Deutsche Bank

Quantitative Strategy

Global Markets Research

22 July 2010

QCD Model

DB Quant Handbook

Research summary
We introduce our main stock-selection model, the QCD model and its unique features. We also outline the six steps of quantitative investing and how we propse to add value in each step.

Introducing the QCD (Quantitative, Computation, and Dynamic) model

Introducing our main stock-selection model – the QCD model
The main purpose of this research is to introduce our stock-selection model, the QCD (Quantitative, Computational, and Dynamic) model. There are a few unique features of our QCD model: factors are dynamically re-selected every month based on pre-determined algorithms; a nonlinear *TREE* model is combined with a linear panel data econometric model; and style rotation and industry timing models are incorporated in the bottom-up stock-selection model.

DB's quantitative equity research
The second purpose of this research is to outline the six steps of quantitative investing (data management, factor research, alpha model, risk model, TCA, and portfolio construction) and how we propose to add value in each step.

Model performance
The QCD model generates excellent results in the past 12 years, with an average monthly IC of 6.7% with consistency. The after transaction costs IRs (and Sharpe ratio) for the long-only large-cap core, large-cap value, large-cap growth, small-cap, and the market neutral portfolios are 1.9, 1.5, 2.0, 2.6, and 3.1, respectively.

Data delivery
QCD model scores and the holdings of our five model portfolios will be available via a spreadsheet. Please contact us to be added to the distribution list.

Source: gettyimages.com, Deutsche Bank

Team Contacts

Yin Luo, CFA
Strategist
(+1) 212 250-8983
yin.luo@db.com

Rochester Cahan, CFA
Strategist
(+1) 212 250-8983
rochester.cahan@db.com

Javed Jussa
Strategist
(+1) 212 250-4117
javed.jussa@db.com

Miguel-A Alvarez
Strategist
(+1) 212 250-8983
miguel-a.alvarez@db.com

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A letter to our readers

This is the fourth series of our US/global quantitative equity strategy publication. In the past three months, we have launched the *Signal Processing* series, which focuses on alpha factors; *Portfolios Under Construction*, which is about risk modeling and portfolio construction research; and *Academic Insights*, where we study the most recent academic research in details (a joint publication with our European colleagues). This series rounds up our initial publications.

In this paper, we describe our quantitative modeling process in detail, from data management, factor research, multi-factor alpha model, risk model, portfolio construction, to transaction cost analysis. In each section, we try to highlight the different alternative approaches used by academics and practitioners. More importantly, we describe our approaches and how we propose to add alpha in each step.

The main purpose of the report is to introduce our stock-selection model, the QCD (Quantitative, Computational, and Dynamic) model. There are a few unique features in the QCD model:

- The QCD model is free from data mining and look-ahead bias. Not only are the data, factor, model estimation, and portfolio simulation purely out-of-sample, but also the entire model construction process is specified prior to the backtesting.
- We have access to high quality data sources and unique/less crowded databases.
- We emphasize new and innovative factors.
- Nonlinear modeling techniques are incorporated in a linear panel data econometric model.
- Top-down style rotation and industry timing models are incorporated in the bottom-up stock selection process.
- Industry specific data, factors, and models are incorporated for 11 industries: airlines, gaming, healthcare facilities, homebuilding, lodging, managed care, oil & gas exploration and production, oil & gas refining and marketing, retail, semiconductor, and bank & thrift.

On a monthly basis, we will publish our most recent model performance and key outlooks. Detailed QCD model scores for all stocks, industries, and sectors will be available via a spreadsheet. Initially, we will provide monthly updates. In a few months time, we will distribute daily model updates. Based on our QCD model, we also create five standard model portfolios: large-cap long only, large-cap value, large-cap growth, small-cap long only, and market neutral. The exact portfolio holdings will be updated every month in the same spreadsheet. Please contact us to be added to the spreadsheet distribution list.

Initially, the QCD model is only available for US stocks. Our QCD-Canada model should be available by fall 2010. By early 2011, we should have similar multi-factor stock-selection models for all major countries (both developed and emerging markets).

Yin, Rocky, Miguel, Javed, and John

Deutsche Bank North American Quantitative Equity Strategy Team

1. Introduction

Philosophy

There seem to be two extreme schools of thoughts in finance. Fama and French's efficient market hypothesis (EMH) dominated academic finance until the 1980s. There are three major versions of the EMH hypothesis: weak, semi-strong, and strong. Weak-form EMH suggests that all information in stock price and volume is already reflected; therefore, it is impossible to predict future returns purely based on price and volume data. Semi-strong EMH claims that stock prices reflect all publicly available information and therefore, investors can not generate consistent positive alpha using only publicly available information. Strong EMH additionally claims that prices instantly reflect even hidden or "insider" information. EMH suggests that the market is efficient; therefore active investing is fruitless.

Behavioral economists, on the other hand, assert that humans, who are endowed with limited processing capacity, rely on simplified models, or imperfect decision making procedures/heuristics, to solve complex problems (Simon [1957], Kahneman and Tversky [1973a], [1973b]). This heuristic decision making process may lead to a cognitive bias (Daniel et al. [1998], Barberis et al. [1998], and Hirshleifer and Teoh [2003]). For almost any market anomaly, we seem to be able to find some behavioral explanations *ex post*. Behavioral economists, however, forget about the recent development in rapid computing power and wide spread of quantitative investing, which enables investors to build complex models, learn from past experience, make more informed decisions, and eventually arbitrage away other people's mistakes.

We believe the market is not efficient, but it is very competitive. More importantly, market and market participants learn from data and their own experience. Therefore, yesterday's market anomaly becomes today's random noise. Profit driven market mechanism makes sure that investors keep searching for the next signal and model to outperform. New signals and models, if they do prove to be useful, will eventually be arbitraged away. The market becomes more efficient over time. For quantitative managers, the only way to keep producing consistent excess returns is to always be on the front line of research. We hope our research will help managers to stay on top of quantitative equity investing.

How are we different

Innovative

True alpha is scarce. Consistently outperforming the market is very difficult. The market may not be efficient, but it is certainly competitive. Traditional factors no longer add consistent alpha. If a factor does produce consistent abnormal returns, more and more investors will invest in the same signal until it loses its predictive power. The same applies to modeling techniques and data sources. We strive to find new data sources, new ways to construct factors, new approaches to build alpha and risk models, and new portfolio construction techniques.

Adding value in every step of the quantitative investing process

As we will elaborate in the next few sections, there are six basic steps of quantitative investing process: data management, factor research, alpha model, risk model, transaction cost analysis, and portfolio construction. Our research encompasses the entire spectrum of the quantitative investing process and we try to add value in every step of the process.

On the alpha side, in particular, there are a few ways to improve performance. Finding a new and less crowded data source is probably the ultimate dream of many quants, e.g., news sentiment data in Cahan, Luo, Jussa, and Alvarez [2010], industry-specific data in Luo, Cahan, Jussa, and Alvarez [2010c], and options data in Cahan, et al [2010].

There are only so many new data sources with meaningful history. With traditional data sources, we want to be more clever and thorough in studying the underlying relationship. Traditional data sources and traditional factors based on these data sources are unlikely to generate consistent alpha. Looking at existing factors from a different angle can produce better and uncorrelated factors, e.g., value decomposition and new accruals factors in Luo, Cahan, Jussa, and Alvarez [2010a].

Model building technique is another great source of alpha. Many firms and analysts spend a great deal of effort in identifying new factors, but not nearly as much time in new modeling techniques. Equally weighting all factors, mean-variance optimization on the factor space (i.e., the Grinold and Kahn's approach), committee decision, and Fama-MacBeth regression are probably the four most common approaches. In statistics and econometrics, there are a wide range of linear, nonlinear, regression, optimization, and data mining techniques to be explored.

Avoid look-ahead and data snooping bias

There are many potential pitfalls in the quantitative backtesting and modeling process. In our opinion, the worst among them all is look-ahead bias. Look-ahead bias typically refers to using data that are not actually available as of the backtesting time. In reality, look-ahead bias presents itself in many other forms. Look-ahead bias is also closely related to data snooping. We try to avoid look-ahead bias by following these steps:

- data are purely point-in-time
- factor selection follows automatic algorithms
- model parameters are estimated only using data available as of the backtesting date
- risk models are estimated using point-in-time data and portfolio simulation is done with realistic assumptions

A robust technology infrastructure

We have invested heavily in our underlying technology infrastructure (Figure 1). By starting from scratch, we also have the luxury of choosing the latest technology, because we do not have any legacy issues.

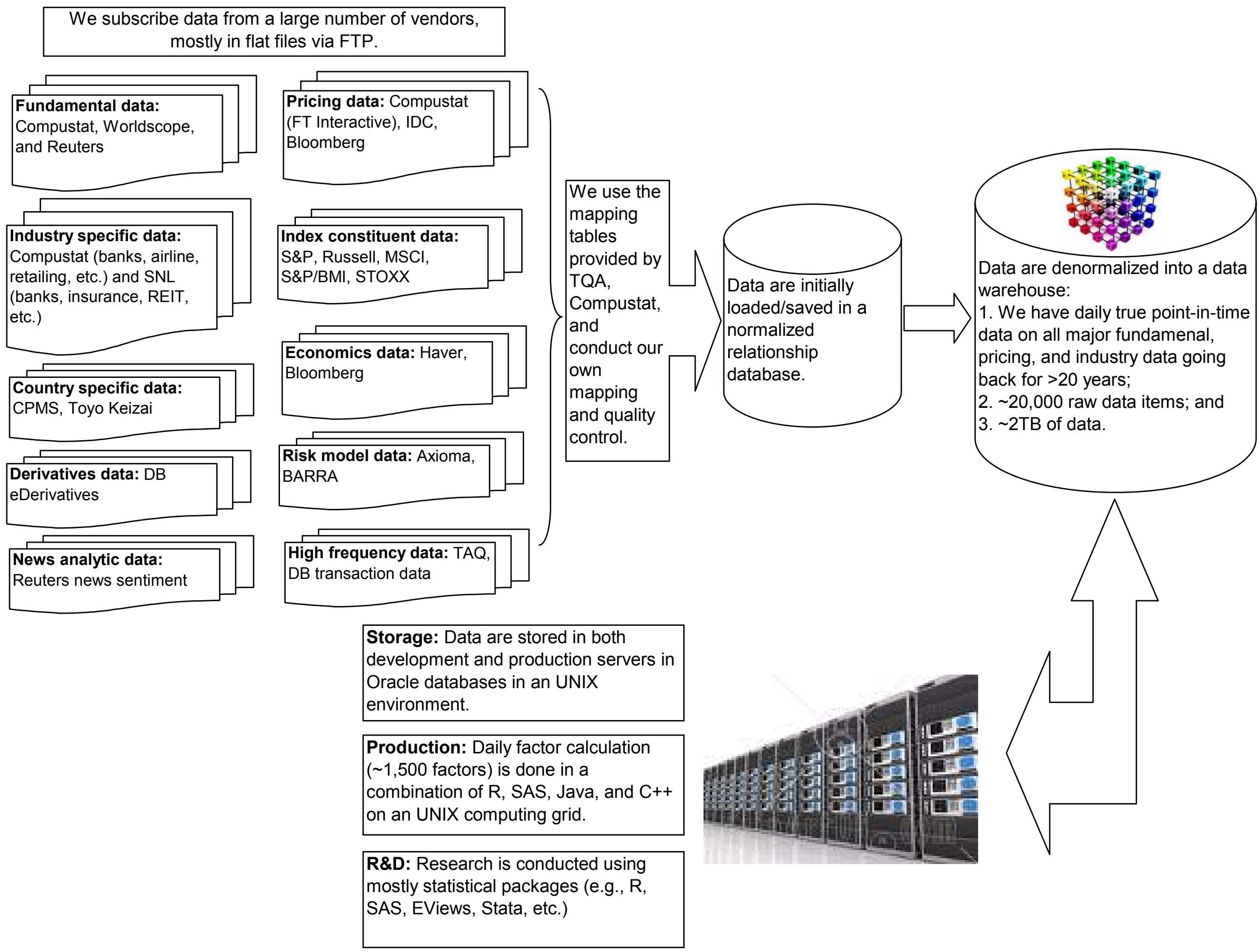
We subscribe to a large number of data vendors: fundamental data (Compustat, Worldscope), market data (IDC, Bloomberg, TAQ), industry-specific (Compustat industry-specific, Compustat banks, SNL), country-specific (CPMS), economic (Haver, Bloomberg), and risk model (Axioma, BARRA).

However, instead of relying on third-party data integrators, we have decided to build our own database and data warehouse, to ensure the ultimate flexibility and quality. Our data warehouse resides on UNIX database server and our computation is performed on a UNIX grid. We structure our data in a pure daily point-in-time fashion for the US market for the past 25 years. The size of our data warehouse is fairly large. The US database alone is about 2TB. Our research is conducted using a blend of mathematical/statistical systems like R, Java, and SAS.

Being objective

Our entire investment process is purely model driven. There are certain subjective elements in the model building process, e.g., which modeling techniques to use. However, once the process is set up, all recommendations are model driven. We would like to give our clients completely unbiased models, while clients are free to adjust the model output based on their own judgment calls.

Figure 1: Deutsche Bank Quantitative Strategy Technology Infrastructure



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

2. Data management

Data management is probably the least "glamorous" part of the quantitative investing process. However, analysts often spend most of their time building databases, mapping data from different sources, understanding the data availability and database schema, cleaning up data, and reshaping the data into a useable format. In some large firms, there is a fully dedicated team that handles data integration. Even if there are some other people collecting the data for you, the data may still not be in the same format as you need. It is often said that once data is well organized, the modeling is actually easy.

