typically do not suffer as much of a rebalancing drag on their portfolios. The S&P 500, for example, tends not to see as much reversion in added stocks, perhaps owing to their higher liquidity or late purchases by closet trackers, who cannot predict S&P additions as easily. Meanwhile, the CRSP US. Total Market Index, which is tracked by Vanguard Group's largest index funds, encompasses the entire US market, from large caps to microcaps, and accordingly does not trigger any trading requirements when cap-size migrations occur. (However, funds benchmarked to the individual capitalization ranges would still need to trade and thus potentially would impact market prices for some illiquid stocks.)

OTHER INDEX ANOMALIES

Captive Capital-Raising by Newly Indexed Companies

Index changes can lead to other market anomalies. For example, when stocks are added to major blue-chip indices, such as the S&P 500, a few of the added companies occasionally engage in opportunistic capital-raising without the usual offering discount, as index funds are forced buyers of stock around that time. Real estate companies are the most notable offenders: more than a quarter of real estate investment trusts (REITs) added to the S&P 500 since 2005 have engaged in this behavior.

Deal pricings around S&P 500 REIT additions since 2008 show an average placing discount of only 17 bps to the previous close for these captive capital raises (and 26 bps for all added companies' offerings), compared with an average discount of 2.8% for all other share offerings by stocks in the same index since 2008 (Figure 28.2).

Thus, syndicate desks can raise capital much more cheaply for the issuer than historical fundamentals would indicate. In essence, the participating index fund becomes a captive buyer that is not being incentivized for the immediate share dilution and potential EPS dilution of the

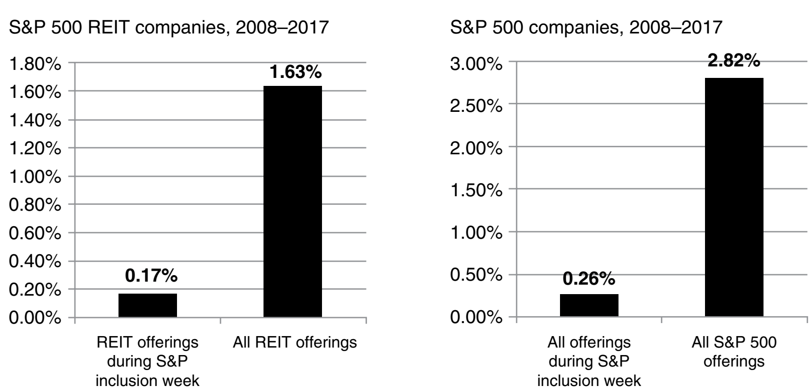

Figure 28.2 Average offering price discounts

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share offering. However, bypassing the offering might result in an even higher purchase cost on the upcoming rebalance date.

Event-driven traders constructing alphas around corporate events therefore should take note of the unique nature of these offerings. The combination of smaller pricing discounts, more placement to passive funds, and follow-on buying from the upcoming index additions could lead to unusual effects on alphas that might otherwise expect strong selling activity immediately after the offering.

Valuation Distortions in Index Versus Nonindex Stocks

The Russell 2000 also suffers from a persistent valuation distortion, perhaps resulting from a premium placed on index versus nonindex stocks. Russell 2000 index members were valued at a premium to nonindex members across every sector as of September 2017 (Figure 28.3), and broadly every year since 2008, even though more than 30% of stocks in

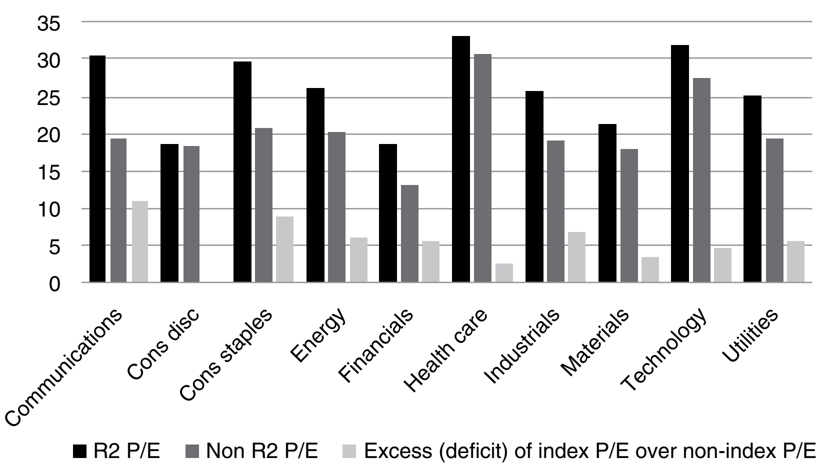

Figure 28.3 Median trailing P/E of Russell 2000 small-cap sectors versus non-Russell stocks (September 2017)

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the index had negative earnings (compared with less than 5% in the S&P 500). Communications stocks, for example, had a median trailing price–earnings ratio (P/E) of 30 times in the Russell 2000, while non-Russell sector peers were priced at only 19 times trailing earnings. A similar but smaller disparity is seen in the other nine major sectors. One possible reason is that ETFs constitute a higher percentage of small caps' average daily volume traded than they do of large caps' – often more than double the percentage of volume, as of mid-2017.

Interestingly, in the US large-cap universe, the effect of index membership is reversed. S&P 500 members trade at a discount to nonmember peers, as measured by year-end median trailing P/E over the past 10 years (Figure 28.4). This may be due not only to the lower proportion

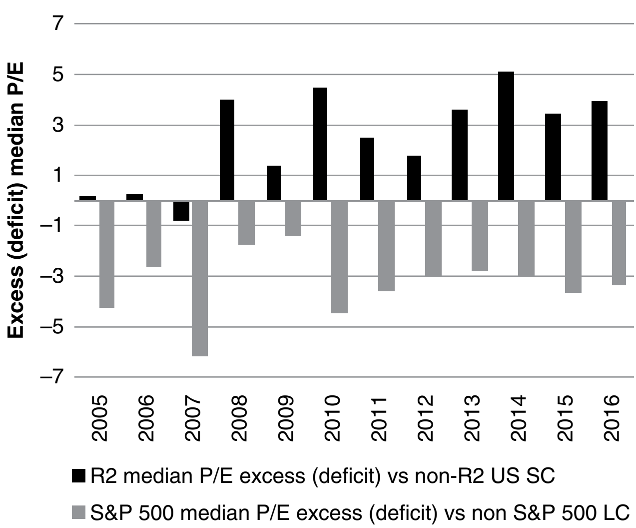

Figure 28.4 Year-end median P/E disparity between index and non-index stocks

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of ETF trading but also to the smaller eligible universe of available companies, as well as different factor exposures. Whereas Russell 2000 candidates include rising microcaps as well as declining large caps, the S&P 500 index already is at the top of the market capitalization range and can only add either new large- or megacap IPOs or rising small- and midcap names that have outperformed recently, thus exposing the index to long momentum factor risk.

CONCLUSION

The rise of index products has created not only a new benefit for the average investor in the form of inexpensive portfolio management, but also new inefficiencies and arbitrage opportunities for many active managers. An extended period of low interest rates has allowed the proliferation of cheaply financed strategies, while the rise of passive investing has created market microstructure distortions, in part as a result of rising ownership concentration.

Fortunately, new index constructions (and associated funds) also have proliferated in recent years, allowing investors to slice and dice passive portfolios in myriad ways that avoid several index drawbacks, including market impact and valuation distortions.

But with legacy index products continuing to reap liquidity and some market inefficiencies persisting, both passive products and the active ones that arbitrage them may prosper for a while longer, implying that perhaps the investment allocation debate is not simply a choice between active and passive but rather the creation of a combined model of active overlays to passive core portfolios to take advantage of the best aspects of both worlds.

29
ETFs and Alpha Research

By Mark YikChun Chan

Exchange-traded funds (ETFs) are investment funds that are traded on stock exchanges. Most of them track an index, such as a stock or bond index; the first such fund, SPDR S&P 500 ETF Trust (SPY), was created in 1993 to track the S&P 500 index. Since then, the ETF universe has expanded rapidly. Today the underlying assets held by ETFs span a broad spectrum that includes not only equities but also bonds, commodities, currencies, and more.

According to research firm ETFGI, as of the end of October 2018 there were 5,785 ETFs and 7,616 exchange-traded products (ETPs) globally, with assets under management (AUM) of $4.78 trillion and $4.94 trillion, respectively (see Figure 29.1). Although the US market has dominated these vehicles – with 1,966 ETFs and 2,210 ETPs, and

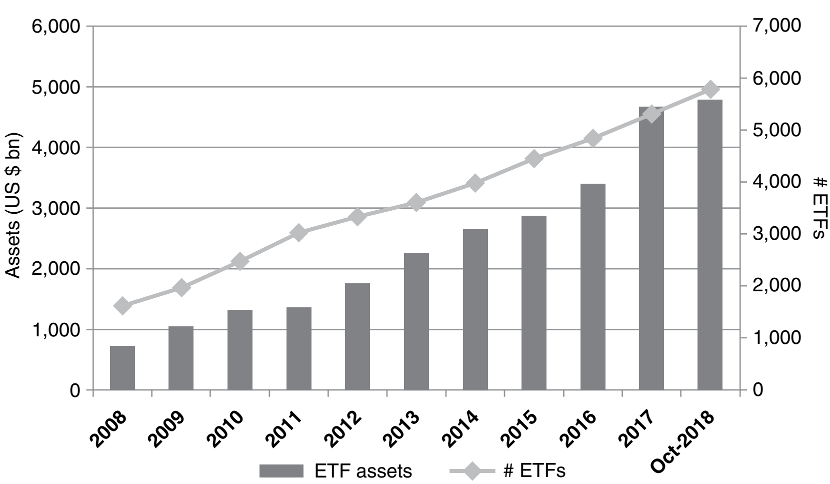

Figure 29.1 Global ETF growth, 2008–2018
Source: ETFGI. ETFGI, based in London, is a leading independent research and consultancy firm covering trends in the global ETF/ETP ecosystem.

Finding Alphas: A Quantitative Approach to Building Trading Strategies, Second Edition. Edited by Igor Tulchinsky et al. an
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assets of \$3.42 trillion and \$3.50 trillion, respectively – the ETF markets in Europe, Asia, and Canada also have experienced steady growth. The huge rise in assets has come with proliferating liquidity, making the instruments more attractive to investors.

Undoubtedly, ETFs are an emerging asset class, but the more intriguing questions are, first, whether they can become a new source of alphas, and, second, how we can seize the opportunity to seek profits. This chapter will start with a review of the basics, highlighting some benefits and risks of trading these instruments. Next, it will shed light on some of the possibilities in the ETF space and examine some examples of alphas or market phenomena that have been suggested by other analysts in their publications. Last but not least, it will discuss some unique potential challenges in ETF alpha research.

MERITS OF INVESTING IN ETFS

ETFs are traded by different kinds of investors in the markets. Some investors are relatively long term, using the funds simply for index investing; others are more active traders, seeking alphas or profits over a shorter term. ETFs have demonstrated remarkable attractiveness to all, as evidenced by their growing popularity and increasing trading volume. Some of their chief advantages for investors are:

- **Exchange trading:** Unlike mutual funds, which can be bought or sold only at the end of each trading day at their net asset value (NAV), ETFs experience price changes throughout the day and can be traded as long as the market is open. This allows active traders to implement intraday strategies or even exploit arbitrage opportunities. ETFs enjoy other stocklike features, such as short-selling, the use of limit orders and stop-loss orders, and buying on margin.
- **Low costs:** In general, ETFs incur lower costs (expense ratio < 1%) compared with traditional mutual funds (1–3%), benefiting all investors. For instance, SPY's expense ratio is 0.09%, and those of some others, such as Schwab US Broad Market ETF (SCHB), are as low as 0.03%. One reason for such low expense ratios is that many ETFs are index funds that are not actively managed – hence they are relatively simple to run. Also, ETFs do not need to maintain a cash reserve for redemptions.

- **Tax efficiency:** Taxable capital gains are created when a mutual fund or ETF sells securities that have appreciated in value. However, as most ETFs are passive index funds with very low turnover of the portfolio securities (most trading happens only for index rebalancing), they are highly tax efficient. More notably, ETFs have a unique creation and redemption mechanism: only authorized participants (APs) – large, specialized financial institutions – can create or redeem ETF shares. When a holder wants to sell an ETF, he just sells it to other investors, like a stock. Even when an AP redeems shares of an ETF with the issuer, the issuer simply pays the AP "in kind" by delivering the underlying holdings of the ETF. In either case, there is no capital gains transaction for the ETF.
- **Transparency:** The underlying holdings of each ETF are disclosed to the public daily. In contrast, mutual funds need to make such disclosures on a quarterly basis only.
- **Market exposure and diversification:** The wide range of available ETFs enables investors to easily achieve their desired market exposures – for example, to the broad market, specific sectors, markets in foreign countries, bond indexes, commodities, and currencies. Such variety makes it possible for short-term alpha traders to do statistical arbitrage across instruments. At the same time, a broad-based index ETF itself can be considered a well-diversified investment for some longer-term investors.

RISKS BEHIND THESE INSTRUMENTS

Risk is always a big topic in investment, and it is hard to give an exhaustive list of the risks behind the diverse ETF instruments. The following section will seek to shed light on some notable examples of the risks, as well as other interesting features that may complicate risk evaluation. These risks include:

- **Tracking errors:** Sometimes ETF providers may not be able to fully replicate the performance of the underlying index, giving rise to tracking errors. (This term should not be confused with the premium discount, which is defined as the difference between an ETF's market price and its NAV.) Such errors often adversely affect long-term index tracking but may potentially give rise to alpha or even arbitrage opportunities for active traders. In general, liquid broad-market equity ETFs like SPY have few tracking errors because they hold a large number of underlying stocks, each of which is liquid. The tracking error issue tends to be more substantial for some futures-based ETFs (which can suffer from negative roll yields) and commodity ETFs, as well as their inverse and/or leveraged counterparts.

- **Inverse or leveraged ETFs:** By using various derivatives and financial engineering techniques, some ETFs are constructed to achieve returns that are opposite and/or more sensitive to the price movements of the underlying securities. The common types of these ETFs are leveraged (2x), triple leveraged (3x), inverse (−1), double inverse (−2x), and triple inverse (−3x). Under volatile market conditions, the rebalancing of these leveraged ETFs may incur significant costs. Also, these instruments are by nature more volatile than nonleveraged ETFs and therefore must be handled with care in a multi-instrument (long–short) portfolio.
- **Factor risk heterogeneity:** ETFs of various asset classes innately take different types of exposure and hence have different factor risks. Equity ETFs generally have considerable market beta. Meanwhile, sector-, country-, or region-specific equity ETFs have risk exposure to their corresponding sectors, countries, or regions. Some ETFs designed for volatility trading are also usually classified as equity ETFs, but they have unique behaviors or characteristics because of their exposure to the CBOE Volatility Index (VIX) or, more precisely, the S&P 500 VIX Futures indices. Bond ETFs make up the second-largest group of ETFs in the US markets. They essentially hold a portfolio of debt securities ranging from Treasury bonds to high-yield corporate bonds, thereby bearing the respective dollar duration or interest rate risks. Commodity ETFs and currency ETFs face corresponding factor risks based on their underlying securities; those can be driven by numerous macro factors.
- **Capacity constraints:** As the ETF industry is booming, with ever-greater AUM, the capacity of an ETF should not be overlooked. This issue is particularly noteworthy for popular equity ETFs targeting niche areas. In April 2017, VanEck Vectors Junior Gold Miners ETF (GDXJ), which focuses on small- and midcap companies in the gold and silver mining industries, attracted so much capital inflow that it ended up suspending creation orders (and later altering the composition of the underlying index) because the ownership in some of its

underlying securities was reaching the 20% threshold, beyond which automatic takeover laws would be triggered. In other words, an ETF can grow too big for its index and, consequently, fail to hold the underlying securities according to its investment mandate, resulting in a suspension of share creation and/or significant tracking errors.

- **Separation from underlying markets:** As mentioned above, an ETF can be bought or sold at its market price throughout the trading day. Many US-listed ETFs track foreign stock markets, but what would happen if the underlying markets closed? Chances are the ETFs could still trade on their own exchanges, not being directly affected. Such incidents happen not only when the underlying local markets have holidays but also occasionally because of trading halts, as experienced by VanEck Vectors Egypt Index ETF (EGPT) in January 2011 and iShares MSCI Brazil Capped ETF (EWZ) in May 2017. One could reasonably argue, however, that such ETFs became useful price discovery tools when the local markets were halted.

ALPHA OPPORTUNITIES

The huge number and wide variety of ETF instruments, together with the availability of different datasets, make it possible to find alphas and take statistical arbitrage in a manner similar to equities: coming up with an idea, designing a numerical alpha formula, assigning alpha values to the ETF instruments, and then performing neutralization across the market or certain instrument groups. In addition, with ETFs tracking the performance of specific sectors, countries, and regions – as well as bond indices and commodities – ETF alphas can achieve better utilization of many macro indicators and data.

As with equities, the possible alpha ideas for ETFs span an array of categories. Among the most commonly discussed concepts are price momentum and seasonality. The following is a review of some examples from the literature.

1. US sector momentum strategy

Samuel Lee proposed this idea in a Morningstar ETFInvestor newsletter (2012). It starts by defining a universe of 10 sector ETFs (Table 29.1).

Table 29.1 Sector ETFs

XLY	Consumer Discretionary Select Sector SPDR Fund
XLP	Consumer Staples Select Sector SPDR Fund
XLE	Energy Select Sector SPDR Fund
XLF	Financial Select Sector SPDR Fund
XLV	Health Care Select Sector SPDR Fund
XLI	Industrial Select Sector SPDR Fund
XLB	Materials Select Sector SPDR Fund
XLK	Technology Select Sector SPDR Fund
XLU	Utilities Select Sector SPDR Fund
IJR	iShares Core S&P Small-Cap ETF

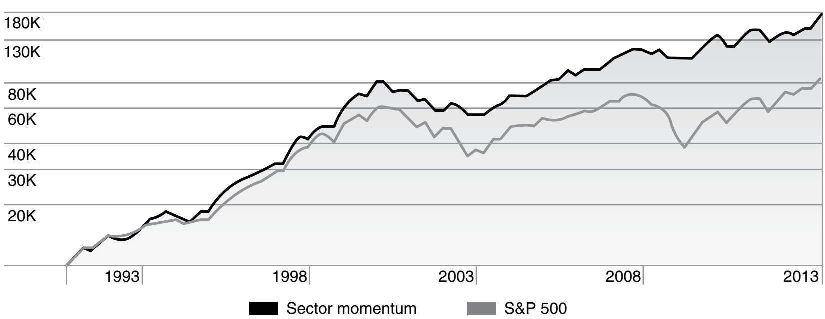

Figure 29.2 US sector momentum strategy versus S&P 500
Source: Seeking Alpha.

Comparing the last close price of each ETF against its 12-month simple moving average (SMA), the momentum strategy considers only those funds that are trading above their SMAs. It then holds equal positions on as many as three ETFs with the best 12-month returns. If fewer than three ETFs meet the criterion, the missing positions are replaced with cash. A comparison between the historical PnLs of this strategy and those of holding S&P 500 is shown in Figure 29.2.

To capture the "alpha," we can take an equal-sized short position on SPY, which will give us a long–short-balanced market-neutral (and dollar-neutral) alpha. The alpha's backtested performance for the 10 years from 2004 through 2013 is shown in Figure 29.3.

Interestingly, the alpha performed best around the 2008 financial crisis because the sectors selected outperformed the broad market. Yet without the market beta, the returns have become much less seductive – only

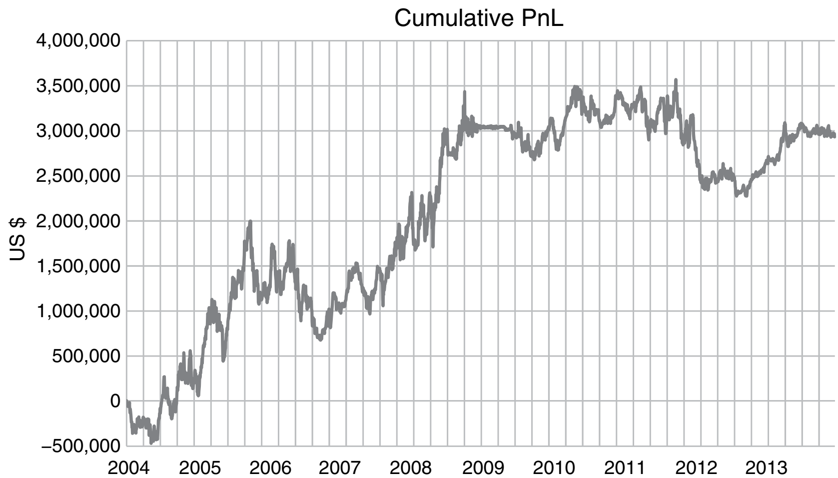

Figure 29.3 Simulation result of the sector momentum alpha from January 2004 to December 2013

about 2.92% per annum; at this stage, the Sharpe ratio of this alpha is only about 0.38. Enhancing the signal would require further research effort. As Lee noted, this simple strategy was not well diversified and therefore should be used only as part of a broader portfolio.

2. Seasonality

Seasonality is a well-known phenomenon in the global securities markets. In US equities, there is a "sell in May and go away" theory that has worked well over many years. In essence, it tells us that US stock markets historically have tended to underperform in the period from May to October relative to the period from November to April.

Some examples in the literature also illustrate such seasonal patterns in equities in other regions. In an article on the Seeking Alpha website, Fred Piard (2016) suggested that the stock markets in Germany, Singapore, and Brazil were good examples of this phenomenon and that the corresponding country ETFs – namely, iShares MSCI Germany ETF (EWG), iShares MSCI Singapore ETF (EWS), and iShares MSCI Brazil ETF (EWZ) – could be used to take advantage of the seasonal tendencies.

To better explain the idea, we simulate and compare two long-only portfolios (see Figure 29.4):

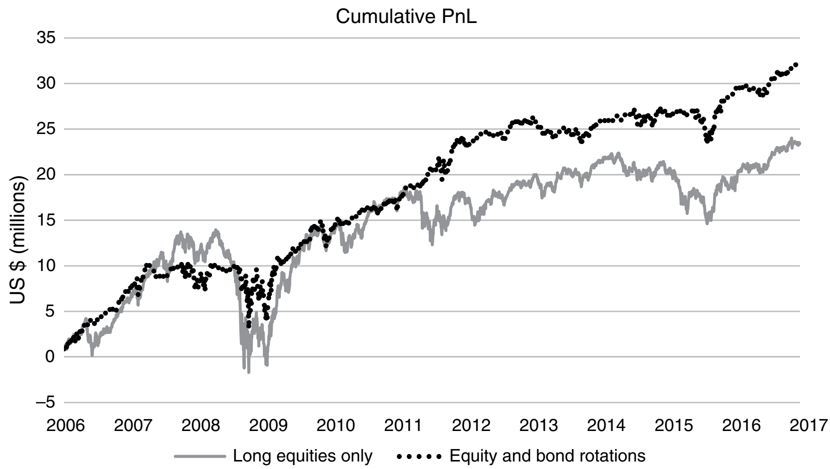

Figure 29.4 Simulation results of two long-only portfolios from January 2006 through June 2017

1. Long equities only, holding equal long positions in SPY, EWG, EWS, and EWZ all the time.
2. Equity and bond rotations, holding equal long positions in SPY, EWG, EWS, and EWZ from November to April and equal long positions in popular bond ETFs – say, iShares Barclays 20+ Year Treasury Bond ETF (TLT) and iShares iBoxx $ High Yield Corporate Bond ETF (HYG) – from May to October.

By staying away from equities from May to October, the equity-and-bond-rotation portfolio outperformed the long-equities-only portfolio. Most notably, the Sharpe ratio almost doubled, from 0.40 to 0.77, while the maximum drawdown was reduced by half.

Seasonal trends appear not only in equities but also in various commodities. Investopedia (Picardo 2018) describes the tendency of gold to gain in September and October, which can be captured by using gold ETFs. On his website, financial engineer Perry Kaufman (2016) has delineated several classic seasonality examples in agricultural products and their related ETFs.

Frankly, the seasonality phenomena discussed so far are more like market-timing tricks than practical hedged alpha ideas. Nonetheless, by studying such patterns one may come up with interesting technical or macro indicators, which, in turn, can be implemented as alphas to capture statistical arbitrage across some correlated instruments.