More importantly, as commonly said, "garbage in, garbage out". If we don't have high quality data, it is difficult to image how we can build high quality models. At the very minimum, analysts have to know what data items are available to them before they can conduct thorough research.

Normalized relational database vs. denormalized data warehouse

We subscribe to data from a large number of vendors. However, in most cases, we only subscribe to the raw data. We tend to stay away from data aggregators. Rather, we do most of the data cleaning and data consolidation ourselves, in order to maintain the highest level of quality control and flexibility.

Our database is structured as a data warehouse to maximize the speed of query and flexibility in research. Data storage, however, is a huge issue. The size of our data warehouse is massive – it exceeds 2TB for US data alone. The reason is that there are a lot of repeated values. Data vendors like Compustat and Worldscope store point-in-time data in a highly normalized schema, which saves storage space, but adds time and complexity for data queries.

A denormalized data warehouse frees users from understanding the complex data schema and focuses then on modeling. It also speeds up the backtesting and factor calculation substantially. In backtesting, analysts work with two-dimensional matrix-type data, which is consistent with most statistical analysis. In production factor calculation, however, data does not need to be denormalized first in order to perform the computation.

Point-in-time data

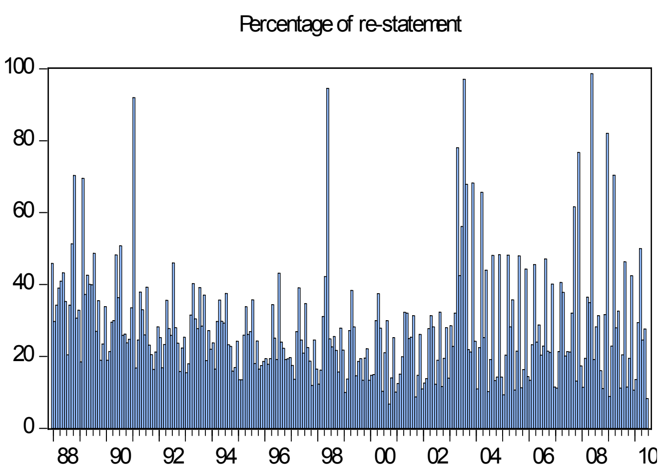
Point-in-time data are now available for Compustat (US and Canadian companies). Recently, Thomson Reuters launched its point-in-time Worldscope database for global markets. Before point-in-time data were made available, researchers had to rely on the traditional databases. The problems with the traditional databases are three fold.

First, analysts have to make reporting lag assumptions. For example, we can not use quarterly EPS for calendar quarter ending December 31, 2000 on January 31, 2001 for all companies, because some companies had not reported their Q4/2000 earnings yet. Therefore, analysts would typically add two months of reporting lag for quarterly data and four months of lag for annual data for US companies. However, this process also adds stale information. Using our previous example, as of January 31, 2001, many companies, especially, large cap companies had already reported the calendar quarter ended on December 31, 2000. Assuming all companies have two months of reporting lag forces us not to use the information actually available to us. Point-in-time data effectively solves the reporting lag assumption problem – we do not need to make such an assumption at all. We simply use the best information available as of any given point of time for our research. In this case, if a company has reported Q4/2000 results, we would use Q4/2000 data; otherwise, we would use Q3/2000 (or whatever was available as of January 31, 2001).

Research based on traditional databases also suffers from look-ahead bias. Companies often need to re-state their financial statements due to corrections to accounting errors or changes in accounting policies. Traditional databases only keep the latest numbers or the last re-stated financial statements. For analysts trying to build realistic investment scenarios going back in time, analysts would be using information that was actually not available as of the backtesting period. Another form of look-ahead of bias arises when data vendors add new companies. Periodically, vendors add new companies to their databases. When they do so, they often add a few years of historical financial statements in the system too. If we use the current databases, we are using companies that were not actually in the databases in the backtesting period, which often introduces overly optimistic results.

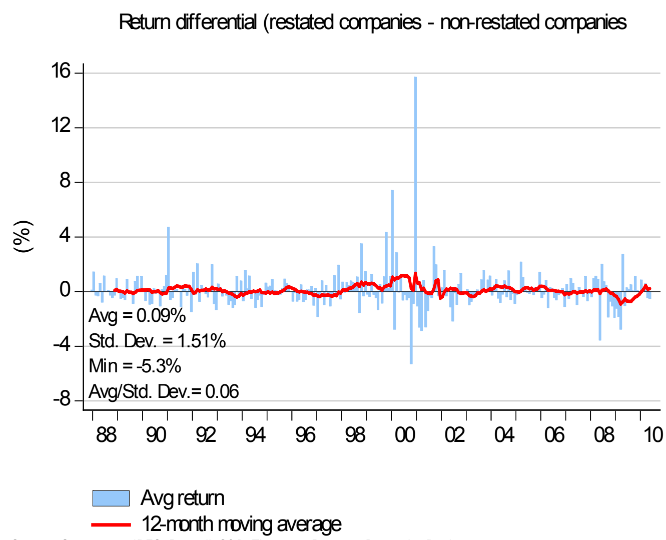
Figure 2 shows the percentage of companies with at least one re-statement of any financial statement data items (either quarterly, year-to-date, or annual statements) in the month. On average, about 28% companies have some sort of re-statement. Figure 3 shows the average month return differential of those companies with at least one re-statement and those companies without any re-statement. Interestingly, re-stated companies actually outperformed non-re-statement companies slightly, albeit not statistically significant. Drilled down deeper, however, we find much of the outperformance is driven by a single month (December 2000). The median return differential, arguably more robust to outliers, shows a negative return of -0.05%. Re-statement can potentially be an alpha source, which we intend to study further in the near future.

Figure 2: Percentage of companies with re-statement



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 3: Do re-stated companies underperform?



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

The third problem in the traditional databases is survivorship bias. As companies engaged in M&A, bankruptcy, delisting, and other forms of corporate actions, companies and stocks are being removed from the database constantly.

Point-in-time database allows analysts to use the "freshest" data as of any given point of time to construct the most realistic investment strategies.

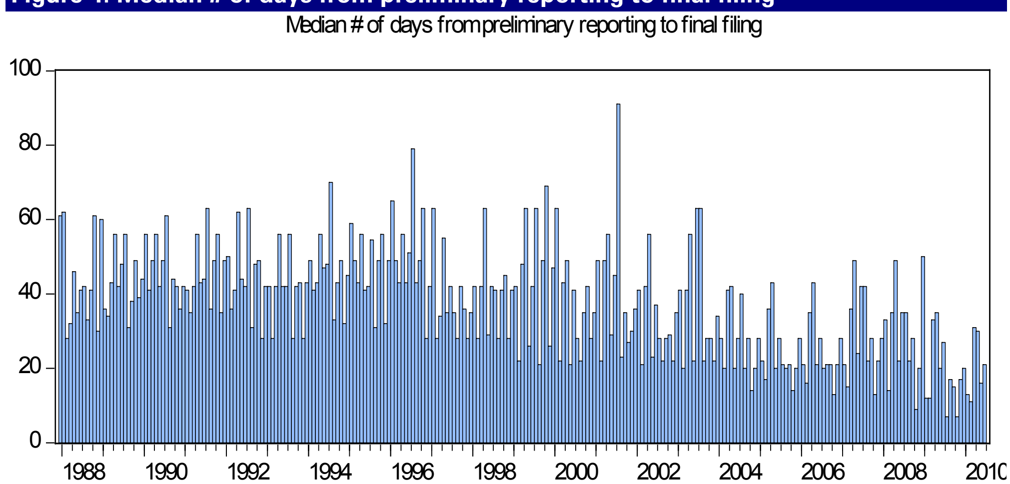
Please note that there are two point-in-time databases provided by Compustat, which often causes confusions. One is called point-in-time (hereafter called "PIT"). In the PIT database, historical final quarterly financial statement data are archived and stored in a column-based structure on a monthly basis. Recently, Compustat introduced a new point-in-time database called "Snapshot", which allows users to access both final and preliminary, both quarterly and annual financial statement data, structured in a row-based system, on a daily basis (note, point-in-time data are available on a weekly basis prior to December 2008, and daily basis after January 2009). We decided to use the new "Snapshot" data to take advantage of the new features, in particular, preliminary data, annual financial statement items, and more importantly, daily point-in-time data. The new "Snapshot" data, however, also imposes a few challenges. For example, by expanding the point-in-time data from monthly to daily, the size of data essentially increases by 21 fold.

Final vs. preliminary data

Most academic research uses annual financial statements. Even worse, most research uses final reported data. Quarterly financial reporting has been widely adopted in the US market for a long time. It provides much more timely data. More importantly, we use both preliminary and final data. In the Compustat database, for example, we found on average, the final data lag the preliminary data by 37 days (Figure 4). Companies report their quarterly/annual financial results in the form of press releases at least a few weeks before they file their 10Q/10K with the SEC. Most market participants start to do their analysis when preliminary data become available, rather than waiting until the final 10Q/10K filings. Market also reacts mostly to preliminary results.

In the final filing, companies often revise their financials. The discrepancy between the initial filing and final statements can be a source of alpha, which we intend to study further in the near future.

Figure 4: Median # of days from preliminary reporting to final filing



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Daily vs. monthly frequency

The traditional Compustat point-in-time database is structured on a monthly frequency. There are two problems. First, most historical Compustat data were updated once a week (since 2009, data are updated daily); therefore, monthly point-in-time data waste a lot of useful information. Secondly, the traditional point-in-time database use different schema for point-in-time data from regular financial statement data items, which means analysts have to have two systems – one for point-in-time data and one for the daily factor update. There is also a significant lag for the point-in-time data update; therefore, the traditional point-in-time data schema can not be used in a production environment.

We use Compustat's new point-in-time database (also called Snapshot data), which allows us build a truly daily point-in-time going back to mid-1980s. Before December 2008, it is actually weekly point-in-time data. However, since January 2009, the data is stored on a truly daily point-in-time basis.

Sources of information

Initially, quantitative analysts mostly relied on financial statement data to build factors. Fama and French [1993]'s two factor model was one of the first papers that addressed this topic. Jegadeesh and Titman's [1993] research on price momentum attracted researchers' attention on market data, while price and volume data have long been used by technical analysts.

The trend in recent years has been on searching for "unconventional" data sources. Text mining or news sentiment are very interesting sources of uncorrelated data (Cahan, Luo, Jussa, and Alvarez [2010c]). Industry-specific data has also been discussed in our recent research (Luo, Cahan, Jussa, and Alvarez [2010]). Cross asset class data, e.g., using options, futures, currency, and fixed income data to predict stock returns (and risk) is yet another interesting topic (see Cahan, et al [2010]). High frequency (on a tick-by-tick level) can also be explored and used in a low frequency investing environment.

Focusing on unconventional data sources does not mean that we should ignore traditional financial and market data. Rather, it suggests that we should take a new look at the traditional data. For example, in Luo, Cahan, Jussa, and Alvarez [2010a], we found that by decomposing traditional valuation factors (e.g., earnings yield, dividend yield, and cash flow yield) into a trend a cyclical component, we can achieve better forecasting accuracy.

One of the best ways to get timely and interesting information is from academia. In order to help clients filter through thousands of published and working papers, on a monthly basis in our *Academic Insights* series, we select about five or six of the most interesting academic papers and go through them in detail. We also highlight another 30 to 40 papers related to quantitative investing.

Data normalization

Financial data tends to be not normally distributed. Outliers can significantly influence the estimated model parameters. Data cleaning and normalization is a very important step before the actual model building process. Figure 5 shows the raw factor distribution for FY1 earnings yield as of June 30, 2010. It appears that the factor is negative skewed with excess kurtosis. Jarque-Bera test easily rejects the null hypothesis of a normal distribution.

There are many different ways to normalize data. The most commonly used approach is the z-score method, where analysts subtract the mean of the series and then divide by the standard deviation. Two other simple, yet popular, transformations are logarithm and square root for positive data. Figure 6 show the z-score transformed factor. Z-score transformation makes factors more comparable and somewhat improves the distribution.

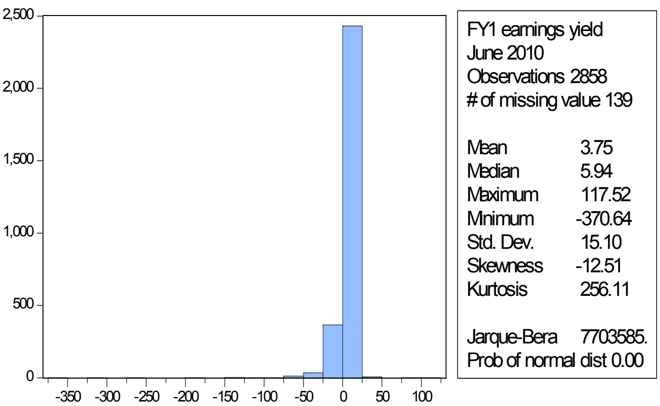
For highly non-normally distributed data, z-scores may not be able to provide enough adjustment. The Box-Cox transformation (Box and Cox [1964]) is another popular approach. The Box-Cox transformation belongs to the power transform, a family of transformations parameterized by a non-negative value λ that includes the logarithm, square root, and multiplicative inverse as special cases. To approach data transformation systematically, it is possible to use statistical estimation techniques to estimate the parameter λ in the power transform, thereby identifying the transform that is approximately the most appropriate in a given setting. Since the power transform family also includes the identity transform, this approach can also indicate whether it would be best to analyze the data without a transformation.

Often, even after data transformation, there are still significant numbers of outliers present. Some analysts further apply winsorization after normalization. For example, any data points outside of +/- 3-standard deviation bands can be either removed from model estimation or the values can be capped at +/- 3. Figure 7 shows the distribution of the winsorized z-scored factor. The distributional properties further improve, but it is still negatively skewed with excess kurtosis.