CHALLENGES IN ETF ALPHA RESEARCH

From the diverse pool of ETF instruments, researchers can apply their quantitative techniques to different datasets and make use of their creativity to test ideas and seek more alphas. Yet the emerging opportunities in this space come with many new challenges.

Among other factors, the liquidity of the instruments should be of particular concern. In the US markets, the aggregate average daily trading volume (ADV) in dollar terms of all ETFs was about $93 billion as of November 2018, accounting for almost 30% of all trading on the exchanges. Nonetheless, the actual liquidity may not be as good as it sounds because of the highly skewed distribution of the ADV values. Taking a closer look, SPY alone represented about 25% of the aggregate trading volume of all US ETFs, and the top 10 liquid ETFs (including SPY) represented about 50% of that. In other words, the actual tradable universe for a robust alpha is likely only a small subset of the thousands of ETFs in the markets.

After filtering based on liquidity, another tricky issue in defining an ETF universe is that many of the funds have highly similar counterparts. For instance, apart from SPY, ETFs like iShares Core S&P 500 ETF (IVV) and Vanguard S&P 500 ETF (VOO) also track the S&P 500. It does not make much sense for a daily or even an intraday (e.g. based on five-minute intervals) alpha to assign opposite values to these almost identical instruments because the room for arbitrage, if any, at such frequencies is not likely to cover the transaction costs.

A further complication is the presence of many inverse or leveraged ETFs. Imagine an extreme scenario in which an alpha has a long position in SPY and a short position in ProShares Short S&P 500 (SH), which gives the opposite of the daily performance of the S&P 500. Though the alpha may be dollar-neutral (long–short balanced), it essentially is taking two long positions in the S&P 500 simultaneously, resulting in pure market beta exposure. As such, the “dollar-neutral” alpha may not be as hedged as it ought to be if such inverse or leveraged instruments are not handled properly.

Eventually, the actual universe for alpha research in ETFs may be much smaller when compared with that of equities, thereby increasing the ease of overfitting and the risk of finding “fake” alphas. Consistent exposure to certain risk factors may generate high Sharpe performance. One example would be a purely short VIX strategy, such as taking a short position in iPATH S&P 500 VIX Short-Term Futures ETN (VXX) since its inception, which could achieve a Sharpe ratio of about 1.1 (see Figure 29.5).

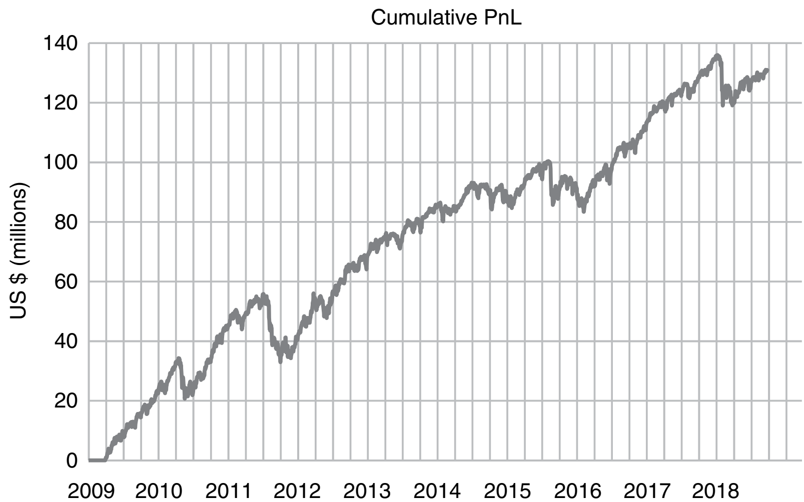

Figure 29.5 Simulation result of the short VXX example from April 2009 to September 2018

Exchange-traded funds have undergone rapid development over the past several years, with more-novel ETFs entering the universe of tradable liquid products. These instruments may exist only in the later part of the backtested period and hence adversely affect the reliability of the simulated in-sample performance. This is not a unique issue for ETFs, but it is a substantial one in this drastically growing investment area.

CONCLUSION

The ETF is a rapidly developing investment vehicle whose rising popularity has been driven by the array of advantages it offers investors. However, the risk profile of strategies and portfolios trading ETFs can be very different from that of other asset classes, especially pure equities. The wide range of ETF instruments makes finding alphas a challenging yet appealing task. With the myriad possibilities, one has to be creative in generating trading ideas, while being cautious at every step of the alpha research process. However, many successful portfolio managers have shown strategies constructed with ETF alphas have the potential to generate PnLs with good Sharpe ratios and very low correlations with other strategies, and thus may add value to overall portfolios.

30
Finding Alphas on Futures and Forwards

By Rohit Agarwal, Rebecca Lehman, and Richard Williams

Finding alphas in the futures and currency forwards markets is an area of great practical interest. It also presents many challenges, some analogous to those in other markets, such as equities and exchange-traded funds, and some unique to these specific instruments. This chapter will discuss some of the techniques and ideas that have been useful in attacking these challenges over the past few years.

KEY MARKET FEATURES

Futures are designed to give the trader exposure to price changes in an underlying asset without the cost of holding the equivalent position in that asset. Tradable futures markets include futures on equity indices, commodities, currencies, and bonds. In the context of alpha research, short-dated forwards on currencies provide a similar form of access to relative currency value exposures. This makes futures and forwards particularly convenient instruments for both hedgers and speculators, and gives rise to their most significant features.

UNDERLYING FACTOR EXPOSURE

Because both futures and forwards give exposure equivalent to that of an underlying asset, it follows that the prices of the futures and forwards depend on the same factors that drive that asset. This simple observation has important implications. There are distinct groups of market traders

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who focus exclusively on particular sets of futures and currencies; the hedgers seek to control their exposure to the risks of particular factors. Commodity futures provide a good example, as producers and consumers of physical commodities use futures to hedge their risk on specific commodities. Each group of traders can have its own characteristic risk limits, tolerances, and trading behavior, which in turn can give rise to qualitatively different market behavior. For example, the farmers and food-producing corporations that use the agricultural markets to control their risks have little in common with the airlines that employ energy futures to hedge their future fuel costs. As a result, in contrast to the equities universe, where the core liquid assets are all traded by the same population of investors for the same purposes, many properties are much less comparable across the entire universe of futures or forwards.

In recognition of the differences among market participants, many market-making and proprietary trading organizations have specialists managing the trading of different classes of futures and currencies, with the classes based on sets of similar underlying assets. This further reinforces the differences among "sectors," as different traders, desks, and business lines manage different futures and forwards. Because much of the correlation observed among assets in a common market is due to the common sentiment, behavioral biases, and practical constraints of the individuals and teams trading them, the correlations in the futures and forwards markets are generally much weaker than in the equities markets. It is interesting to note, however, that seemingly different asset classes become more correlated during periods of financial crisis.

CONSEQUENCES OF INSTRUMENT GROUPING

These instrument groups present both opportunities and challenges in seeking alphas. One of the most obvious challenges is that as we consider smaller groups of more closely connected instruments, we have fewer instruments that we can trade together in one alpha. All else being equal, the expected Sharpe ratio of an alpha is proportional to the square root of the breadth of the universe. The futures universe as a whole already contains many fewer instruments than the equity universe; when we segment the futures universe into relevant subsets, the universe for many alphas is even smaller – often between one and a few dozen instruments. Therefore, futures alphas require greater depth of information per instrument to achieve the same aggregate results than alphas on a larger instrument set. As the quality of the per-instrument alpha increases, it becomes more obvious to other market participants and its expected lifetime is reduced. Conversely, as we identify sets of more-similar instruments, we have higher expectations that any particular alpha should be present across the whole set. The cross-validation test of deleting each instrument in turn and retesting the identified relationship becomes more meaningful. Finding the right-size group on which to test our alpha candidates is therefore a key building block of alpha research.

Though generating alphas in these small and heterogeneous universes is definitely more difficult, the reward is the far greater liquidity in these markets. Robust alphas on liquid futures can be traded at large sizes without incurring the costs and regulatory risks of market impact.

BASIC CHECKLIST FOR ALPHA TESTING

Starting from a core alpha idea, the first step is to identify the sectors where we expect it to appear and the timescales on which we expect it to manifest. As an example, consider the US energy market and an alpha based on the forecast of extreme weather in a major offshore US oil and gas field. Before we even look at the data, we can identify the instruments we expect will be relevant (oil, gas, and their products) and the timescale on which we expect the data to have an impact – in this case, the duration of a typical storm and the time it takes to stop and restart production. (There will be a range of views on both of these horizons, but we can still use the implied causal relationship between the extreme weather and the commodity supply to narrow the range of candidates.) We can now test our idea by gathering data on historical weather forecasts and price changes for the major energy contracts, and testing for association between the two datasets, using a partial in-sample historical dataset.

The next step is to fit a simple statistical model and test it for robustness, while varying the parameters in the fit. One good robustness test is to include a similar asset for comparison, where we expect the effect to be weaker. In the case of our weather alpha example, Brent crude oil would be a reasonable choice. Crude oil is a global market, so we would expect some spillover from a US supply disruption. However, oil delivered in Europe is not a perfect substitute for the US supply, so we would expect a diluted impact. Again, we can test this on in-sample data.

Having investigated the cases where we would expect the alpha to work, we can now test the converse: where do we expect there to be no relationship? In the case of our example, the core idea is quite closely targeted to one sector, so we would expect to detect no relationship if we retested it on other sectors, such as industrial metals or bond futures. This step is surprisingly good at finding incorrectly coded or specified statistical tests.

Depending on the results of our tests, we could now be in a position to test our idea on our out-of-sample dataset. With such a small set of instruments, the out-of-sample test becomes a crucial part of the process, helping to avoid unintentional overfitting.

The following phenomena and information sources are some of the most interesting and useful sources of alpha for futures traders.

Follow the (Smart) Money

The Commitments of Traders (COT) report (Figure 30.1) is released every Friday by the Commodity Futures Trading Commission (CFTC). It can be extremely valuable to know what the "smart money" is betting on and then follow it. The report gives a breakdown of the open interest by different market participants, such as commercial traders (big businesses and producers), noncommercial traders (large speculators), and nonreportable traders (small speculators). More information on this report can be found at http://www.cftc.gov/marketreports/commitmentsoftraders/index.htm.

The value of the COT report is based on the premise that the trades of commercial traders tend to reflect their hedging needs, which may be

```
 Disaggregated Commitments of Traders- Options and Futures Combined Positions as of November 13, 2018
:                                              Reportable Positions                                            :
:------------------------------------------------------------------------------------------------------------- :
: Producer/Merchant :                             :                              :                             :
:  Processor/User   :         Swap Dealers        :        Managed Money         :     Other Reportables       :
:   Long  :  Short  :   Long  :  Short  :Spreading:   Long  :  Short  :Spreading:   Long  :  Short  :Spreading :
--------------------------------------------------------------------------------------------------------------
WHEAT-SRW - CHICAGO BOARD OF TRADE   (CONTRACTS OF 5,000 BUSHELS)                                              :
CFTC Code #001602                                                     Open Interest is   623,342              :
: Positions                                                                                                    :
:   81,356  151,594   97,073    5,169   48,564   79,481  106,165  100,427   38,939   25,384  137,369 :
:                                                                                                              :
: Changes from:     November 6, 2018                                                                           :
:  -17,182   -4,628   -1,012     -155  -23,978   -1,321  -15,780   -4,284    1,101     -431   -8,658 :
:                                                                                                              :
: Percent of Open Interest Represented by Each Category of Trader                                              :
:     13.1     24.3     15.6      0.8      7.8     12.8     17.0     16.1      6.2      4.1     22.0 :
:                                                                                                              :
: Number of Traders in Each Category                                   Total Traders:   451                    :
:      100      112       26        6       23       69       56       79       84       68      106 :
--------------------------------------------------------------------------------------------------------------
```

Figure 30.1 COT report on wheat as of November 13, 2018
Source: US Commodity Futures Trading Commission.

uncorrelated or even negatively correlated with their views on the value of the assets, while speculators' trades express their views of the market. If speculators have access to relevant information, their trades may be predictive. When speculators exhibit trend-following and bandwagon effects, their trades may even be self-fulfilling. Consider the alpha idea to go long instruments with increasing open interest by speculators and short instruments with decreasing speculator open interest. This idea can be expected to work on assets in markets where speculators account for a significant proportion of the activity. It makes sense to compare speculator flow cross-sectionally across small groups of instruments – such as grain, energy, European currencies, or North American equity indices – that tend to be traded by the same speculators. The relevant time horizons for each asset group should be the most common time horizons for speculators in that group. This alpha should not work on groups of unrelated assets or assets with low speculator coverage. It also can be expected to fail if something unanticipated catches speculators by surprise; it may make sense to hedge or exit this alpha when a surprise is likely to happen – say, when a Federal Reserve meeting (for financial futures) or a crop report release (for agricultural futures) is scheduled.