In quantitative equity research, grouping data into quantiles (e.g., deciles or percentiles) is also popular. Quantile transformation translates continuous variables into ordered factors of 1-10 (deciles) or 1-100 (percentiles). Outliers are automatically dealt with. The downside of using quantiles is that some information is lost.

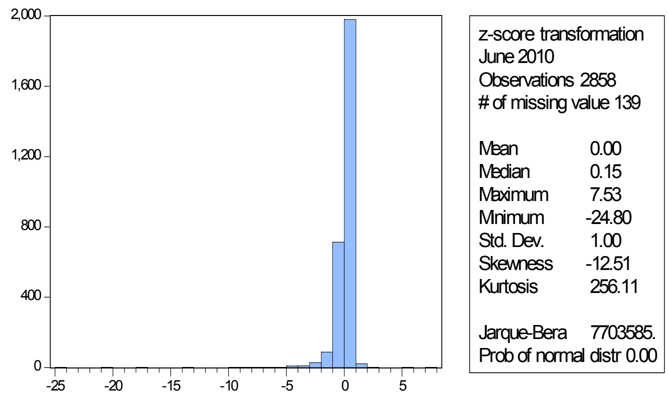
Figure 8 shows our transformation. Now the negative skewness and excess kurtosis are mostly eliminated. Jarque-Bera statistics can not reject the null hypothesis of a normal distribution.

Figure 5: Raw factor distribution – FY1 earnings yield



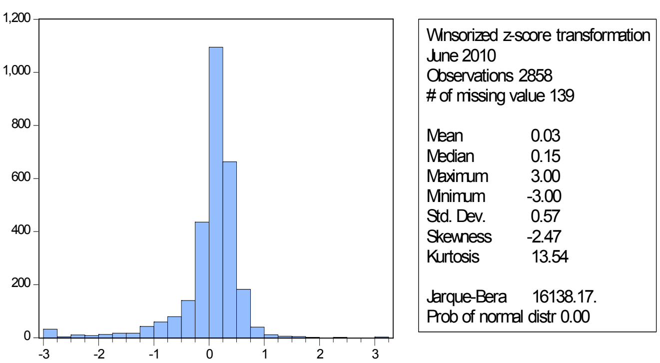
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 6: Factor distribution – z-score transformation



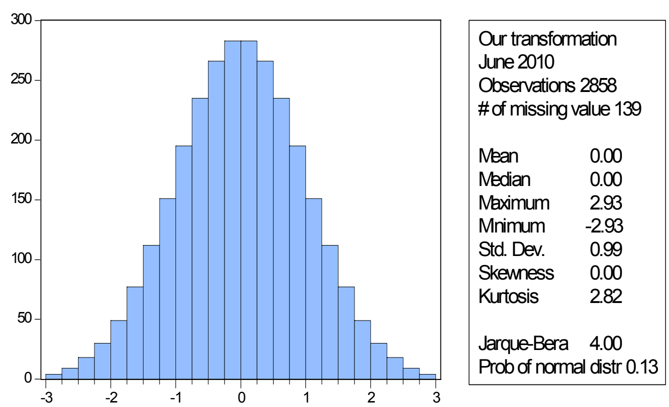
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 7: Factor distribution – winsorized z-score



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 8: Factor distribution – our transformation



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

3. Factor research

Factors are the raw ingredients of quantitative investing. Factors are also called signals. Even the best cook can not make a delicious meal without high quality raw ingredients. The same is true for quantitative portfolio managers. In reality, most analysts and managers spend most of their time looking for factors. In previous research, we found factor selection plays a more important role than factor weighting.

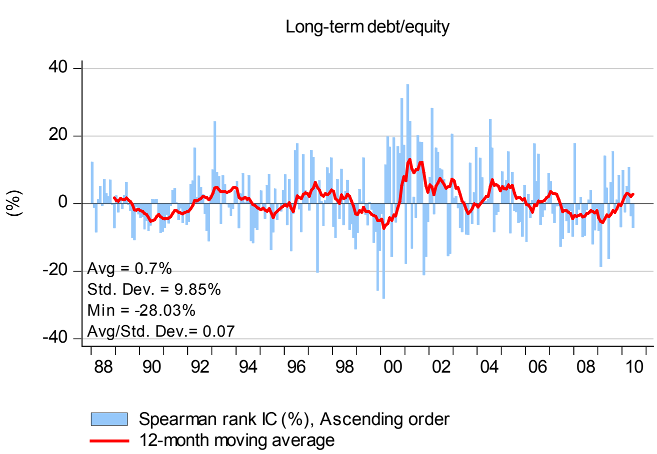
Alpha vs. risk factors

Some people further differentiate alpha factors from risk factors. The traditional definition is that if a factor can explain cross sectional stock returns, it could be a candidate factor. If furthermore, the factor return volatility is significant over time, it could be a potential risk factor (Figure 9). The requirement for alpha factors tends to be higher – we typically need the factor performance to be consistent (Figure 10). In another words, risk factors only require that the unconditional variance to be significant, while alpha factors also need to have significant unconditional mean.

In our research, we do not explicitly differentiate alpha factors from risk factors. The reasons are two fold. First, in recent years, the difference has blurred. The performance of most traditional alpha factors has shown substantial decay in recent years, due to arbitrage. The market is becoming more and more efficient.

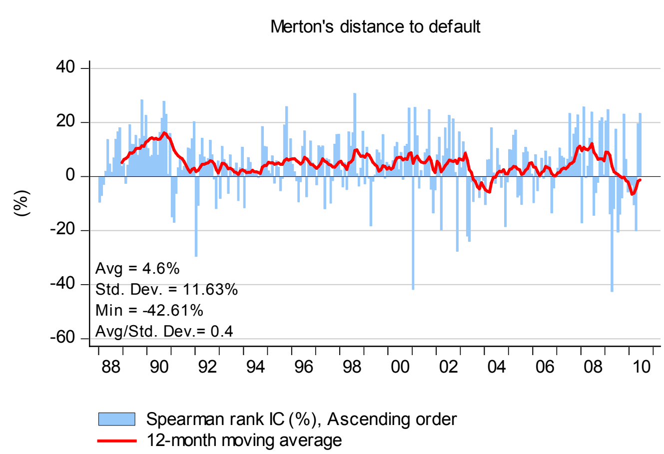
Second, we explicitly incorporate factor timing in our model building. Not only do we want to capture the incremental value by timing the factors, but that we feel that today it becomes a necessity to time the factors – for the reason that very few factors provides consistent alpha nowadays.

Figure 9: Risk factor – debt/equity ratio



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 10: Alpha factor – Merton's default model



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Identifying factors

Factors can be constructed using both traditional financial statement and market data and less traditional data sources like news sentiment.

We classify factors in our factor library into six broad categories: value, growth, momentum/reversal, sentiment, quality, and technicals.

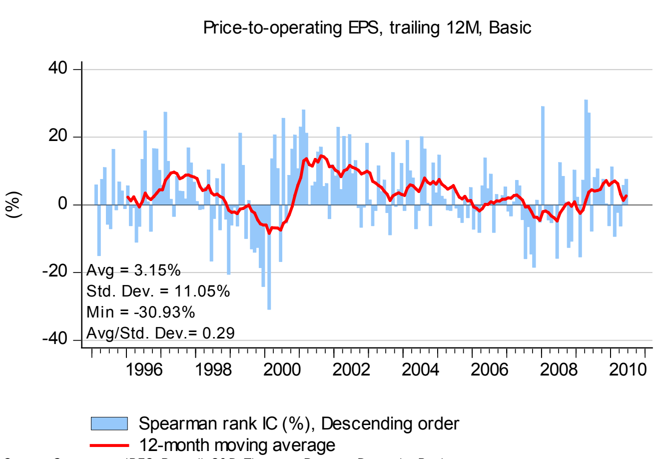
Value

Value is based on Graham and Dodd's concept (Graham and Dodd [1934]). The first real quantitative driven fund, Wells Fargo's dividend tilt fund, was based on value or dividend yield, in 1978. Academic literature has a long history of documenting the value phenomenon. Basu [1977] found stocks with low PE or high earnings yield tend to provide higher returns. Fama and French [1992] formally outlined value investing by proposing book-to-market as a way to measure value and growth.

Although academics and practitioners agree that value stocks provide higher returns, they have considerable disagreements on the reason. Fama and French [1992, 1996] suggest that the value premium exists simply to compensate for higher distress risk. Lakonishok, Shleifer, and Vishny [1994] cited behavioral reasons. For quantitative portfolio managers, the practical reason of using value is that as long as the particular value factor they want to use is not highly correlated with the value factor defined in the risk model, hopefully, it will have some predictive power for subsequent stock returns. Value and momentum have long been the two cornerstones of quantitative investing.

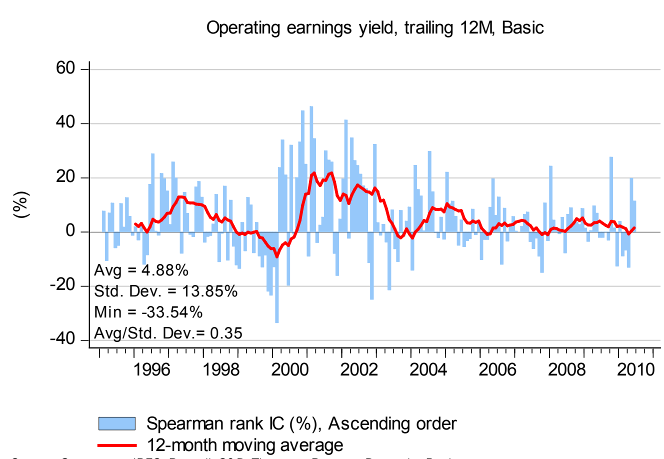
An example of a traditional value factor is trailing earnings yield. We prefer earnings yield to price-to-earnings multiple. The key reason is that when calculating price-to-earnings, for stocks with no earnings or negative earnings, the multiple is not applicable; therefore, causing a significant number of missing values for the factor. More importantly, negative earnings actual convey important information about the company's valuation, but this information is wasted in the price-to-earnings multiple. On the other hand, earnings yield can be calculated for companies with positive, zero, or negative earnings. Typically the higher the yield, the higher subsequent return. Simply reversing the order of price and EPS improves IC by 55% (Figure 11 and Figure 12) and increases the breadth by 21% (Figure 13 and Figure 14).

Figure 11: Price-to-operating EPS



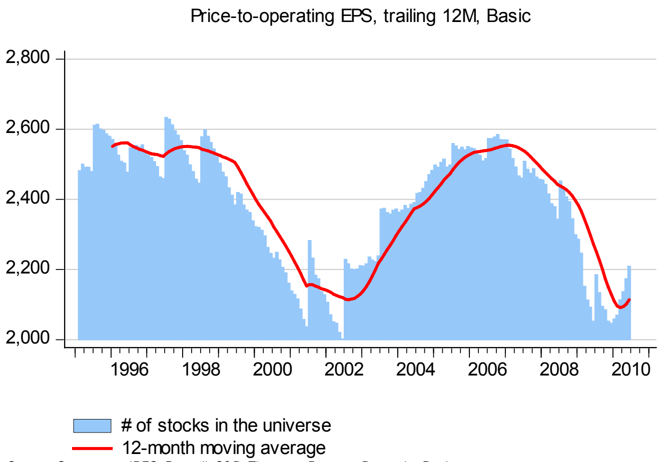
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 12: Operating earnings yield



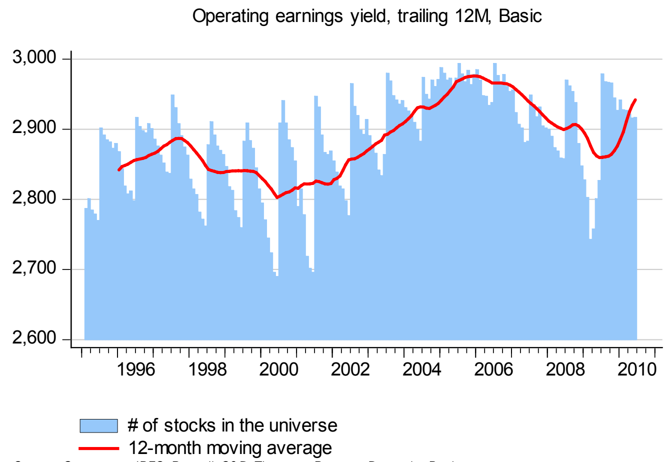
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 13: Breadth – PE



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 14: Breadth – earnings yield



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Value factors can be based on the following metrics: dividend, earnings, cash flow, EBIT, EBITDA, sales, and book value. Qian, Hua, and Sorensen [2007] suggested that valuation factors should be separated from value factors, while we combine them together in the value category.

Analysts often make two more variations on most value factors by adjusting for sector (or industry) and historical differences. The justification for sector-relative value factors is that stocks in certain sectors (e.g., technology) are always more expensive than stocks in other sectors (e.g., utilities); therefore, without adjusting for sector differences, stocks in the former sector always rank lower than stocks in the latter sector. Similarly, some analysts argue that valuation ratios for stocks in the cyclical business (e.g., materials and industrial companies) vary widely in different business cycles; therefore, a naïve value ratio would not be able to capture the cycles. Despite being intuitive, our backtesting does not seem to find either adjustment adding much extra alpha on top of the traditional value factors.

Another common misconception is that forward-looking valuation ratios are better gauges of future stock performance than backward-looking ratios. This view is especially prominent among fundamental managers. Supposedly, sell-side analysts would provide better forecasts of the future (earnings, cash flow, etc.) than simple history. Therefore, price-to-forward earnings should be a better indicator than price-to-trailing earnings. Our research, however, found backward-looking valuation ratios are generally better alpha signals than forward-looking ones.

Growth

Value and growth are the two traditional definitions of investment style. Growth factors try to measure a company's growth potential. Growth factors can be calculated backwards, i.e., the company's historical growth rates, or forward, i.e., the company's projected growth rates. Growth factors can also be classified as short-term growth (last quarter's, last year's, next quarter's, or next year's growth) and long-term growth (last five year's or next five year's growth). For our purposes, we also classify earnings surprise as growth factors.

For the US market, we find it is particular challenging to find good growth factors. Earnings surprise, or post-earnings-announcement-drift, used to be a good signal for US stocks, but in recent years, the signal has lost most of its predictive power. Cahan et al [2010] proposed that we could enhance the signal by overlying it with capital gains overhang.

Momentum and reversal

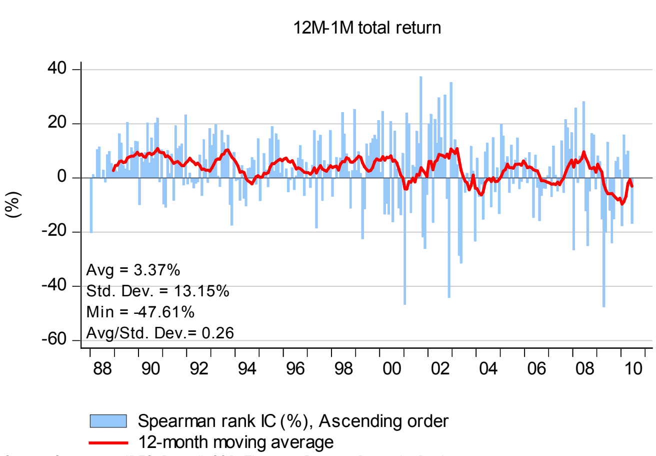
Along with value, momentum has been the other cornerstone of quantitative investing. Researchers have found strong momentum effect in almost all asset classes (equity, commodity, currency, etc.) in most countries.

Jegadeesh and Titman [1993] first documented past winners tend to outperform past losers over the next two to 12 months during 1965 to 1989 in the US market. The authors also found there is a short-term reversal effect along with the mid-term price momentum. The price momentum anomaly is commonly attributed to behavioral bias. An interesting observation is that after academics came up with the behavioral explanation of why momentum worked, the price momentum effect seems to have largely disappeared, at least in the US market (Figure 15).

Short-term reversal, on the other hand, seems to be much stronger than mid-term price momentum (Figure 16). The problem with short-term reversal is associated with the extremely high turnover, and this may be the reason it has not been arbitraged away. The month-to-month factor score serial correlation is close to zero for reversal (Figure 18), compared to almost 90% for momentum (Figure 17).

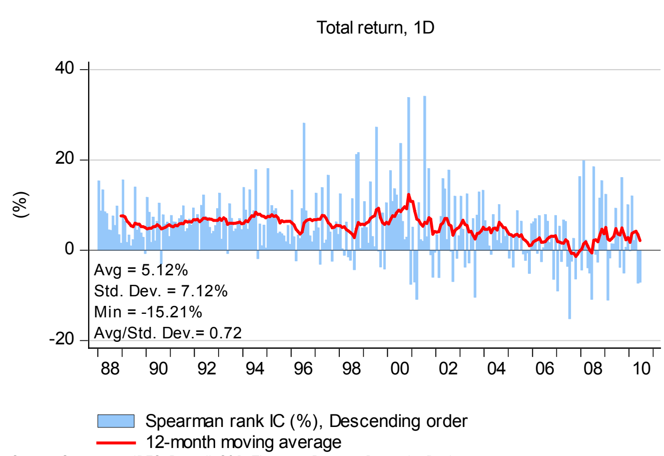
We prefer a behavioral factor called the "lottery" factor. The lottery factor is based on the idea that some investors pay too much attention to the most recent news on a stock (especially extraordinary price performance); therefore they temporarily push up the price for these high-flying stocks. Eventually, fundamentals do not justify the elevated price and share price falls back. We define the lottery factor as the highest daily return in the previous month. As shown in Figure 19, the lottery factor performs in line with short-term reversal factor in the long-term (doubled the performance in the past three years) and has much lower turnover – serial correlation is about 50% (Figure 20).

Figure 15: Mid-term price momentum



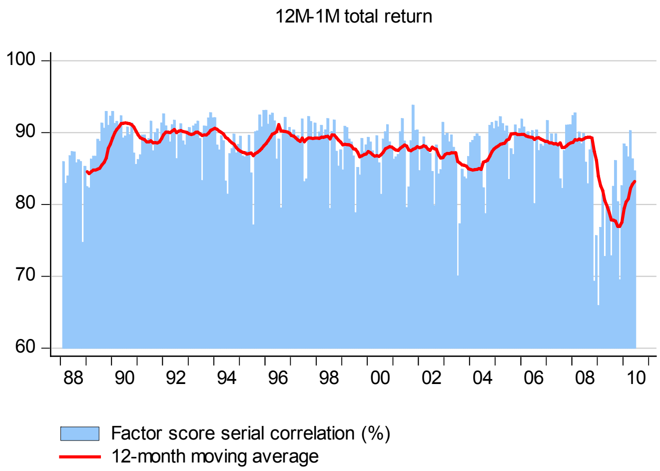
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 16: Short-term price reversal



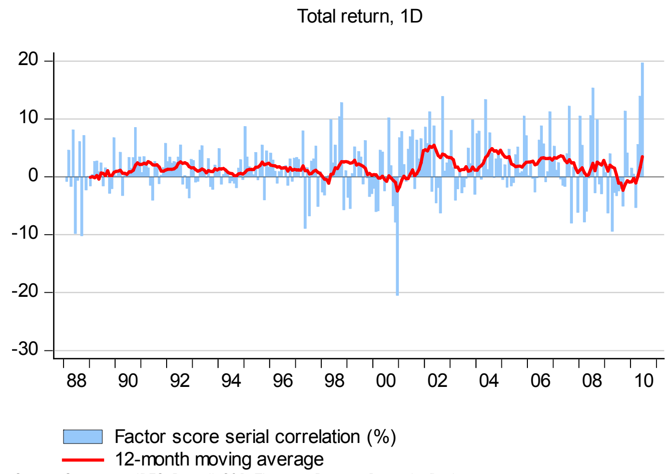
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 17: Signal serial correlation – momentum



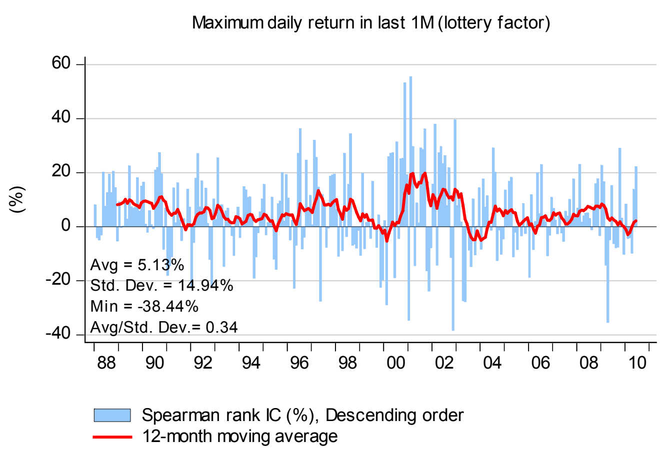
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 18: Signal serial correlation – reversal



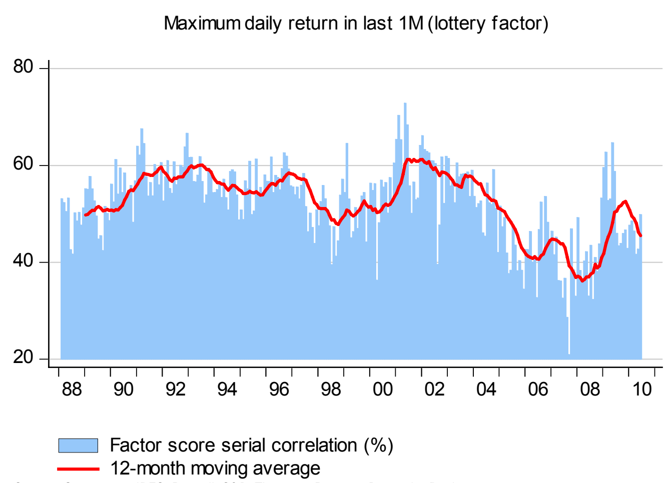
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 19: Rank IC, lottery factor



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 20: Signal serial correlation – lottery factor



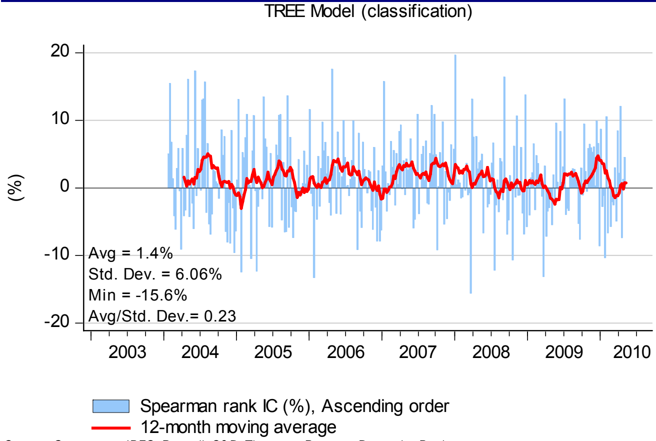
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Sentiment

Traditionally, sentiment refers to earnings momentum or sell-side analyst earnings revision (Givoly and Lakonishok [1979]). In recent years, analysts have been going through data items well beyond earnings revision to include cash flow revision, sales revision, ROE revision, recommendation and target price changes, etc. For the US market, we find most of the traditional revision factors behave more like risk factors than alpha factors.

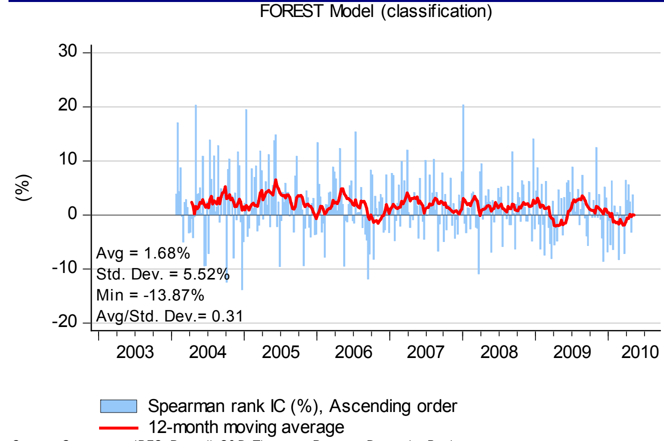
A new and exciting area of research involves news sentiment. Rather than just relying on sell-side analysts providing sentiment on stocks, we could data mine the large volume of news stories to quantify the news sentiment of stocks. As shown in Cahan, Luo, Jussa, and Alvarez [2010], news sentiment does appear to add incremental value on top of traditional analyst sentiment (Figure 21 and Figure 22). One possible explanation is that sell-side analysts are better at quantifying number-related stories while news reporters are better at capturing “soft” news like new product launches or corporate restructuring.

Figure 21: Rank IC, news sentiment factor using *TREE* model, weekly



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 22: Rank IC, news sentiment using *FOREST* model, weekly



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Quality

Value and quality factors are both rooted in fundamental research. One of the best known examples of how in-depth accounting knowledge can impact investment performance is probably Richard Sloan's seminal paper published in 1996 (Sloan [1996]). Unfortunately, after the wide adoption of earnings quality in the quantitative investing community, the earnings quality anomaly has also shown serious challenges as documented in Luo, Cahan, Jussa, and Alvarez [2010a] and Green, Hand, and Soliman [2009]. Figure 23 shows the performance of the original Sloan's earnings quality factor, while Figure 24 shows the performance of our "new" accruals factor as discussed in Luo, Cahan, Jussa, and Alvarez [2010a].

When people refer to quality, they may actually refer to very different things. We define quality as profitability, balance sheet and solvency risk, earnings quality, stability, dividend payout sustainability, capital utilization, and management efficiency.

Profitability measures how profitable a company is. Profitability can be calculated as gross margin, net margin, return on equity, return on assets, sales turnover, etc. Balance sheet and solvency risk measures the leverage and downside risk of a company. Traditional factors include currency ratio, debt/equity ratio, and Altman's z-score. In our research, we found that Merton's default model, Ohlson's probability and Campbell, Hilscher, and Szilagyi's model not only predict corporate bankruptcy better, but also are better predictors of future stock returns.

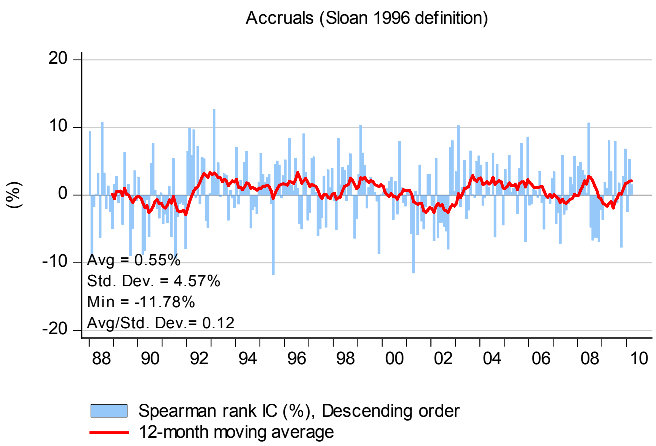
Since Sloan [1996], there have been a large number of papers published trying to either expand Sloan's definition of earnings quality or explain the earnings quality anomaly. We find the earnings quality anomaly has been largely arbitraged away. There might be some potential in improving the signal performance on the margin, especially in early recessionary environments, but it is difficult to find any earnings quality factor that works all the time.