Seasonality in Markets

Seasonality is the tendency of markets to move in a given direction at certain times of the year. It is particularly prominent in the agricultural and energy commodity markets because of harvest patterns and heating and cooling cycles. But it is not restricted to agricultural and energy commodities; cyclical patterns in demand, consumption, inventory, or supply can give rise to similar behavior in other markets. A simple alpha can use the previous years' behavior to predict the current period. This alpha can be expected to work best on commodity futures and currencies, such as the Australian dollar (AUD), that are closely linked to commodities. It should also have some significance in equity markets that are driven by short-term consumer sentiment. It should be weakest on bonds and noncommodity currencies. The most likely time horizon is 1–3 months – short enough to pick up on the differences among seasons but long enough to average out the daily noise. Seasonal patterns can be expected to fail in the event of unusual shocks to supply or demand (such as unseasonable weather or a hurricane in the Gulf of Mexico for energy alphas) or to short-term sentiment (such as news).

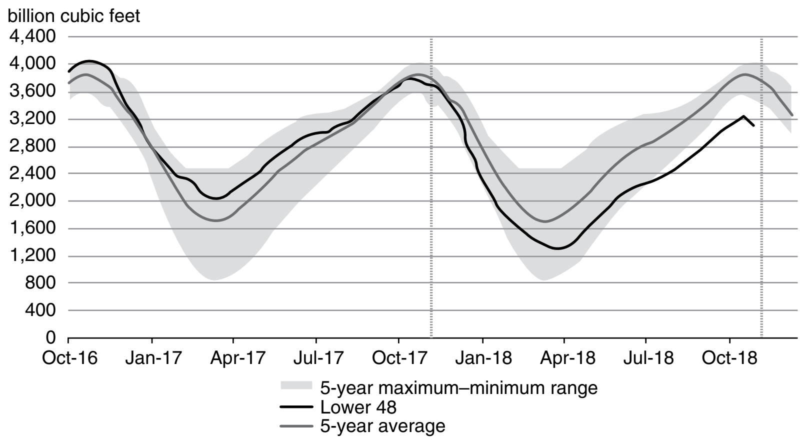

Figure 30.2 Working gas in underground storage compared with the five-year maximum and minimum (as of November 2018)
Source: US Energy Information Administration.

Figure 30.2 shows the seasonality in natural gas reserves. When winter approaches, the demand for natural gas increases as inventory is reduced because of its use in home heating.

Risk-On and Risk-Off

There are times when market sentiment is generally positive and investors are optimistic and willing to take more risk to get better returns. Such an environment is called a risk-on market because market participants are seeking to take on more risk. On the other hand, there are times when investors are pessimistic and trying to cut risk by selling their positions in risky assets and moving money to cash positions or low-risk safe havens, like US Treasury bonds. These are called risk-off times (Figure 30.3).

This investor behavior – to flock to assets perceived as risky during risk-on times and to assets perceived as risk-free during risk-off times – increases the correlation among different asset classes.

To construct a risk-on/risk-off alpha, we must identify whether the market is in a risk-on or risk-off regime on a daily, weekly, monthly, and quarterly basis; categorize different assets as risk-on or risk-off assets (either absolutely or relative to other assets in the group); and assign them positions based on the current market state.

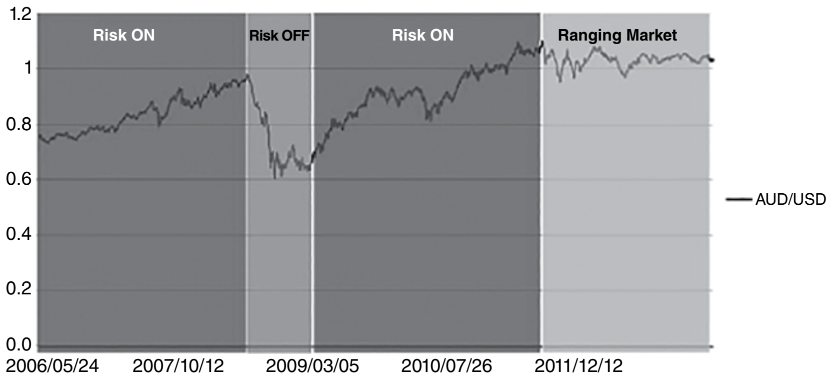

Figure 30.3 Risk-on/risk-off regimes on the AUD/USD price curve

One popular indicator of market risk perception is the VIX, a volatility index constructed from the implied volatility of S&P 500 options. Traditionally, the correlation between price and volatility is negative for equities, which generally are a risk-on asset. Therefore, high or increasing VIX levels are associated with money moving out of equity markets into safer assets, indicating the arrival of a risk-off regime. The VIX itself is a tradable futures instrument that is used by many to benefit from falling markets. Other indicators include the yield curve (higher and steeper is risk-on; lower and flatter or inverted is risk-off); sector flows among risk-on sectors such as consumer discretionary and risk-off sectors such as utilities, or among emerging (risk-on) and developed (risk-off) markets; carry currency pairs, such as AUD/JPY; and the covariance structure of the market (the top eigenvector is usually risk-off).

Risk-on/risk-off alphas can be traded on the VIX and on broad cross-sectional markets because they are based on broad market correlations. They work better on longer time horizons of weeks to months.

Carry and Contango/Backwardation

When near-month futures are cheaper than those at further expiries, the price curve slopes upward and the contract is said to be in contango (Figure 30.4). This is generally the case for commodities and can be attributed to the storage cost, or cost of carry.

However, in some cases the near-month futures are more expensive than far-month futures, which creates a downward-sloping curve, and

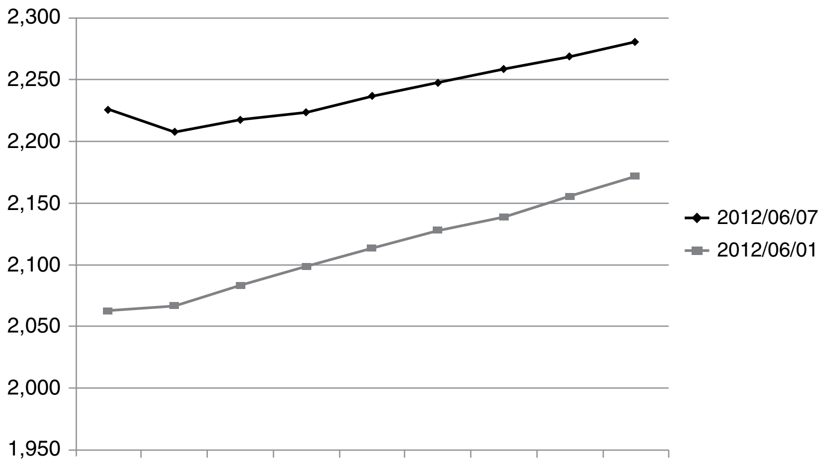

Figure 30.4 Cocoa distribution in contango

the contract is said to be in backwardation. Financial futures tend to be in backwardation because the underlying assets pay premiums or coupons and do not impose storage costs.

Some traders make money by selling contracts in contango and buying contracts in backwardation, which is known as a carry trade. The profit comes from two sources: the returns of the individual contracts as they approach expiration and the roll yield realized when the portfolio rolls from one contract to the next. This contango and backwardation alpha can be expected to work on commodities, equities, bonds, and currency pairs where at least one side has a significant nonzero interest rate. It does not work when the curves are all flat. The classic G-10 currency carry trade stopped working in the aftermath of the 2008–2009 global financial crisis, when many central banks lowered their lending rates to zero. Carry trades tend to make slow and steady profits when they are working, but they are vulnerable to sudden risk-off crashes. For financial assets (equities, bonds, currencies, rates), the yield is supposed to be a return on risk. When the market enters a risk-off phase, investors pull out of the high-yield assets that they consider too risky.

CONCLUSION

The grouping of instruments into sectors based on the underlying asset is an important aspect of futures and currency alpha research, as the behaviors of distinct groups of market actors within each sector and the common participants across all sectors give rise to the correlations among these instruments. Futures and currency traders are a relatively small group who follow particular assets and metrics, and respond in predictable and often self-fulfilling ways to common knowledge. Understanding the key ideas that drive human traders can be a fruitful source of alpha research ideas. If you take a moment to consider how the factor exposure of each sector should respond to the idea you are exploring, you may find a useful place to start testing your ideas.

PART IV
New Horizon – WebSim

Finding Alphas: A Quantitative Approach to Building Trading Strategies, Second Edition. Edited by Igor Tulchinsky et al. an
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31
Introduction to WebSim

By Jeffrey Scott

INTRODUCTION

Having read all of the ideas presented in previous chapters, you may ask, "How can I test my own ideas?" The answer is simple: WebSim.

WebSim is WorldQuant's web-based market simulation platform, which is publicly accessible and can be used to test ideas with past market data. This chapter will focus on:

- Why WebSim was developed
- How WebSim is used globally
- Who uses WebSim
- Where alpha ideas come from
- Sample data types
- Creating an alpha
- Managing simulation settings
- Analyzing results
- An alpha example

WHY WEBSIM WAS DEVELOPED

WebSim was designed as a tool to allow individuals to create and test alphas. WebSim is also used to qualify potential research consultants who work remotely as part of WorldQuant's Virtual Research Center.

As a market simulation platform with a built-in knowledge base and educational component, WebSim allows individuals to learn the art *and* science of creating alphas, to test their ideas, and to get quantitative feedback on their performance, both against the market and compared with their quantitative peers. It is the foundational platform for

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competitions such as the WorldQuant Challenge and the International Quant Championship, where top performers have received various opportunities, including becoming paid research consultants.

HOW WEBSIM IS USED GLOBALLY

Though its initial focus was to qualify research consultants and provide a framework for them to develop alphas, WebSim has evolved over the years and is currently used in several capacities:

- **Traditional and nontraditional educational environments:** These include both universities and massive open online courses (MOOCs) that choose to use WebSim in curricula related to quantitative finance and similar topics.
- **Self-education:** Many individuals around the world access WebSim for the sole purpose of self-paced learning, taking advantage of the educational component of the platform, which includes educational videos, tutorials, and access to research papers.
- **Competitions:** Global universities have used WebSim as a platform for conducting competitions within a specific class or department, or on a larger scale: the scoring features within WebSim are used to quantify top performers.

WHO USES WEBSIM

WebSim users are incredibly diverse and come from all over the world. While many WebSim users are university students, they have varying backgrounds and include executives, video gamers, professors, dentists – even farmers. Their common attributes tend to be a high level of mathematical knowledge and a desire to learn more about financial markets.

WHERE ALPHA IDEAS COME FROM

As a simulation platform, WebSim takes user input and performs backtesting to determine the overall quality of an idea. The challenge for many users is how to find ideas in the first place. Although there is no simple answer to this question, there are many resources that can help generate ideas for alphas. Research papers, finance journals, blogs, and technical indicators all can be useful starting points. Helpful papers can often be found on websites such as SSRN, Seeking Alpha, and Wilmott.

Technical indicators can be used to analyze short-term price movements. They are derived from generic price activity in a stock or other asset and seek to predict the future price levels or general price direction of a security by looking at past patterns.

Examples of common technical indicators are the relative strength index, the money flow index, moving average convergence/divergence (MACD), and Bollinger Bands. Descriptions of some of these indicators, along with formulae and corresponding interpretations, can be found on websites such as StockCharts and Incredible Charts.

SAMPLE DATA TYPES

The use of new and alternate datasets on the WebSim platform continues to increase, and the set of available data is expected to keep growing over time. Below, you will find a nonexhaustive list of some sample data types:

- Price–volume data (information about the performance of specific stocks, including open/close price, high/low price, and daily volume traded).
- Fundamental data (details about a company's financial performance as reflected in its quarterly earnings release or financial statements, such as sales, expenses, Ebitda, and debt).
- News data.
- Sentiment data, including social media.
- Relationship data, including companies that are competitors or customers.