Stability factors measure a company's historical earnings (or sales, cash flow, dividend) variation or dispersion among sell-side analysts about its future. Generally, a company with more stable history (or less dispersed views about the future) tends to have higher returns, especially in uncertain times.

Higher dividend yield alone is not enough to invest in high-yield securities. Often, conservative payout policy is more useful to identify winning stocks than yield alone.

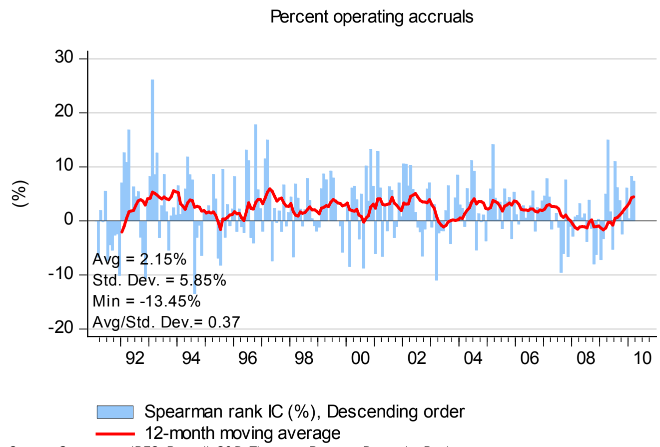
Capital utilization is closely linked to external financing and the agency problem. The traditional argument is that corporate management tends to over invest in low return projects; therefore, companies engaged in excessive external financing activities or capital expenditures are more likely to underperform the market in the future.

Figure 23: Rank IC, traditional accruals factor



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 24: Rank IC, new accruals factor



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Technical

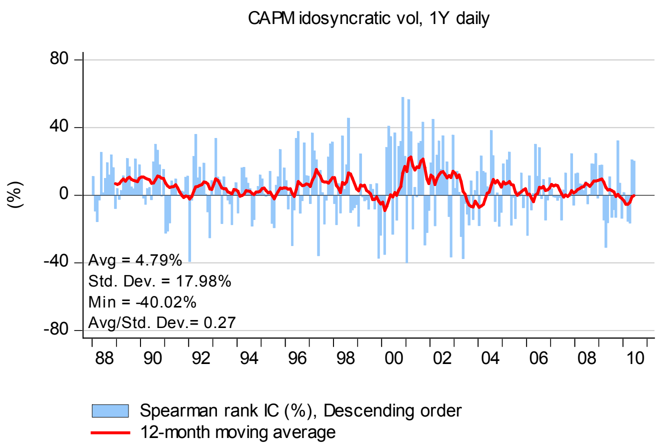
The last category in our factor library is broadly called technicals, which is more of a catch-all category. We believe factors in this category can be further broken down into factors based on short interest, institutional ownership, risk, volume, liquidity, technical trading rules, size, and high frequency data.

Two most promising research topics in the technical category are: 1) using derivatives data to build factors (Cahan, et al [2010]); and 2) using high frequency tick-by-tick data to build factors.

Figure 25 shows one of our favorite technical indicator, idiosyncratic volatility. Finance theory suggests that investors should not get compensated for taking idiosyncratic risk, because they can fully diversify stock-specific risk by investing in a fully diversified portfolio. In our research, we find the opposite result – stocks with higher idiosyncratic risk tend to systematically underperform over time, which is consistent with Ang, Hodrick, Xing, and Zhang [2004].

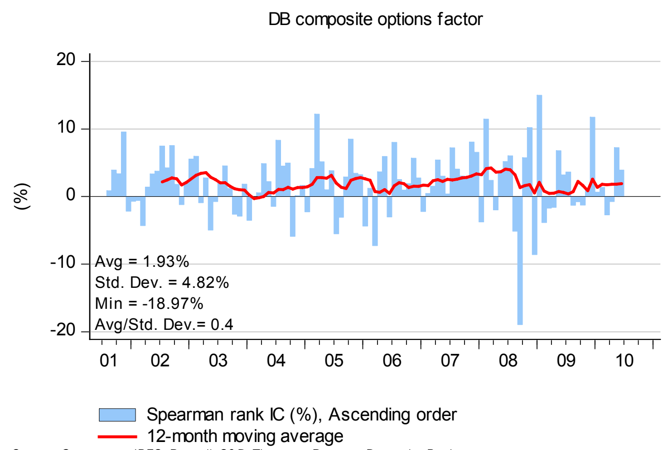
Figure 26 shows the performance of Deutsche Bank's composite options factor, which is an equally weighted factor of four signals based on options data: put-call parity, options implied skew, changes in implied volatility, and options volume/stock volume. Details can be found in Cahan, et al [2010].

Figure 25: Idiosyncratic volatility



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 26: DB composite options factor



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Factor backtesting

Once we identify a potential factor, we need to perform a series of tests to assess the factor's predictive power and efficacy. The most important test, however, is probably the "smell" test – does the factor make intuitive sense? A factor can easily pass the statistical backtesting, but it might simply be data mining. A client once told us, "I have never seen a factor that does not work in the backtesting", which simply means that analysts tend to only present those factors that perform well in a backtest. However, good backtesting results do not imply that the factor will continue to add alpha in the future.

In order to measure the performance of a factor's ability to predict future stock returns, we also perform a series of statistical tests.

Hedge portfolio

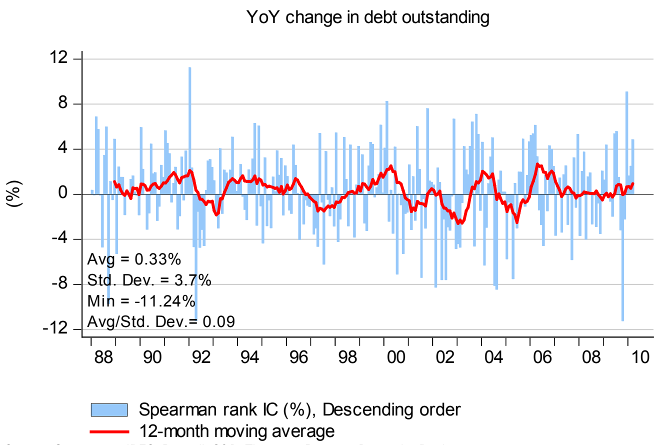
The most traditional and still the most widely used method is the hedged portfolio approach, pioneered and formulated by Fama and French [1993]. In this approach, analysts divide the investable universe into quantiles (typically in quintiles or deciles) to form quantile portfolios. Stocks are either equally weighted or cap weighted within each quantile. Each quantile portfolio's performance is then tracked over time. A long/short hedged portfolio is typically formed by going long the best quantile and shorting the worst quantile.

There are at least two drawbacks to this approach. First, the information contained in the middle quantile is wasted. Only the top and bottom quantiles are used in forming the hedged portfolio. More importantly, the portfolio built on this approach tends to be concentrated. If too many managers use similar factors, portfolios will be concentrated in certain stocks.

For example, in Figure 27, we show the performance of a factor called "year-over-year change in debt outstanding". The factor is calculated by taking year-over-year percentage change of the per share long-term debt outstanding on the balance sheet. The bars in the chart indicate the monthly portfolio returns (buying companies that reduce their debt and shorting firms that issue the most debt). The average month return of the strategy is about 0.25% (or 3% per year). In the worse month (October 2000), the strategy lost -6.4%. The reward/risk ratio is 0.13, meaning for every 1% of risk, the strategy generates about 0.13% of return. All these statistics can be found on Figure 27. In the legend, we also include a note "descending order", which means that we should sort the factor in descending order to compare the attractiveness of stocks. In another words, higher factor scores are more likely to be associated with lower subsequent returns.

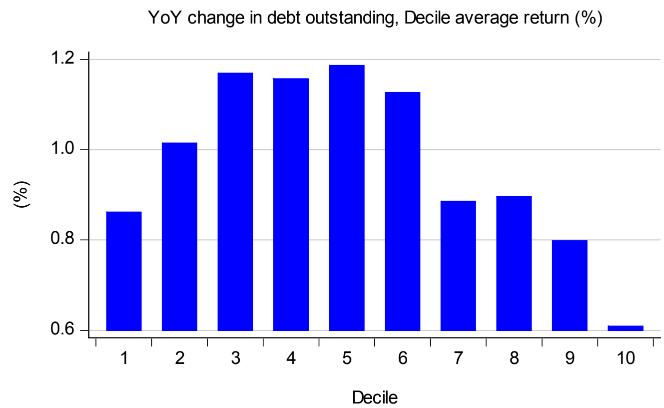
Figure 28 shows the average monthly returns of the 10 decile portfolios. It shows that companies with excessive debt financing marginally underperform (average monthly return of 0.6%) those firms with the most conservative debt financing (average monthly return of 0.9%). However, we can also see that the best performing stocks correspond to companies with reasonable financing leverage in deciles three to six. A simple long/short hedge portfolio approach would not reveal this important information.

Figure 27: Hedged portfolio return, YoY change in debt



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 28: Decile portfolio return, YoY change in debt



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Pearson information coefficient

The pioneering work on using information coefficient, or IC, as a way to measure skill or factor performance is based on Grinold and Kahn's [1999] fundamental law of active management. The fundamental law of active management suggests that a manager's performance can be measured using the information ratio or IR, which can be decomposed as:

$$IR = IC \times \sqrt{Breadth}$$

where, IC or information coefficient is calculated as the cross-sectional correlation coefficient between the current period's factor scores and next period's stock returns; and Breadth is typically just the number of stocks in the potential investment universe.

Pearson's IC is the simple correlation coefficient between the factor scores for the current period (e.g., earnings yield of all the stocks in our universe) and the next period's stock returns. IC is always between -100% and 100%. The higher the IC, the higher the predictive power of the factor for the subsequent returns. In practice, any factor with an average monthly IC of 5%-6% is considered very strong.

Because most quantitative models are linear, IC captures the entire spectrum of stocks while long/short quantile portfolios only capture the top (and bottom) extremes. Generally, we consider IC to be a better measure with which to identify factors than the hedged portfolio approach.

Spearman's rank correlation

Pearson IC is sensitive to outliers. Since raw alpha factors are typically normalized before entering in most stock-selection models and outliers are either removed or winsorized, Pearson IC may not be the ideal method.

A similar, but more robust measure is Spearman's rank IC, which is often preferred by practitioners. Spearman rank IC is essentially the Pearson correlation coefficient between the ranked factor scores and ranked forward returns.

As show in Figure 29, the Pearson IC is slightly negative at -0.8%, suggesting that the signal does not do well. Looking at the data more carefully, however, we can see the sample factor is generally in line with the subsequent stock returns. The only exception is stock I, where the factor predicts the highest return, while the stock turns out to perform the worst. A single outlier turns a good factor into a bad one. This exemplifies how the Pearson IC is sensitive to outliers. In contrast, the Spearman rank IC is at 43.3%, suggesting that the factor has strong predictive power of subsequent returns. If we were to form three equally weighted tercile portfolios, the long basket (stocks G, H, and I) would have outperformed the short basket (stocks A, B, and C) by 56bps in this period.

Figure 29: Pearson IC and Spearman rank IC

Stock	Factor score	Subsequent return (%)	Pearson IC	Spearman rank IC
A	(1.45)	(3.00)		
B	(1.16)	(0.60)		
C	(0.60)	(0.50)		
D	(0.40)	(0.48)		
E	0.00	1.20		
F	0.40	3.00		
G	0.60	3.02		
H	1.16	3.05		
I	1.45	(8.50)		
Mean	0.00	(0.31)		
Std Dev	1.00	3.71		
			(0.80%)	**43.30%**

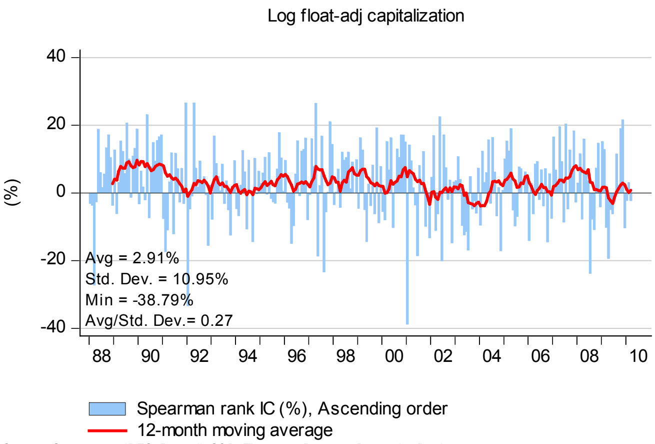
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Average vs. consistency

The average of IC is only one side of the story. As shown in Qian, Hua, and Sorensen [2007], what eventually determines a manager's performance is the ratio of the average IC and the standard deviation of IC. Therefore, the consistency of IC is more important.

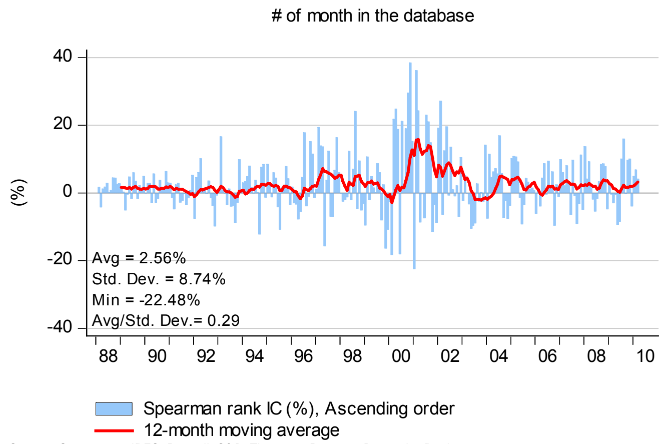
Figure 30 and Figure 31 show the IC history of two somewhat related factors: 1) size, as measured by the log of float-adjusted market capitalization; and 2) age, as measured by number of months in the database. Large-cap companies are more likely to be included in the database by data vendors, so there is a natural relationship between these two factors. If we simply look at the average IC, size outperformed age. However, if we take into account IC volatility, age seems to be a better factor than size – the risk/reward ratio improves from 0.27 to 0.29.

Figure 30: IC, size



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 31: IC, number of months in the database

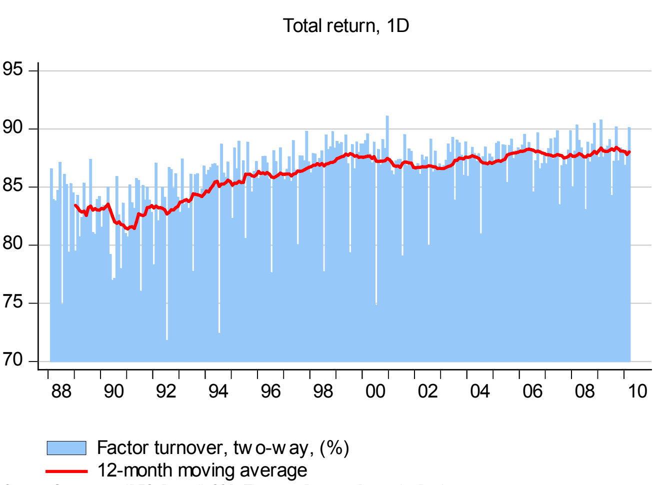


Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Factor turnover

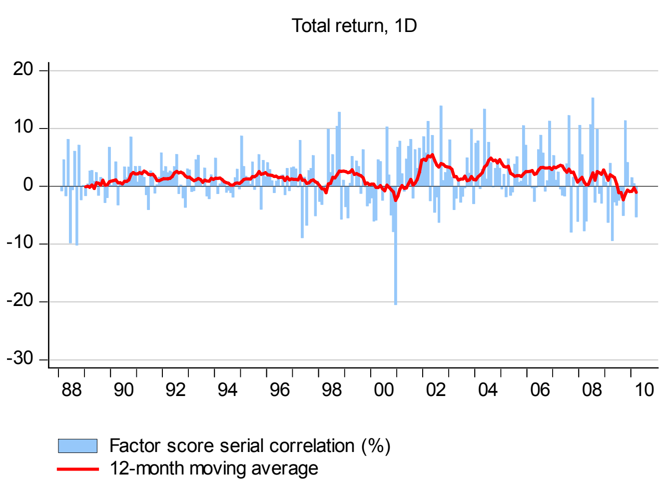
Another key measure that needs to be taken into consideration is factor turnover. Some factors can produce attractive paper returns, but can hardly be implemented in practice, because of the prohibitively high turnover. Short-term reversal is such an example. For the US market, one-day price reversal had an average IC of 5.2%, but the factor has a monthly turnover of 43% (Figure 32), as measured by changes in deciles. A more robust way to measure factor turnover is month-to-month factor serial correlation (Figure 33). For one-day price reversal, the monthly factor autocorrelation is close to zero, suggesting that the factor scores and thus portfolio positions change completely from month to month.

Figure 32: Factor decile turnover



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 33: Factor monthly serial correlation



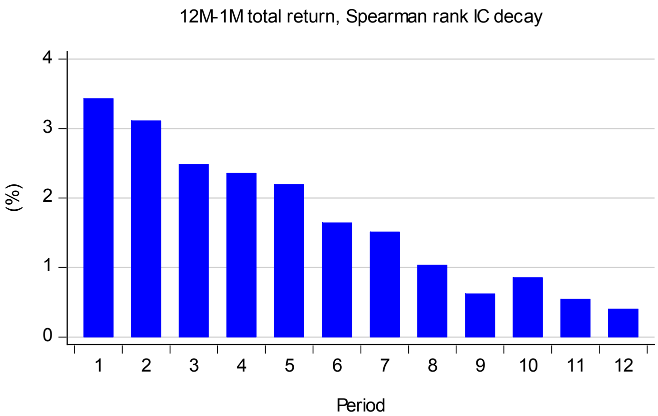
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Factor IC decay

A related concept to factor turnover is factor IC decay. It is generally believed that value factors have longer shelf life, i.e., factor performance tends to last for a certain period of time. On the other hand, momentum factors are perceived as quick burners, losing their predictive power soon and requiring more frequent rebalance.

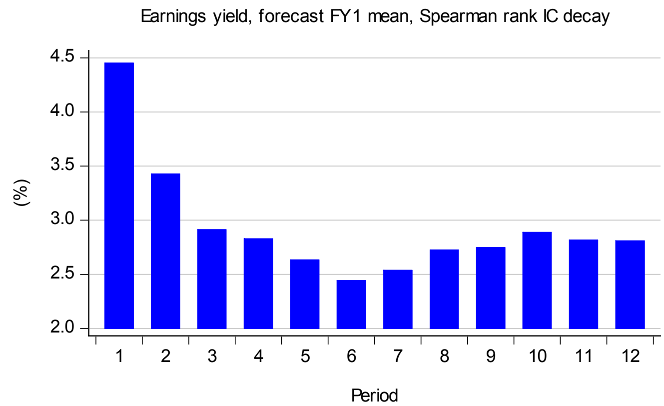
Conventional wisdom, however, is not always true. As shown in Figure 34 and Figure 35, price momentum still has reasonable forecast power even after five months, while value IC decays sharply after the first two months. One word of caution on IC decay is that the decay profile is not stable over time. Depending on the time window we use to calculate the decay, it can be drastically different.

Figure 34: IC decay, price momentum



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 35: IC decay, value



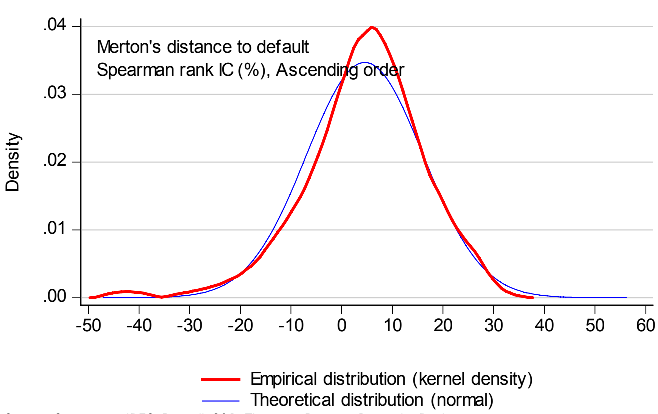
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Factor IC distribution

The traditional way to measure factor efficacy, e.g., the average IC and volatility-adjusted IC, is only concerned about the first two moments (mean and standard deviation). We argue that the overall distribution is more important in choosing factors. Some factors may have an attractive payoff in a mean-variance context, but may subject investors to serious downside risk.

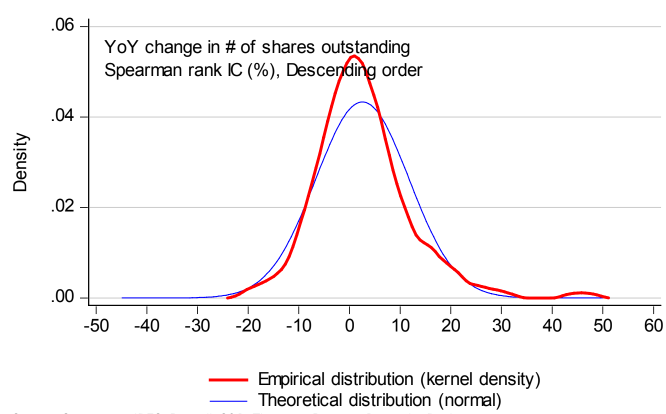
For example, both Merton's default model and year-over-year change in number of shares outstanding are historically good stock-selection factors. The problem with Merton's default model is the higher chance of getting a negative surprise (the lowest monthly IC was -42.6% for Merton's model and -18.7% for share change).

Figure 36: IC distribution, Merton's default model



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 37: IC distribution, YoY change in shares O/S



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Sector-adjusted rank IC

Stocks in different economic sectors tend to behave differently. Therefore, it might be worthwhile to adjust for sector differences. More importantly, our research suggests that most common factors are better at selecting stocks than selecting sectors. In reality, many quantitatively driven portfolios are managed under a sector neutral constraint.

There are a few ways to calculate sector-neutral IC. Our approach is to adjust returns.

As shown in Figure 38, the factor is generally able to rank stocks within the sector, but the factor fails to identify the correct ranking of the three sectors. The non-sector-neutral

Spearman rank IC is negative at -80.0%, indicating the factor fails miserably in predicting returns. However, the factor is actually very strong at identifying winning stocks, after controlling for sector difference. The sector-neutral IC is at 31.7%. If we were to form a sector-neutral portfolio by going long stocks C, F, and I (equally weighted) and shorting stocks A, D, and G (equally weighted), we would have returned almost 3% in this period!

Figure 38: IC and sector-neutral IC

Stock	Factor Score	Sector	Sector Return (%)	Subsequent Return (%)	Sector Adj Rtn (%)	Spearman Rank IC	Sector Neutral IC
A	(1.45)	1	2.00	0.50	(1.50)		
B	(1.16)	1	2.00	3.00	1.00		
C	(0.60)	1	2.00	5.00	3.00		
D	(0.40)	2	0.50	0.00	(0.50)		
E	0.00	2	0.50	0.80	0.30		
F	0.40	2	0.50	0.90	0.40		
G	0.60	3	(5.00)	(6.00)	(1.00)		
H	1.16	3	(5.00)	(4.50)	0.50		
I	1.45	3	(5.00)	(2.50)	2.50		
Mean	0.00			(0.31)			
Std Dev	1.00			3.49			
						(80.00%)	**31.67%**

Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Regression coefficient

Some analysts prefer to measure a factor's performance using regression. In a standard regression setting, the dependent variable would be the forward stock returns. There would be just one independent variable, i.e., the factor we want to test. Mathematically, the regression coefficient on the factor is closely related to the Pearson's IC defined in the previous section.

$$r_{i,t+1} = \alpha_t + \beta_t f_{i,t}$$

Where $r_{i,t+1}$ is stock i's return in period t+1;

$f_{i,t}$ is stock i's forecast in period t (based on the factor we want to study)

Then the regression coefficient β_t is:

$$\beta_t = \frac{Cov(r_{i,t+1}, f_{i,t})}{Var(f_{i,t})} = \frac{Corr(r_{i,t+1}, f_{i,t}) Disp(r_{i,t+1})}{Disp(f_{i,t})}$$

Where $Cov(r_{i,t+1}, f_{i,t})$ is the covariance between forecast and returns;

$Var(f_{i,t})$ is the variance of forecast;

$Corr(r_{i,t+1}, f_{i,t})$ is the correlation coefficient between forecast and returns, i.e., IC;

$Disp(r_{i,t+1})$ is the dispersion (cross-sectional standard deviation) of the returns; and

$Disp(f_{i,t})$ is the dispersion (cross-sectional standard deviation) of the forecast

When the signal is standardized, i.e., with zero mean and unit standard deviation, $Disp(f_{i,t}) = 1$ and therefore,

$$\beta = Corr(r_{i,t+1}, f_{i,t}) \times Disp(r_{i,t+1}) = IC \times Disp(r_{i,t+1})$$

Since the dispersion of stock returns is out of our control, what determines the regression coefficient is essentially IC. It also illustrates that IC is a better measure of factor performance because it excludes the return dispersion that is exogenous.

Risk adjusted factor and factor performance

Qian, Hua, and Sorensen [2007] suggested that the best way to measure a factor's performance is to calculate IC using risk-adjusted factor scores and returns.

In our research, we prefer to separate the signal research from risk modeling for a few reasons. The risk-adjusted IC approach heavily relies on the particular risk model at hand. Our clients may use risk models provided by different vendors or may decide not to use risk models at all (DeMiguel, Garlappi, and Uppal [2009] found that naïve equally weighted portfolios outperformed most sophisticated portfolio construction techniques under certain conditions).

More importantly, we decide to pursue a less aggressive but hopefully more realistic approach in the *Signal Processing* series. When choosing factors, we focus on the return predictive power. We leave the risk management to the portfolio construction stage, which is the focus of our *Portfolios Under Construction* research series, e.g., factor neutralization in Luo, Cahan, Jussa, and Alvarez [2010d] and decile portfolios vs. mean-variance optimization in Luo, Cahan, Jussa, and Alvarez [2010b].

Our approach

Usually, the above mentioned approaches would give similar conclusions. However, there are times that the results can be very different. We mostly rely on sector-neutral Spearman rank IC as our first pass of factor selection. The implications on risk and portfolio will be addressed in the following sections. More importantly, factor performance has to be measured in a multi-factor context.

4. Multi-factor alpha model

Traditional multi-factor models

Traditionally, researchers build multi-factor models by selecting the factors a priori. Analysts may follow different factor selection methods, whether purely based on algorithms or subjective analysis. Most academic research on asset pricing or market anomaly follows similar patterns, i.e., the factors being tested are specified first. In addition, in most research, the set of factors remain the same across the entire backtesting period.