CREATING AN ALPHA

As defined throughout this book, alphas are mathematical models that seek to predict price movements in global financial markets.

In WebSim, an alpha is typically made up of three elements:

- Data
- Mathematical operators
- Constants

The WebSim platform allows the use of simple mathematical expressions as the primary form of input. For example, consider the following alpha:

```
delta (close, 5)
```

This simple expression assigns to each stock a positive or negative position equal to the difference between the daily close price of the stock and the close price from five days earlier.

In WebSim, the alpha value for each instrument is interpreted as a positive or negative relative weight in the simulated portfolio. Stocks with positive weights are assigned long positions, and those with negative weights are assigned short positions. Later in this chapter, we will discuss the universe, which specifies the set of equities to be assigned positions in a specific alpha.

Alphas can be very simple, as in the example above, or more complex. Users have access to various libraries that can assist them in the alpha creation process.

MANAGING SIMULATION SETTINGS

Before creating an alpha, the user should consider several settings that will affect the simulation results. A sample of these settings can be seen in Figure 31.1, followed by a brief description of each.

The first parameter to consider is the **region** used in the simulation. This could be US, European, or Asian markets. Only stocks from the selected region will be included in the simulation.

After selecting the region, the user should select the **universe** of stocks within that region. This could be the top 200 stocks, the top 1,000 – up to the top 3,000; the number reflects the top most-liquid stocks in the chosen region (determined by the highest average daily dollar volume traded).

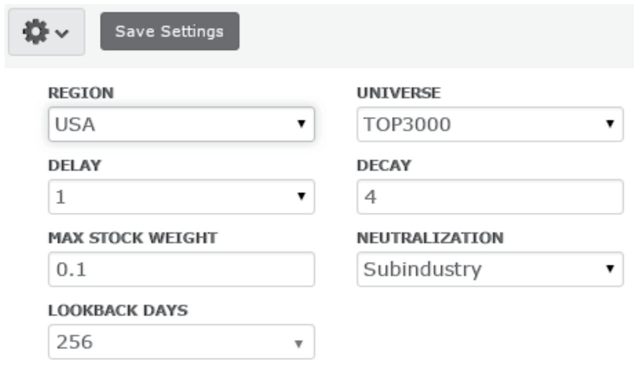

Figure 31.1 WebSim settings

The **delay** setting refers to the availability of data and indicates whether today's prices or yesterday's prices are used in the analysis. Delay-0 uses today's price and Delay-1 uses yesterday's price.

Another important parameter is called **decay.** This performs a linear decay function of a specified number of days by applying a weighted linear combination of today's alpha value with previous days' values. This provides a smoothing effect and can be useful in lowering the turnover of an alpha. (Turnover will be discussed later.)

The **max stock weight** caps the weight assigned to any individual stock in the simulation. This is recommended to be between 0.05 and 0.1, indicating a maximum of 5–10% weight for any given stock in the selected universe. This helps guard against unnecessary exposure to any specific stock. Higher values of max stock weight allow the alpha to assign more weight to its strongest predictions, potentially increasing the return at the expense of greater idiosyncratic risk. Lower values flatten the alpha, controlling the individual stock risk. The max stock weight may be larger for smaller universes, where there are fewer stocks to which to assign weights.

Neutralization allows a user to group stocks and neutralize (demean) based on industry, market, or subindustry, ensuring that the overall portfolio is market neutral, without directional exposure.

Lookback days sets the number of prior days' data to analyze when running the alpha for each day. While this parameter does not affect the values the alpha generates, a lower value can speed up the simulation by limiting the amount of data used in each iteration. A higher value allows the alpha to use older historical data; this is useful for fundamental datasets that tend to be updated quarterly or annually.

ANALYZING RESULTS

Once the parameters are established and the alpha expression is entered, WebSim performs a backtest of the idea using historical data. Typically, the simulator will use a fictitious $20 million book, redistributing the capital on a daily basis to long and short positions across the selected universe of stocks corresponding to the positive and negative values of the alpha function after applying neutralization and decay.

Simulated trading takes place on a daily basis, and WebSim produces the results of the simulation in both graphical and numeric display.

The first result a user will see is a graph showing the PnL (profit and loss) of the simulated trading results. The graph in Figure 31.2 is an example of a good alpha.

Figure 31.2 PnL graph for sample WebSim alpha[1]

[1] Alpha = rank (sales/assets).

Year	BookSize	Long Count	Short Count	Pnl	Sharpe	Fitness	Returns	Drawdown	Turnover	Margin
2013	20.0M	1324	1362	765K	3.17	5.52	8.69%	0.45%	2.87%	60.51bpm
2014	20.0M	1315	1359	495K	1.58	2.17	4.91%	1.71%	2.60%	37.78bpm
2015	20.0M	1295	1362	567K	1.56	2.22	5.63%	0.86%	2.78%	40.46bpm
2016	20.0M	1312	1368	1.09M	2.34	4.92	10.77%	1.54%	2.44%	88.09bpm
2017	20.0M	1314	1364	46.6K	0.16	0.07	0.46%	1.59%	2.22%	4.19bpm
2018	20.0M	1323	1389	−52.7K	−2.61	−5.16	−8.24%	0.34%	2.11%	−78.22bpm
2013-2018	20.0M	1312	1363	2.91M	1.68	2.53	5.84%	1.71%	2.57%	45.50bpm

Table 31.1 Performance metrics for sample WebSim alpha in Figure 31.2

In addition, numerous metrics are displayed, giving the user an opportunity to evaluate the aggregate performance of the alpha, as shown in Table 31.1.

These performance metrics reflect the distribution of capital across the stocks and the alpha's performance, including the annual and aggregate PnL, Sharpe ratio, turnover, and other parameters.

The first thing to consider is whether the alpha is profitable. Were the PnL and returns adequate?

The **Sharpe ratio** is a measure of the risk-adjusted returns (returns/volatility). It can be treated as a proxy for the predictive ability of a model. The higher the Sharpe ratio, the more reliable the alpha tends to be.

Turnover is a measure of the volume of trading required to reach the alpha's desired positions over the simulation period. Each trade in or out of a position carries transaction costs (fees and spread costs). If the turnover number is high – for example, over 40% – the transaction costs may eradicate some or all of the PnL that the alpha generated during simulation.

The other performance metrics and their uses in evaluating alpha performance are discussed in more detail in the WebSim user guides and in videos in the educational section of the website.

In addition to the aggregate performance metrics, WebSim data visualization charts and graphs help to confirm that an alpha has an acceptable distribution of positions and returns across equities grouped by capitalization, industry, or sector.

If established thresholds are met, alphas can be processed in out-of-sample testing using more-current data to confirm the validity of the idea.

AN ALPHA EXAMPLE

As explained earlier, many websites provide publicly accessible research papers that can be used to develop alphas. Alpha ideas can come from many sources and can be constructed by using different approaches. An alpha may focus on a specific financial ratio, as in the following example, or it may attempt to implement a classic trading strategy, such as momentum or reversion.

For a specific example, consider the concept of the debt-to-equity ratio from fundamental analysis. The idea is that if a company has a high and growing debt-to-equity ratio, it is at risk, so you would want to short the stock; conversely, if the debt-to-equity ratio is low, the stock has good value, so you would want a long position. Using this hypothesis, an alpha may be developed that uses the debt-to-equity ratio to select stocks to long and short, as illustrated below:

```
Ts_rank(-debt/equity, 240)
```

In this example, a time-series rank operator is applied to the debt-to-equity ratio over a period of 240 days. Through the simulation period, WebSim would determine which stocks to go long on and which to short based on their most recent balance sheets, using the selected universe. Simulated trading would take place using the entered parameters, and WebSim would produce the results.

CONCLUSION

WebSim is a financial market simulation platform that users can use to implement and test their ideas using simple expressions. WebSim is accessible on a global basis and is used professionally by contracted research consultants and also as an educational tool, both individually and through education providers. WebSim takes user input and performs simulated trading using historical data, according to the parameters entered by the user. As a self-contained platform, WebSim stores historical data for the simulation, along with numerous predefined mathematical operators that can be used for alpha generation.

As a publicly available platform, WebSim can be accessed at www. WorldQuantVRC.com.

PART V
A Final Word

32 The Seven Habits of Highly Successful Quants

By Richard Hu and Chalee Asavathiratham

A quant is sometimes referred to as the "rocket scientist of Wall Street," a phrase that conjures up an image of someone who is smart, well educated, and very highly paid. In a typical buy-side quantitative investment firm, the work environment is collegial and professional, and it offers plenty of opportunities to gain new knowledge. Therefore, it's not hard to understand why many top engineering and science graduates from the best universities in the world want to become quants.

But what does it take to become a successful quant? We have encountered this seemingly simple query countless times, and it took us more than a decade of managing hundreds of quants to be able to answer it. Yes, successful quants are highly intelligent; they are usually top graduates of quantitative disciplines like mathematics, engineering, and computer science. Yet we have noticed some additional traits that characterize the most successful quants. To confirm our observations, we ran a survey among the top quants in our firm and synthesized the results. In a nod to Stephen Covey's *The 7 Habits of Highly Effective People*, here are the seven habits of successful quants.

1. WORK HARD WITHOUT EVEN REALIZING IT

Highly successful quants are willing to put in the extra effort necessary to maximize their potential. If failure is the mother of success, extra effort is the father.

We once hired an extremely smart young man from a top-tier university. During the interviews, he was able to solve our difficult analytical questions at such a fast speed that we suspected he had already seen the

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questions. Because he did so well in all of our interviews, we decided to make up a brand-new set of very tough questions for him; again, he aced them at lightning speed. We were pleased that we had found such a gem. After he came on board, however, we discovered he had a serious flaw: he did not work hard. He would party in the evening and stay out late, then wake up late and run into the office at 10 a.m., when others would already have been working for two hours. We talked to him about this. He would shape up for a while, but shortly thereafter he would return to his old ways and fall behind like a sleeping hare. He never became the best.

Then we have hired people who were smart but not necessarily the smartest, but they were among the first employees to come into the office in the morning and among the last to leave – day after day, month after month, and year after year. Such people would slowly yet steadily get ahead of the others, eventually reaching the level of our top performers.

The most amazing observation is that these top performers usually don't even feel as though they're working hard; they're just having fun doing it. When asked about their work, they simply smile and say something like:

"This is the best job anyone could ever have."

"I can't believe I'm getting paid to do this."

"This feels more like a game to me than work."

They enjoy working with mathematics, code, data, and finance – the four key components of a quant job. They enjoy discovering new signals first, before anyone else in the market. They love the job and enjoy every minute.

2. SET AMBITIOUS LONG-TERM TARGETS BUT ATTAINABLE WEEKLY GOALS

A successful researcher always works with two kinds of goals: one long-term target and one set of short-term steps. The long-term targets can be lofty goals and should be well-defined, tangible achievements – for example, reaching a certain level of PnL, becoming an expert on a particular asset class, or becoming a manager of quants. Short-term goals are usually more task-specific, such as writing a certain tool, script, or piece of analysis – generally, tasks that take no more than a day to accomplish.

One of our very successful researchers describes his routine as follows:

> *“Every Monday, I start off the week by writing down a plan of what I want to achieve that week. Then, at the end of the week, I revisit that list point by point and add what has actually been accomplished. To make it matter, I write this weekly plan as if I need to send it to our CEO.”*

Quants who have high long-term targets but who can also set and pursue short-term goals will be able to maintain a balanced perspective and eventually succeed.

3. PRIORITIZE BASED ON RISK AND REWARD

Quantitative researchers are like investors whose investments are made using time rather than money. Given the variety of tasks facing a quant, how should he or she prioritize them? To answer this question, it can be helpful to evaluate the tasks based on their estimated risks and rewards.