In our opinion, the more static factor model suffers from least two problems. First of all, the market is dynamic. The underlying economic environment keeps changing. More importantly, market efficiency means that old alpha factors are constantly being arbitraged away and new factors are being discovered. In reality, portfolio managers and analysts keep revising their models by adjusting the factors in their models. Following the same set of factors is unrealistic.

The most serious issue with specifying factors manually is look-ahead bias. If we want to build a model today, we have already known what factors have been performing well and not so well in the past few years. If we want to show investors good "out-of-sample" model performance, we would naturally choose those factors that have been generating positive alpha. Going back point-in-time, we did not know these factors would perform well. This, however, is nothing but look-ahead bias. Furthermore, there is no guarantee that the same factors that performed well in the past few years will keep performing well in the next few years; therefore, the "out-of-sample" performance is not exactly out-of-sample. Although the data is out-of-sample, the factor selection process is in-sample. The backtesting results tend to be overly optimistic.

In this section, we show a simple example. We build two models to illustrate the above in-sample vs. out-of-sample point. The first model is in-sample, in the sense that we intentionally choose six best factors from July 2007 to June 2010, from our 80-representative factor database. The second model is out-of-sample, i.e., we choose the six best factors based on their performance from the previous three years, i.e., July 2004 to June 2007. We then track the performance of both models in the period of July 2007-June 2010.

As shown in Figure 39, the best six out-of-sample factors are completely different from the best six in-sample factors. Even more striking, in the momentum/reversal category, the best in-sample factor (i.e., best factor in July 2007-June 2010) is our lottery factor (essentially a reversal factor), while the best out-of-sample factor (i.e., best factor in July 2004-June 2007) is price-to-52 week high (essentially a momentum factor). If we are only able to run our model using factor performance data realistically (i.e., out-of-sample), we would be betting on exactly the opposite of what actually performed the best in the actual live environment. That probably explains why actual investing is always so much more difficult than backtesting.

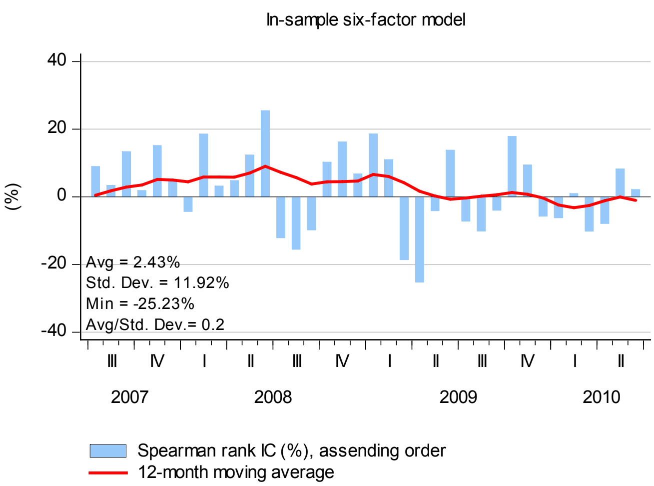
Even more striking, in the past three years from July 2007 to June 2010, the in-sample model produced an average monthly IC of 2.4% (Figure 40), which is very strong, given that most quant models broke down in this period. The out-of-sample model, however, delivered an average monthly IC of -0.06% (Figure 41). When an analyst is being asked to build a model on July 1, 2010, it is natural for him to consider what factors worked well in the past. If he did choose the best factors in the past three years and did the backtesting, he would have thought he built a great model with positive IC in the period of July 2007 to June 2010. However, this is nothing but look-ahead bias, because on July 1, 2007, he would not have known the factor performance in the next three years (July 2007 to June 2010); therefore, the best model he is likely to build is the out-of-sample model, which was slightly negative over the next three years. This example perfectly illustrates a look-ahead bias that is not widely documented in the academic literature and has not received all the attention it deserves in practice.

Figure 39: Comparison of in-sample vs. out-of-sample factor selection

	Best in-sample factors (i.e., best factors in 2007:07-2010:06)	Best out-of-sample factors (i.e., best factors in 2004:07-2007:06)
Value	Operating earnings yield, trailing 12M, Basic	Cash flow yield, FY1 mean
Growth	IBES FY2 mean DPS growth	Year-over-year quarterly EPS growth
Momentum/Reversal	Maximum daily return in last 1M (lottery factor)	Price-to-52 week high
Sentiment	IBES FY1 Mean ROE Revision, 3M	IBES FY1 Mean SAL Revision, 3M
Quality	Merton's distance to default	ROE, trailing 12M
Technical	CAPM idosyncratic vol, 1Y daily	Realized vol, 1Y daily

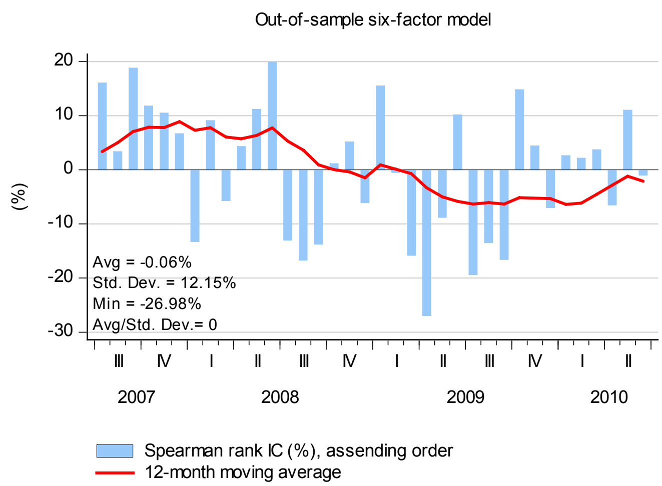
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 40: Rank IC, in-sample six-factor model



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 41: Rank IC, out-of-sample six-factor model



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

In our research, instead of specifying a set of factors, we define a set of decision rules or algorithms. We have a set of factor selection algorithms that the computer can follow to choose the factors in the model at every given point-of-time. The same algorithms are repeated every month, so the factors in the model are also being adjusted monthly.

Our approach

Our philosophy is that the market is not efficient but competitive. When a factor is first being "discovered", it tends to generate high and consistent alpha. Once it becomes widely known, more and more industry participants would gradually adopt the same signal. Eventually, the factor will get arbitraged away. As there is limited number of market anomalies but sufficient amount of quantitatively driven capital, it is more and more difficult to identify the good factors.

We also believe that the market keeps evolving over time. The economy follows boom and bust cycles. One set of factors may work well in a certain economic environment but not others.

Therefore, the factors in our model are dynamic. We do not have a fixed set of factors. Rather, we build certain logic into the model. The model follows the pre-determined logic to select the factors automatically every month. The process is very computational intensive. However, not only is the model adaptive to the changing market environment, but it is also free from look-ahead bias when choosing the factors.

Linear factor selection algorithm

We choose panel data econometrics as our main tool to select factors. We choose regression over optimization, because we think there are more useful tools at our disposal on the regression side.

One of the common problems with regression is multicollinearity, i.e., if the regressors are highly correlated, the regression coefficients estimated are imprecise and sensitive to small changes in the model or the data. In order to reduce the multicollinearity problem, we design a factor preprocessing algorithm that first removes highly correlated factors. Starting from our factor library of over 1000 factors, at any given point-of-time, we choose those that performed well in recent years and are not highly correlated as our candidate variables.

Panel data econometrics (or mixed linear model in bioinformatics) can also be applied in our setting. Traditional panel data econometrics typically treats the heteroskedasticity among individuals rather than the time dimension. More importantly, it is typically assumed that only the intercept term is different among individuals, while the slope terms are kept constant.

We first fit a panel data econometric model with all potential candidate variables. The initial model is intentionally overfit. We then apply a backward elimination algorithm, i.e., a step-wise regression model using BIC (Bayesian Information Criterion) to keep only the most relevant variables in a multivariate context.

In the most general setup, forward stock returns can be modeled as:

$$r_{i,t+1} = \sum_{j=1}^{J_t} \beta_{j,t} F_{j,i,t} + \sum_{k=1}^{K_t} \gamma_{k,t} S_{k,i,t} + \sum_{m=1}^{M_t} \pi_{m,t} D_{m,i,t} + \varepsilon_{i,t}$$

where,

$r_{i,t+1}$ is the forward one-period ahead return for stock *i* in period *t+1*;

$F_{j,i,t}$ is the *j*th factor score for stock *i* in period *t*, e.g., where the *j*th factor is PE, then $F_{j,i,t}$ is the PE for stock *i* in period *t*);

$\beta_{j,t}$ is the estimated factor return for factor *j* in period *t*;

$S_{k,i,t}$ is a dummy variable indicating whether stock *i* belonged to sector *k* in period *t*;

$\gamma_{k,t}$ is the estimated sector *k* return in period *t*;

$D_{m,i,t}$ is the *TREE* model forecast terminal node (a 0/1 dummy variable), e.g., whether stock *i* fell into tree node *m* in period *t* (the *TREE* model will be explained in the next section);

$\pi_{m,t}$ is the estimated node m return in period *t*;

$\varepsilon_{i,t}$ is the regression residual, i.e., the random noise that can not be accounted for by the linear regression model;

i = 1 to N_t indicating the number of stocks in period *t*;

j = 1 to J_t indicating the number of factors in period *t*;

k = 1 to K_t indicating the number of industries in period *t*; and

m = 1 to M_t indicating the number of *TREE* nodes in period *t*.

In a traditional pooled time-series cross-sectional regression, the time dimension t will be dropped from coefficients (β_j , γ_k , and π_m). Therefore, it essentially assumes factor payoffs are identical over time.

In a traditional panel data econometric model, the individual effect *i* is more prominent than the time dimension *t*. Therefore, the equation is estimated with the following coefficients: $\beta_{j,i}$, $\gamma_{k,i}$, and $\pi_{m,i}$. This is probably more intuitive for fundamental analysts, as now we are assuming stock-specific reaction to the underlying fundamental factors dominates. The coefficients can be estimated using either fixed effect or random effect models.

The first adjustment we make to the traditional panel data econometric model is to reverse the roles of the individual effect *i* and time effect *t*. In another words, we argue that for a given factor, there is a common payoff across all individual stocks at a given point-in-time.

A more significant adjustment is that instead of using the more traditional fixed effect/random effect techniques, we treat the coefficients as functions of another set of exogenous variables (i.e., macroeconomic variables, capital market variables, seasonality dummy variables, etc.) In essence, we assume the factor returns can be explained and predicted using macro-type of variables. We will elaborate this point in the next section.

Traditional approaches for nonlinear patterns

The relationship between many factors and forward stock returns is often nonlinear. Nonlinear patterns can be modeled in either full-blown nonlinear techniques or approximated in linear models.

Traditional approach of dealing with nonlinearity

Qian, Hua, and Sorensen [2007] gave a thorough and outstanding description of how to deal with nonlinearity in a linear modeling framework. The authors used capital expenditure as an example to show the nonlinear effect. They showed that companies with either very low level of capital expenditure (i.e., underspenders) or very high level of capital expenditure (i.e., overspenders) tend to underperform the market. Underspenders are likely to lose their competitive position for lack of long-term investments. Overspenders are likely to underperform because of the agency problem. The authors further suggested three alternatives to deal with the nonlinear effect:

- **Quadratic models.** A quadratic term can be added to the linear model. The downside of this approach is the potential of over-fitting as we include more and more second-order terms in the model.
- **Conditional models.** We can use another factor to partition the universe into two subgroups and construct two linear models for each subgroup. Qian, Hua, and Sorensen [2007] suggested ROE as the conditioning variable for capital expenditure.
- **Interaction models.** The conditioning variable in the above approach (i.e., ROE) can be added along with the interaction term (i.e., ROA x Capital expenditure) to capture the nonlinear effect.

For this simple example, analysts can study the nonlinear effect in detail and find a potential conditioning variable. However, there are many other factors that potentially may also have nonlinear effects. More importantly, the market keeps changing. A good factor (linear or nonlinear) today may be arbitraged away tomorrow. Therefore, we need an automated system to identify the nonlinear effect and build that into our stock selection model. The combined *TREE* and linear model solves this puzzle nicely.

Contextual modeling

Sorensen, Hua, and Qian [2005] proposed an interesting way of equity modeling called contextual modeling. In essence, the authors find typical alpha factors behave very differently among different contexts, e.g., value/growth universes. In Qian, Hua, and Sorensen [2007], the authors further show three contexts along three risk partitions, high/low value, high/low growth, and high/low variability. Under contextual modeling, different factor weights (or even different factors) can be applied to different contexts. Then, a composite model can combine the different views together.

Our view is that we are less interested in the partitions defined by common risk model vendors. Rather, we would like to pursue the contexts defined by different industries. A few specialized industries stand out, e.g., banks, insurance companies, and REITs. Luo, Cahan, Jussa, and Alvarez [2010b] is our first attempt at building industry-specific models.

Nonlinear models

Nonlinear models like neural networks, CART (classification and regression tree), and SVM (support vector machine) have broader appeal among computer scientists and data mining practitioners, but have only gained limited attraction in quantitative finance. The biggest critique of nonlinear models is the potential of overfitting, i.e., good in-sample fit but poor out-of-sample forecast. In addition, this type of model is also difficult to interpret. Sorensen, Miller, and Ooi [2000] pioneered the work of using the CART model in stock selection. The CART model looks for optimal splits. The model is easy to understand and intuitive. CART-type models have gained some limited attraction in the quantitative equity investment community.

In recent years, there have been a large number of papers using support vector machine in stock selection (e.g., Huang, Nakamori, and Wang [2005] and Nalbantov, Bauer, and Sprinkhuizen-Kuyper [2006]).