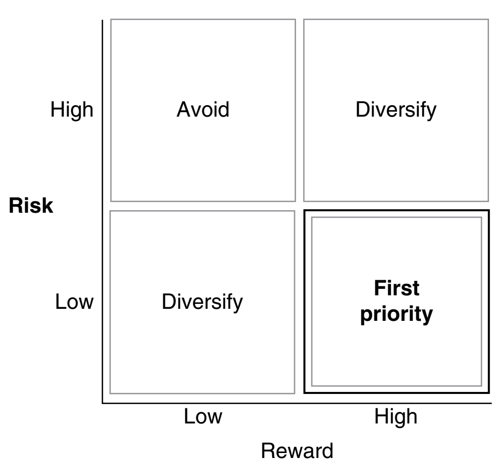

Figure 32.1 The risk–reward matrix

For each task, the quant should assess its relative risk and reward, and place it into the risk–reward matrix shown in Figure 32.1. This will help the quant rank the actions to take:

- Low-risk, high-reward tasks deserve to be the first priority.
- High-risk, high-reward tasks should be paired with low-risk, low-reward tasks as a form of diversification.
- High-risk, low-reward tasks should simply be avoided.

In addition, a quant should periodically update his or her view of the probable risks and rewards of each initiative, and always be alert for new opportunities to add to the matrix.

4. STAY CURIOUS

As a wise trader once remarked, "You are only as good as your last trade." A successful quant should never be complacent but instead should always be eager to experiment with new ideas. Quants should never settle into their comfort zone, for a few reasons. First, all alphas have a finite and unpredictable shelf life; you can never tell when the predictive power of an alpha will drop off. Unless quants keep innovating, their alphas could eventually become obsolete. It's best to keep diversifying a portfolio of alphas into new datasets, methods, projects, or asset classes.

Second, there is always a better way to do things. A successful quant is continually exploring new and different ideas beyond the path of least resistance. Top researchers are always learning; they join seminars, read research journals, and participate in group discussions. They seek interesting books to read and share the most useful ones with their teammates. At any point in time, their to-do lists are filled with ideas to pursue, which they prioritize using the risk–reward analysis described above.

Successful quants are innately curious creatures. When they read news articles, they stop and wonder, "Can that be turned into an alpha?" When they hear about new projects, they are keen to learn how they can contribute. They constantly look for opportunities to exchange ideas with other quants, portfolio managers, and technologists. In short, successful researchers think about alphas all the time.

5. PERFORM VALUE-ADDED WORK – AND AUTOMATE, AUTOMATE, AUTOMATE

Successful researchers spend their time on the most-value-added streams of work. Ideally, most of a quant's time should focus on truly innovative work, such as reading about new research, creating tools, and devising new quality tests. Any type of routine work should be automated. Quants generally require sufficient coding skills to implement time-saving scripts. For instance, a quant researcher's work often entails a series of steps: data cleaning, data visualization, formulating, coding, simulating, parameter tuning, statistical analysis, and so on. Almost all of these steps can be automated, except perhaps the formulation and coding of the core idea.

At WorldQuant, it used to take an average of three months to create a single alpha. Now, thanks to our extensive range of automation tools, our quants can produce an average of one new alpha per day from existing tools and methods, while devoting much of their human time to pursuing new research directions with higher risk–reward payoffs.

6. MAKE SENSIBLE CHANGES, AND BEWARE OF OVERFITTING

Overfitting is one of the most common mistakes of both rookie and veteran quants. Overfitting occurs when someone tries too hard to make a model perform well against historical data at the expense of its robustness under unknown future conditions. There are a number of ways a quant can overfit. For instance, in an attempt to make a model perform well, a researcher might introduce additional parameters or keep "twisting the knobs" to maximize historical performance. The risk of overfitting is higher when the model has fewer data points available, as is the case with lower-frequency data or asset classes that have relatively few instruments, such as currencies. Sometimes overfitting can creep up on a model without the researcher realizing it. One key differentiating characteristic between an experienced quant and a new quant is the ability to tell when a model has reached the "sweet spot" – the point at which it strikes the perfect balance between performance optimization and overfitting.

How do you avoid overfitting? Although there is no straightforward answer, successful quants tend to follow a few golden rules. First, always make sensible changes to your model; avoid simply fitting the model to the data. Before making a change to the model, always ask whether the change has an economic underpinning, a rationale, or any reasonable justification for expecting it to improve the model. Second, it is a good practice to leave out a portion of the data for out-of-sample testing. The appropriate amount of data to leave out depends on a variety of factors, such as the expected range of volatility, the number of underlying instruments, and the consistency of the performance. This is a delicate trade-off that a quant must balance carefully; although leaving out too little data can lead to overfitting, leaving out too much can lead to underfitting the model.

Another good habit to gauge whether a proposed change makes sense is to come up with a suite of robustness tests. How does the model's performance change when you adjust the parameters? Does the model perform equally on much of the universe, or is the profit concentrated in just a few instruments? How fast does the model decay over time? These and other, similar tests help the successful quant to detect and avoid overfitting.

7. FORM SYNERGISTIC TEAMS

It is rare to come across a highly successful quant who is not working as part of a tight-knit team. While most people understand the benefits of teamwork in general, it offers several specific advantages for quants. First, having a good team is great for idea incubation. The best ideas often do not spring instantly from somebody's head; rather, they tend to start as a vague intuition in the mind of a team member. With good team dynamics, the idea can be described, debated, and built upon by the team until it crystallizes and becomes an actionable set of tasks that add value.

In addition, a good quant team helps distribute the workload. This can be especially effective when it comes to creating time-saving tools to automate the research process. Teamwork can also allow quant members to diversify their research. Because each research project offers a different profile of risks and rewards, forming teams is an efficient way to optimize for the best output.

Last – and this is perhaps the least obvious reason – having a good team emboldens a quant to dream up big, ambitious projects. Quants who work alone will eventually be constrained by what they can do within a reasonable amount of time. As a result, they are unlikely to commit to large, long-term projects, for fear of falling behind their peers before the project bears fruit.

These are just some of the most important common habits of successful quants – but they need not be the only ways to prosper. Just remember the old saying: "Shoot for the moon. If you miss, you'll land among the stars."

References

JOURNAL ARTICLES (PRINTED)

Abarbanell, J. and Bushee, B. (1997) "Fundamental Analysis, Future Earnings and Stock Prices." *Journal of Accounting Research* 35, no. 1: 1–24.

Amihud, Y. (2002) "Illiquidity and Stock Returns: Cross-Section and Time-Series Effects." *Journal of Financial Markets* 5, no. 1: 31–56.

Amihud, Y. and Mendelson, H. (1986) "Asset Pricing and the Bid-Ask Spread." *Journal of Financial Economics* 17: 223–249.

Bailey, D., Borwein, J., Lopez de Prado, M., and Zhu, Q. (2014a) "Pseudo-Mathematics and Financial Charlatanism: The Effects of Backtest Overfitting on Out-of-Sample Performance." *Notices of the American Mathematical Society* 61, no. 5: 458–471.

Banz, R. (1981) "The Relationship Between Return and Market Value of Common Stocks." *Journal of Financial Economics* 9, no. 1: 3–8.

Barberis, N., Shleifer, A., and Vishny, R. (1998) "A Model of Investor Sentiment." *Journal of Financial Economics* 49, no. 3: 307–343.

Barroso, P. and Santa-Clara, P. (2015) "Momentum Has Its Moments." *Journal of Financial Economics* 116, no. 1: 111–120.

Bartov, E. and Mohanram, P. (2004) "Private Information, Earnings Manipulations, and Executive Stock-Option Exercises." *Accounting Review* 79, no. 4: 889–920.

Finding Alphas: A Quantitative Approach to Building Trading Strategies, Second Edition. Edited by Igor Tulchinsky et al. an
WorldQuant Virtual Research Center.

Basu, S. (1983) "The Relationship Between Earnings' Yield, Market Value and Return for NYSE Common Stocks: Further Evidence." *Journal of Financial Economics* 12, no. 1: 129–156.

Bengio, Y. (2009) "Learning Deep Architectures for AI." *Foundations and Trends in Machine Learning* 2, no. 1: 1–127.

Bertsimas, D., Lauprete, G., and Samarov, A. (2004) "Shortfall as a Risk Measure: Properties, Optimization and Applications." *Journal of Economic Dynamics and Control* 28, no. 7: 1353–1381.

Black, F. (1975) "Fact and Fantasy in the Use of Options." *Financial Analysts Journal* 31, no. 4: 36–72.

Bollen, J., Mao, H., and Zeng, X. (2011) "Twitter Mood Predicts the Stock Market." *Journal of Computational Science* 2, no. 1: 1–8.

Bollen, N. and Whaley, R. (2004) "Does Net Buying Pressure Affect the Shape of Implied Volatility Functions?" *Journal of Finance* 59, no. 2: 711–753.

Breiman, L. (2001) "Random Forests." *Machine Learning* 45, no. 1: 5–32.

Burges, C. (1998) "A Tutorial on Support Vector Machines for Pattern Recognition." *Data Mining and Knowledge Discovery* 2, no. 2: 121–167.

Butterworth, S. (1930) "On the Theory of Filter Amplifiers." *Experimental Wireless and Wireless Engineer* 7: 17–20.

Chan, K., Hameed, A., and Tong, W. (2000) "Profitability of Momentum Strategies in the International Equity Markets." *Journal of Financial and Quantitative Analysis* 35, no. 2: 153–172.

Chan, L., Jegadeesh, N., and Lakonishok, J. (1996) "Momentum Strategies." *Journal of Finance* 51: 1681–1713.

Chan, L., Lakonishok, J., and Sougiannis, T. (2001) "The Stock Market Valuation of Research and Development Expenditures." *Journal of Finance* 56, no. 6: 1681.

Chang, S., Chang, L., and Wang, F. (2014) "A Dynamic Intraday Measure of the Probability of Informed Trading and Firm-Specific Return Variation." *Journal of Empirical Finance* 29: 80–94.

Clare, A., Seaton, J., Smith, P., and Thomas, S. (2013) "Breaking into the Blackbox: Trend Following, Stop Losses and the Frequency of Trading – the case of the S&P 500." *Journal of Asset Management* 14, no. 3: 182–194.

Cortes, C. and Vapnik, V. (1995) "Support-Vector Networks." *Machine Learning* 20, no. 3: 273–297.

Corwin, S. and Schultz, P. (2012) "A Simple Way to Estimate Bid-Ask Spreads from Daily High and Low Prices." *Journal of Finance* 67, no. 2: 719–760.

Cremers, M. and Weinbaum, D. (2010) "Deviations from Put-Call Parity and Stock Return Predictability." *Journal of Financial and Quantitative Analysis* 45, no. 2: 335–367.

Daniel, K., Hirshleifer, H., and Subrahmanyam, A. (1998) "A Theory of Overconfidence, Self-Attribution, and Security Market Under- and Over-Reactions." *Journal of Finance* 53: 1839–1885.

Daniel, K. and Titman, S. (1999) "Market Efficiency in an Irrational World." *Financial Analysts Journal* 55, no. 6: 28–40.

Easley, D., Hvidkjaer, S., and O'Hara, M. (2002) "Is Information Risk a Determinant of Asset Returns?" *Journal of Finance* 57, no. 5: 2185–2221.

Easley, D., Lopez de Prado, M., and O'Hara, M. (2011) "The Microstructure of the 'Flash Crash': Flow Toxicity, Liquidity Crashes, and the Probability of Informed Trading." *Journal of Portfolio Management* 37, no. 2: 118–128.

Fama, E. and French, K. (1992) "The Cross-Section of Expected Stock Returns." *Journal of Finance* 47, no. 2: 427–466.

Fama, E. and French, K. (1993) "Common Risk Factors in the Returns on Stocks and Bonds." *Journal of Financial Economics* 33, no. 1: 3–56.

Fama, E. and French, K. (2015) "A Five-Factor Asset Pricing Model." *Journal of Financial Economics* 116, no. 1: 1–22.

Ferguson, N., Philip, D., Lam, H., and Guo, J. (2015) "Media Content and Stock Returns: The Predictive Power of Press." *Multinational Finance Journal* 19, no. 1: 1–31.

Francis, J., Schipper, K., and Vincent, L. (2002) "Earnings Announcements and Competing Information." *Journal of Accounting and Economics* 33, no. 3: 313–342.

Frankel, R., Kothari. S., and Weber, J. (2006) "Determinants of the Informativeness of Analyst Research." *Journal of Accounting and Economics* 41, no. 1: 29–54.

Freund, Y. and Schapire, R. (1997) "A Decision-Theoretic Generalization of On-Line Learning and an Application to Boosting." *Journal of Computer and System Sciences* 55, no. 1: 119–139.

Freund, Y. and Schapire, R. (1999) "A Short Introduction to Boosting." *Journal of Japanese Society for Artificial Intelligence* 14, no. 5: 771–781.

Gârleanu, N. and Pedersen, L. (2016) "Dynamic Portfolio Choice with Frictions." *Journal of Economic Theory* 165: 487–516.

Glosten, L. and Milgrom, P. (1985) "Bid, Ask and Transaction Prices in a Specialist Market with Heterogeneously Informed Traders." *Journal of Financial Economics* 14, no. 1: 71–100.

Grundy, B. and Martin, J. (2001) "Understanding the Nature of the Risks and the Source of the Rewards to Momentum Investing." *Review of Financial Studies* 14, no. 1: 29–78.

Hafez, P. and Xie, J. (2016) "News Beta: Factoring Sentiment Risk into Quant Models." *Journal of Investing* 25, no. 3: 88–104.

Hastings, C., Mosteller, F., Tukey, J., and Winsor, C. (1947) "Low Moments for Small Samples: A Comparative Study of Order Statistics." *Annals of Mathematical Statistics* 18, no. 3: 413–426.

Hinton, G. (2007) "Learning Multiple Layers of Representation." *Trends in Cognitive Sciences* 11, no. 10: 428–434.

Hirshleifer, D. and Shumway, T. (2003) "Good Day Sunshine: Stock Returns and the Weather." *Journal of Finance* 58, no. 3: 1009–1032.

Hong, H., Lim, T., and Stein, J. (2000) "Bad News Travels Slowly: Size, Analyst Coverage, and the Profitability of Momentum Strategies." *Journal of Finance* 55, no. 1: 265–295.

Hong, H. and Stein, J. (1999) "A Unified Theory of Underreaction, Momentum Trading, and Overreaction in Asset Markets." *Journal of Finance* 54, no. 6: 2143–2184.

Huber, P. (1964) "Robust Estimation of a Location Parameter." *Annals of Mathematical Statistics* 35, no. 1: 73–101.

Hush, D. and Scovel, C. (2001) "On the VC Dimension of Bounded Margin Classifiers." *Machine Learning* 45, no. 1: 33–44.

Jain, P. and Joh, G. (1988) "The Dependence Between Hourly Prices and Trading Volume." *Journal of Financial and Quantitative Analysis* 23, no. 3: 269–283.

Jegadeesh, N. and Titman, S. (1993) "Returns to Buying Winners and Selling Losers: Implications for Stock Market Efficiency." *Journal of Finance* 48, no. 1: 65–91.

Jegadeesh, N. and Titman, S. (2001) "Profitability of Momentum Strategies: An Evaluation of Alternative Explanations." *Journal of Finance* 56, no. 2: 699–720.

Jegadeesh, N. and Titman, S. (2011) "Momentum." *Annual Review of Financial Economics* 3: 493–509.

Jensen, M. (1967) "The Performance of Mutual Funds in the Period 1945–1964." *Journal of Finance* 23, no. 2: 389–416.

Jin, W., Livnat, J., and Zhang, Y. (2012) "Option Prices Leading Equity Prices: Do Option Traders Have an Information Advantage?" *Journal of Accounting Research* 50, no. 2: 401–432.

Jung, M., Wong, M., and Zhang, F. (2015) "Analyst Interest as an Early Indicator of Firm Fundamental Changes and Stock Returns." *Accounting Review* 90, no. 3: 1049–1078.

Kozak, S., Nagel, S., and Santosh, S. (2018) "Interpreting Factor Models." *Journal of Finance* 73, no. 3: 1183–1223.

Kuremoto, T., Kimura, S., Kobayashi, K., and Obayashi, M. (2014) "Time Series Forecasting Using a Deep Belief Network with Restricted Boltzmann Machines." *Neurocomputing* 137: 47–56.

LeCun, Y., Kavukcuoglu, K., and Farabet, C. (2010) "Convolutional Networks and Applications in Vision." *Proceedings of 2010 IEEE International Symposium on Circuits and Systems*: 253–256.

Ledoit, O. and Wolf, M. (2004) "Honey, I Shrunk the Sample Covariance Matrix." *Journal of Portfolio Management* 30, no. 4: 110–119.

Lee, C. and Swaminathan, B. (2000) "Price Momentum and Trading Volume." *Journal of Finance* 55, no. 5: 2017–2069.

Lesmond, D., Schill, M., and Zhou, C. (2004) "The Illusory Nature of Momentum Profits." *Journal of Financial Economics* 71, no. 2: 349–380.

Li, X., Miffre, J., Brooks, C., and O'Sullivan, N. (2008) "Momentum Profits and Time-Varying Unsystematic Risk." *Journal of Banking & Finance* 32, no. 4: 541–558.

Lin, H. and McNichols, M. (1998) "Underwriting Relationships, Analysts' Earnings Forecasts and Investment Recommendations." *Journal of Accounting and Economics* 25, no. 1: 101–127.

Lintner, J. (1965) "The Valuation of Risk Assets and the Selection of Risky Investments in Stock Portfolios and Capital Budgets." *Review of Economics and Statistics* 47, no. 1: 13–37.

Lo, A. (2004) "The Adaptive Markets Hypothesis: Market Efficiency from an Evolutionary Perspective." *Journal of Portfolio Management* 30, no. 5: 15–29.

Markowitz, H. (1952) “Portfolio Selection.” *Journal of Finance* 7, no. 1: 77–91.

McConnell, J., Sibley, S., and Xu, W. (2015) “The Stock Price Performance of Spin-Off Subsidiaries, Their Parents, and the Spin-Off ETF, 2001–2013.” *Journal of Portfolio Management* 42, no. 1: 143–152.

McInish, T. and Wood, R. (1992) “An Analysis of Intraday Patterns in Bid/Ask Spreads for NYSE Stocks.” *Journal of Finance* 47, no. 2: 753–764.

Michaely, R. and Womack, K. (1999) “Conflict of Interest and the Credibility of Underwriter Analyst Recommendations.” *Review of Financial Studies* 12, no. 4: 653–686.

Moskowitz, T. and Grinblatt, M. (1999) “Do Industries Explain Momentum?” *Journal of Finance* 54, no. 4: 1249–1290.

Mossin, J. (1966) “Equilibrium in a Capital Asset Market.” *Econometrica* 34, no. 4: 768–783.

Nissim, D. and Penman, S. (2003) “Financial Statement Analysis of Leverage and How It Informs About Profitability and Price-to-Book Ratios.” *Review of Accounting Studies* 8, no. 4: 531–560.

Novy-Marx, R. and Velikov, M. (2015) “A Taxonomy of Anomalies and Their Trading Costs.” *Review of Financial Studies* 29, no. 1: 104–147.

Ofek, E., Richardson, M., and Whitelaw, R. (2004) “Limited Arbitrage and Short Sales Restrictions: Evidence from the Options Markets.” *Journal of Financial Economics* 74, no. 2: 305–342.

Ormos, M. and Timotity, D. (2016a) “Market Microstructure During Financial Crisis: Dynamics of Informed and Heuristic-Driven Trading.” *Finance Research Letters* 19: 60–66.

Pástor, L. and Stambaugh, R. (2003) “Liquidity Risk and Expected Stock Returns.” *Journal of Political Economy* 111, no. 3: 642–685.

Pearson, K. (1895) “Notes on Regression and Inheritance in the Case of Two Parents.” *Proceedings of the Royal Society of London* 58: 240–242.

Pedersen, L. (2009) "When Everyone Runs for the Exit." *International Journal of Central Banking* 5, no. 4: 177–199.

Piotroski, J. (2000) "Value Investing: The Use of Historical Financial Information to Separate Winners from Losers." *Journal of Accounting Research* 38: 1–41.

Rabiner, L. (1989) "A Tutorial on Hidden Markov Models and Selected Applications in Speech Recognition." *Proceedings of the IEEE* 77, no. 2: 257–286.

Rodgers, J. and Nicewander, W.A. (1988) "Thirteen Ways to Look at the Correlation Coefficient." *American Statistician* 42, no. 1: 59–66.

Rosenberg, B., Reid, K., and Lanstein, R. (1985) "Persuasive Evidence of Market Inefficiency." *Journal of Portfolio Management* 11, no. 3: 9–17.

Ross, S. (1976) "The Arbitrage Theory of Capital Asset Pricing." *Journal of Economic Theory* 13, no. 3: 341–360.

Rouwenhorst, K. (1998) "International Momentum Strategies." *Journal of Finance* 53, no. 1: 267–284.

Schorfheide, F. and Wolpin, K. (2012) "On the Use of Holdout Samples for Model Selection." *American Economic Review* 102, no. 3: 477–481.

Selesnick, I. and Burrus, C. (1998) "Generalized Digital Butterworth Filter Design." *IEEE Transactions on Signal Processing* 46, no. 6: 1688–1694.

Sharpe, W. (1964) "Capital Asset Prices: A Theory of Market Equilibrium under Conditions of Risk." *Journal of Finance* 19, no. 3: 425–442.

Siegel, L., Kroner, K. and Clifford, S. (2001) "The Greatest Return Stories Ever Told." *Journal of Investing* 10, no. 2: 91–102.

Sloan, R. (1996) "Do Stock Prices Fully Reflect Information in Accruals and Cash Flows About Future Earnings?" *Accounting Review* 71, no. 3: 289–315.

Spearman, C. (1904) "The Proof and Measurement of Association Between Two Things." *American Journal of Psychology* 100, nos. 3–4: 441–471.

Sprenger, T., Tumasjan, A., Sandner, P., and Welpe, I. (2014) "Tweets and Trades: The Information Content of Stock Microblogs." *European Financial Management* 20, no. 5: 926–957.

Vapnik, V. (1999) "An Overview of Statistical Learning Theory." *IEEE Transactions on Neural Networks* 10, no. 5: 988–999.

Wood, R., McInish, T., and Ord, J. (1985) "An Investigation of Transactions Data for NYSE Stocks." *Journal of Finance* 40, no. 3: 723–739.

Xing, Y., Zhang, X., and Zhao, R. (2010) "What Does Individual Option Volatility Smirk Tell Us about Future Equity Returns?" *Journal of Financial and Quantitative Analysis* 45, no. 3: 335–367.

Yan, Y. and Zhang, S. (2012) "An Improved Estimation Method and Empirical Properties of the Probability of Informed Trading." *Journal of Banking & Finance* 36, no. 2: 454–467.

Zadeh, L. (1996) "Fuzzy Logic = Computing with Words," *IEEE Transactions on Fuzzy Systems* 4, no. 2: 103–111.

Zhang, X. (2006) "Information Uncertainty and Stock Returns." *Journal of Finance* 61, no. 1: 105–137.

Zou, H., Hastie, T., and Tibshirani, R. (2006) "Sparse Principal Component Analysis." *Journal of Computational and Graphical Statistics* 15, no. 2: 265–286.

JOURNAL ARTICLES (ELECTRONIC/ONLINE)

Bailey, D., Borwein, J., Lopez de Prado, M., and Zhu, Q. (2014b) "The Probability of Backtest Overfitting." https://papers.ssrn.com/sol3/Papers.cfm?abstract_id=2326253

Beaudan, P. (2013) "Telling the Good from the Bad and the Ugly: How to Evaluate Backtested Investment Strategies." http://ssrn.com/abstract=2346600

Bochkay, K., Chava, S., and Hales, J. (2016) "Hyperbole or Reality? Investor Response to Extreme Language in Earnings Conference Calls." https://ssrn.com/abstract=2781784

Boudoukh, J., Feldman, R., Kogan, S., and Richardson, M. (2016) "Information, Trading, and Volatility: Evidence from Firm-Specific News." https://ssrn.com/abstract=2193667

Burns, P. (2006) "Random Portfolios for Evaluating Trading Strategies." http://ssrn.com/abstract=881735

Chan, W. (2001) "Stock Price Reaction to News and No-News: Drift and Reversal After Headlines." https://ssrn.com/abstract=262452

Chen, S., Hollander, S., and Law, K. (2016) "In Search of Interaction." https://ssrn.com/abstract=2449341

Druz, M., Wagner, A., and Zeckhauser, R. (2016) "Reading Managerial Tone: How Analysts and the Market Respond to Conference Calls," Swiss Finance Institute Research Paper no. 16-004. https://ideas.repec.org/p/ecl/harjfk/16-004.html

Dzieliński, M. and Hasseltoft, H. (2017) "News Tone Dispersion and Investor Disagreement." https://ssrn.com/abstract=2192532

Fodor, A., Krieger, K., and Doran J. (2010) "Do Option Open-Interest Changes Foreshadow Future Equity Returns?" http://ssrn.com/abstract=1634065

FTSE Russell. (2017) "Russell 2000 Reconstitution Effects Revisited." http://www.ftserussell.com/sites/default/files/research/russell_2000_reconstitution_effects_revisited_final.pdf

Gray, W. (2015) "Momentum Investing: Why Does Seasonality Matter for Momentum?" Alpha Architect, November 30, 2015. https://alphaarchitect.com/2015/11/30/momentum-seasonality/

Gulen, H. and Hwang, B. (2012) "Daily Stock Market Swings and Investor Reaction to Firm-Specific News." https://ssrn.com/abstract=1934873

Harvey, C., Liu, Y. and Zhu, C. (2014) ". . . and the Cross-Section of Expected Returns." http://ssrn.com/abstract=2249314

Johnson, T. and So, E. (2011) "The Option to Stock Volume Ratio and Future Returns." https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1624062

Karabulut, Y. (2013) "Can Facebook Predict Stock Market Activity?" https://ssrn.com/abstract=1919008

Khandani, A. and Lo, A. (2007) "What Happened to the Quants in August 2007?" https://papers.ssrn.com/sol3/papers.cfm?abstract_id=1015987

Lagadec, P. (2009) "Decalage: A Mini Python Tutorial." http://www.decalage.info/files/mini_python_tutorial_0.03.pdf

Larrabee, D. (2014) "A Little Industry Experience May Make You a Better Analyst." CFA Institute. http://blogs.cfainstitute.org/investor/2014/02/18/career-matters-prior-industry-experience-improves-odds-of-success-for-wall-street-analysts

Lopez de Prado, M. (2013) "What to Look for in a Backtest." https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2308682

Matloff, N. (2011) "Fast Lane to Python." University of California, Davis. http://heather.cs.ucdavis.edu/~matloff/Python/PLN/FastLanePython.pdf

Meucci, A. (2010) "Managing Diversification." Bloomberg Education & Quantitative Research and Education Paper. https://ssrn.com/abstract=1358533

Mohanram, P. (2004) "Separating Winners from Losers Among Low Book-to-Market Stocks Using Financial Statement Analysis." http://ssrn.com/abstract=403180

Ormos, M. and Timotity, D. (2016b) "Microfoundations of Heteroscedasticity in Asset Prices: A Loss-Aversion-Based Explanation of Asymmetric GARCH Models." https://ssrn.com/abstract=2736390

Preis, T., Moat, H., and Stanley, H. (2013) "Quantifying Trading Behavior in Financial Markets Using Google Trends." http://www.nature.com/srep/2013/130425/srep01684/full/srep01684.html

Roll, R., Schwartz, E., and Subrahmanyam, A. (2009) "O/S: The Relative Trading Activity in Options and Stock." http://ssrn.com/abstract=1410091

Scherbina, A. and Schlusche, B. (1915) “Cross-Firm Information Flows and the Predictability of Stock Returns.” https://ssrn.com/abstract=2263033

Shlens, J. (2014) “A Tutorial on Principal Component Analysis.” https://arxiv.org/abs/1404.1100

Sloan, R., Khimich, N., and Dechow, P. (2011) “The Accural Anomaly.” http://ssrn.com/abstract=1793364

Sprenger, T. and Welpe, I. (2011) “News or Noise? The Stock Market Reaction to Different Types of Company-Specific News Events.” https://ssrn.com/abstract=1734632

Strauts, T. “Seeking Alpha: Momentum Investing with ETFs.” *Seeking Alpha*, April 18, 2013. https://seekingalpha.com/article/1350651-seeking-alpha-momentum-investing-with-etfs

BOOKS

Antonacci, G. (2014) *Dual Momentum Investing: An Innovative Strategy for Higher Returns with Lower Risk*. McGraw-Hill Book Company.

Downey, A. (2012) *Think Python*. http://www.greenteapress.com/thinkpython

Edwards, W. (1968) “Conservatism in Human Information Processing.” *Formal Representation of Human Judgment* (Benjamin Kleinmuntz, ed.). Wiley.

Foucault, F., Pagano, M. and Röell, A. (2013) *Market Liquidity: Theory, Evidence, and Policy*. Oxford University Press.

Graham, B. and Dodd, D. (2009) *Security Analysis: Principles and Techniques* (Sixth Edition). McGraw-Hill Book Company.

Grinold, R. and Kahn, R. (1999) *Active Portfolio Management: A Quantitative Approach for Producing Superior Returns and Controlling Risk*. McGraw-Hill Book Company.

Huber, P. and Ronchetti, E. (2009) *Robust Statistics* (2nd edition). Wiley.

Hull, J. (2008) *Options, Futures and Other Derivatives*. Pearson Prentice Hall.

Kahneman, D. (2011) *Thinking, Fast and Slow*. Farrar, Straus and Giroux.

Lefèvre, E. (2006) *Reminiscences of a Stock Operator*. Wiley.

Maronna, R., Martin, D., and Yohai, V. (2006) *Robust Statistics: Theory and Methods*. Wiley.

Mertz, D. (2006) *Text Processing in Python*. Addison Wesley. Also available from Gnosis Software: http://gnosis.cx/TPiP

Nicholas, J.G. (2004) *Hedge Fund of Funds Investing: An Investor's Guide*. Bloomberg Press.

Popper, K. (1959) *The Logic of Scientific Discovery*. Hutchinson.

Rousseeuw, P. and Leroy, A. (1987) *Robust Regression and Outlier Detection*. Wiley.

Swaroop, C. (2014) *A Byte of Python*. http://www.swaroopch.com/notes/python

UNPUBLISHED MANUSCRIPTS/WORKING PAPER SERIES

Beneish, M. and Nichols, D. (2009) "Identifying Overvalued Equity." Johnson School Research Paper Series No. 09-09. http://ssrn.com/abstract=1134818

Boudoukh, J., Feldman, R., Kogan, S., and Richardson, M. (2013) "Which News Moves Stock Prices? A Textual Analysis." National Bureau of Economic Research Working Paper no. 18725. https://www.nber.org/papers/w18725

Bradshaw, M., Hutton, A., Marcus, A., and Tehranian, H. (2010) "Opacity, Crash Risk, and the Option Smirk Curve." Working Paper. Boston College. http://ssrn.com/abstract=1640733

Chan, K., Chan, L., Jegadeesh, N., and Lakonishok, J. (2001) "Earnings Quality and Stock Returns." NBER Working Paper no. 8308. https://www.nber.org/papers/w8308

Frazzini, A. and Lamont, O. (2007) "The Earnings Announcement Premium and Trading Volume." National Bureau of Economic Research Working Paper no. 13090. https://www.nber.org/papers/w13090

Gârleanu, N., Pedersen, L., and Poteshman, A. (2009) "Demand-Based Option Pricing." EFA 2005 Moscow Meetings Paper. http://ssrn.com/abstract=676501

Kamstra, M., Kramer, L., and Levi, M. (2002) "Winter Blues: A SAD Stock Market Cycle." Federal Reserve Bank of Atlanta Working Paper no. 2002-13a; Sauder School of Business Working Paper. http://ssrn.com/abstract=208622

Luo, X., Zhang, J., and Duan, W. (2013) "Social Media and Firm Equity Value." Fox School of Business Research Paper no. 14-016. https://ssrn.com/abstract=2260316

Mohr, M. (2005) "A Trend-Cycle (-Season) Filter." European Central Bank Working Paper Series no. 499. https://www.ecb.europa.eu/pub/pdf/scpwps/ecbwp499.pdf

Treynor, J. (1962) "Toward a Theory of Market Value of Risky Assets." Unpublished manuscript.

Van Buskirk, A. (2011) "Volatility Skew, Earnings Announcements, and the Predictability of Crashes." http://ssrn.com/abstract=1740513

WEBSITES

Bloomberg. www.bloomberg.com

CFA Institute. *Financial Analysts Journal*. www.cfapubs.org/loi/faj

Cornell University Library. ArXiv https://arxiv.org

Elsevier. *Journal of Banking and Finance*. www.journals.elsevier.com/journal-of-banking-and-finance

Elsevier. *Journal of Corporate Finance*. www.journals.elsevier.com/journal-of-corporate-finance

Elsevier. *Journal of Empirical Finance*. www.journals.elsevier.com/journal-of-empirical-finance

Elsevier. *Journal of Financial Intermediation*. www.journals.elsevier.com/journal-of-financial-intermediation

Elsevier. *Journal of Financial Markets*. www.journals.elsevier.com/journal-of-financial-markets

Elsevier. *Journal of International Money and Finance.* www.journals.elsevier.com/journal-of-international-money-and-finance

Elsevier. *Pacific-Basin Finance Journal*. www.journals.elsevier.com/pacific-basin-finance-journal

Google Finance. www.google.com/finance

Google Scholar. https://scholar.google.com

Incredible Charts. "Indicator Basics: How to Use Technical Indicators." http://www.incrediblecharts.com/indicators/indicators.php

IPR Journals. *Journal of Portfolio Management*. http://jpm.iijournals.com

Investopedia. "Identifying Market Trends." http://investopedia.com/articles/technical/03/060303.asp

JSTOR. *Journal of Business*. https://www.jstor.org/journal/jbusiness

Kaufman, P. (2016) "Capturing Seasonality with Commodity ETFs." Kaufmansignals.com

Lee, S. (2012) "Morningstar ETF Investor Strategies: Model ETF Portfolios." www.morningstar.com

Morningstar. www.morningstar.com

NasdaqTrader. Options Market Share Statistics. http://www.nasdaqtrader.com/trader.aspx?id=marketsharenom

National Bureau of Economic Research.www.nber.org

Numpy Developers. www.numpy.org

Piard, F. (2016) “3 of the Best Seasonal ETFs.” https://seekingalpha.com/article/4014414-3-best-seasonal-etfs

Picardo, E. (2018) “7 Best ETF Trading Strategies for Beginners.” www.investopedia.com

Pilgrim, M. “Dive into Python.” http://www.diveintopython.net

Renater. “SourceSup Documentation.” https://sourcesup.renater.fr/projects/scientific-py

SciPy. www.scipy.org

SciPy. “NumPy Reference.” http://docs.scipy.org/doc/numpy/reference

SciPy. “NumPy User Guide.” http://docs.scipy.org/doc/numpy/user

SciPy. “Statistical Functions.” http://docs.scipy.org/doc/scipy/reference/stats.html

Social Science Research Network. https://ssrn.com/en/

StockCharts. “Technical Indicators and Overlays.” http://stockcharts.com/school/doku.php?id=chart_school:technical_indicators

Time. “The 25 Best Financial Blogs.”

http://content.time.com/time/specials/packages/completelist/0,29569,2057116,00

Tutorialspoint. “Python Quick Guide.” www.tutorialspoint.com/python/python_quick_guide.htm

University of Washington. *Journal of Financial and Quantitative Analysis*. http://depts.washington.edu/jfqa

Wall Street Journal. www.wsj.com

Wiley Online Library. *Financial Review*. http://onlinelibrary.wiley.com/journal/10.1111/(ISSN)1540-6288

Wiley Online Library. *Journal of Financial Research*. http://onlinelibrary.wiley.com/journal/10.1111/(ISSN)1475-6803

Wiley Online Library. *Journal of Futures Markets*. http://onlinelibrary.wiley.com/journal/10.1002/(ISSN)1096-9934

Wilmott. www.wilmott.com

WolframMathWorld. *Reuleaux Triangle*. http://mathworld.wolfram.com/ReuleauxTriangle.html

WorldQuantChallenge. https://websim.worldquantchallenge.com

Yahoo Finance. www.finance.yahoo.com

PUBLIC REPORTS

Options Clearing Corporation. Annual Report 2013. https://www.optionsclearing.com/components/docs/about/annual-reports/occ_2013_annual_report.pdf

Securities and Exchange Commission. (2000) Final Rule: Selective Disclosure and Inside Trading. https://www.sec.gov/rules/final/33-7881.htm

U.S. Commodity Futures. Commitments of Traders. https://www.cftc.gov/marketreports/commitmentsoftraders/index.htm

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