Adding nonlinear techniques in a linear panel data econometric model

One of the unique features of our research is that we try to incorporate nonlinear modeling techniques into a linear modeling framework. We try to capture the nonlinear factor payoff pattern automatically using a recursive partitioning algorithm (also called classification and regression tree or CART model). The prediction from the *TREE* model is then assigned into the linear panel data model described in the previous section.

In this research, we use the *TREE* model to analyze the nonlinear patterns, for its simplicity, interpretability, and robustness. *TREE*-type models are also being used in our news sentiment research (Cahan, Luo, Jussa, and Alvarez [2010]).

As the name suggests, *TREE* models are constructed by "growing" a (upside-down) tree-like classification structure. Think of it as something of a flow-chart, that can then be used to classify out-of-sample data points.

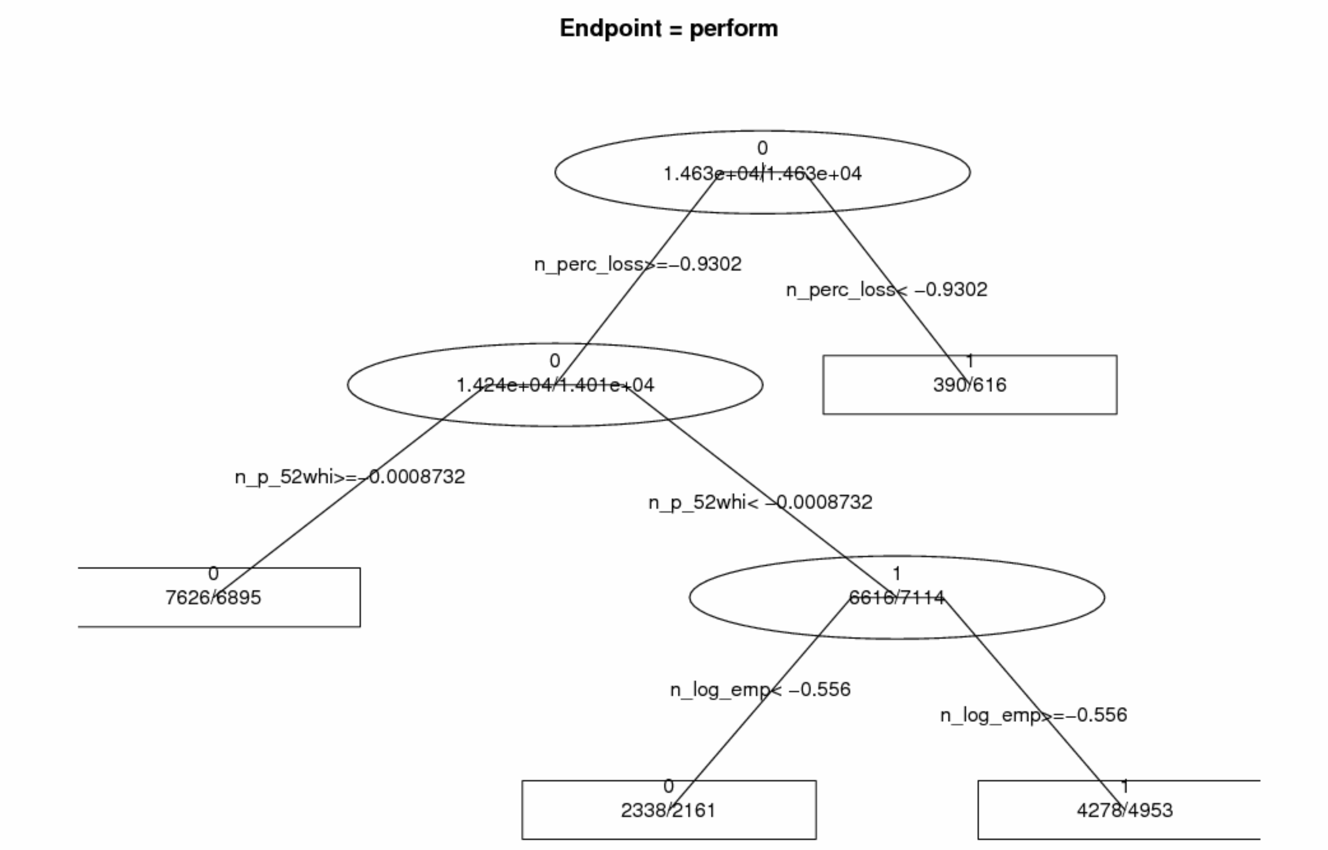
The model starts with the whole dataset and looks for the explanatory variable in the data that best splits the dependent variable into two groups. Within the groups, the dependent variable is homogenous as possible, and between groups it is as different as possible. The process is then repeated for each of the two new groups. Again, we look for dependent variables that will best subdivide the data into smaller groups.

For example, let's take the simple example of a classification tree on stock performance. In this case the dependent variable (i.e. what we want to predict) is one-month ahead stock returns. *TREE* models come in two flavors: classification trees or regression trees. Classification trees are used when the dependent variable is categorical, whereas regression trees are used for a continuous dependent variable. In this example, we focus on a classification tree; this requires us to transform continuous returns into a categorical variable. This is easily done. We just define two categories: outperform (forward returns > universe median) and underperform (forward returns <= universe median).

Figure 42 shows the results of fitting the *TREE* model to explain the forward returns. One of the most useful features of the output is that it gives a good sense of the hierarchy of importance for explanatory variables. In this example, *N_PERC_LOSS*, which is normalized percentage of loss quarters in the past three years, is the single most important variable in determining whether a stock is likely to outperform or underperform. We will come back to this point shortly.

One of the main weaknesses with *TREE* models is the tendency to overfit. Left unchecked, there is nothing to stop the tree from continuing to grow until it fits the data perfectly, i.e. the end of each branch (or node) represents a single stock. Clearly such a tree will work beautifully in-sample, but will fail completely when used in out-of-sample forecasting. For this reason we apply a technique called (naturally enough) pruning. This is a process where we cut back the tree based on how well it works out-of-sample, with a technique called cross-validation. Essentially in cross-validation we divide the dataset up into *n* subsets, and then build a *TREE* using data from *n*-1 subsets and test it on the remaining subset. Initially making the tree bigger helps reduce error, since using more variables better describes the data. But the improvement quickly reaches a plateau, i.e. at this point the loss in out-of-sample predictive ability from overfitting outweighs the gain from adding more explanatory variables.

Figure 42: *TREE* model built on June 1, 2010 to predict June 2010 performance

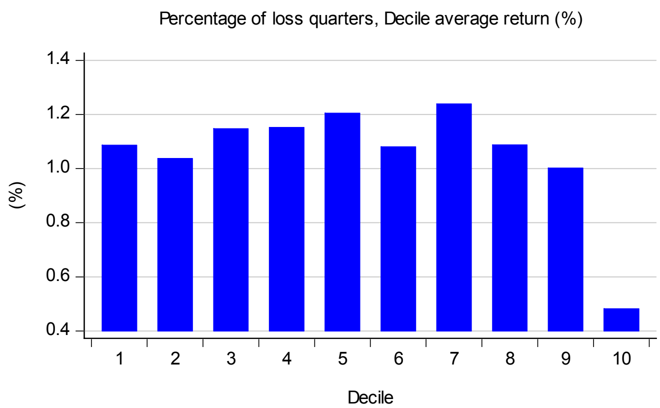


Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 42 shows the pruned tree, after applying 10-fold cross-validation. With this simplified tree, we can start to see some interesting relationships. For example, stocks that have less loss quarters in the past three years tend to outperform on average (see the first node on the right). On the second split, stocks with high price momentum (measured by price-to-52-week-high) are likely to underperform, i.e., we would bet against momentum. The last split uses the natural log of number of employees – larger companies with more employees are more likely to outperform.

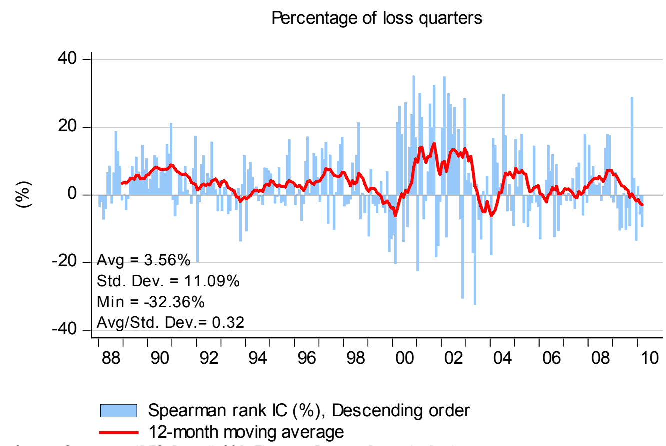
Interestingly, in this example, the most useful factor in the *TREE* model is percentage of loss quarters. The payoff pattern for this factor is clearly nonlinear, as shown in Figure 43 – stocks with excessive number of loss quarters are likely to do poorly, but companies being consistently profitable are not necessarily always continue the winning trend. If we were to use a traditional linear model, it would be almost impossible to capture this nonlinear pattern – as shown in Figure 44, the linear Spearman rank IC is moderate, but not spectacular.

Figure 43: Decile portfolio performance



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

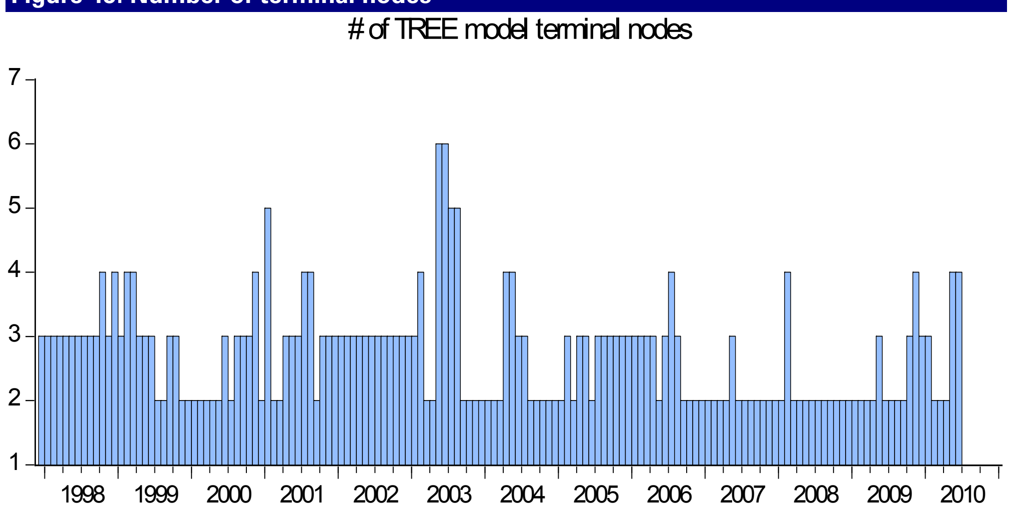
Figure 44: Rank IC



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 45 shows the number of terminal nodes as predicted by the *TREE* model. On average, we have only about two or three nodes, as we really try to keep the model parsimonious. At most, we have only six nodes. The *TREE* model predicted nodes are then combined into the linear panel data econometric model.

Figure 45: Number of terminal nodes



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

5. Factor weighting and style rotation

Common factor weighting models

Once we have a set of alpha factors that we want to use, the next step is how to combine them together to build a composite alpha model. In practice, there are a few common factor weighting approaches as discussed below.

Equally weighted
Equally weighting all factors is probably the simplest approach. Surprisingly, in our previous research, we found it actually gives higher alpha than most sophisticated techniques. The intuition is that there are few assumptions underlying the equally weighted approach, while in finance, fewer assumptions typically mean fewer potential mistakes.

Grinold & Kahn
Grinold & Kahn's method is essentially a mean-variance optimization on the factor space. In essence, we need to solve for the optimal weighting of a set of factors. The objective of the optimization is to maximize expected IR. The expected IR of a multi-factor model is:

$$IR = \frac{v' \widetilde{IC}}{\sqrt{v' \Sigma_{IC} v}}$$

Where,

v is the weight vector;

$\widetilde{IC}$ is the expected IC vector of the factors; and

Σ_{IC} is the IC covariance matrix.

This is an unconstrained optimization. Taking the partial derivative of the above equation with respect to the weight vector and setting it equal to zero allow us to solve for the optimal weight vector v.

$$\hat{v} = \Sigma_{IC}^{-1} \widetilde{IC}$$

$\hat{v}$ can be further normalized, so that the sum of the weights equals to one.

As in any optimization problem, the results critically depend on the accuracy of the inputs. There are two key inputs in this IR optimization, the expected IC vector $\widetilde{IC}$ and the IC covariance matrix Σ_{IC}. We find the IC covariance matrix is reasonably stable over time; therefore, we can reasonably estimate it. On the other hand, in reality, IC varies over time and as we demonstrated in the previous sections, it could include structural breaks. The non-stationary nature of IC makes the estimated IC imprecise, which causes the Grinold & Kahn's model to underperform the simple equally weighted model in many cases.

Incorporating higher moments
One potential remedy of estimating the future IC is to incorporate higher moments in the optimization problem. Covariance, co-skewness, and co-kurtosis matrices are likely better behaved than the mean vector. Therefore, incorporating higher moments is essentially shifting weights from less reliable input (i.e., the mean vector) to more reliable inputs (covariance, co-skewness, and co-kurtosis matrices).

Another benefit of higher moment optimization is that tail risk is taken into account in the alpha model. Traditionally, when analysts choose factors, only the first two moments, i.e., factor IC and the volatility of IC are considered. Factor performance is measured as the ratio of mean and standard deviation, or IR (see Qian, Hua, and Sorensen [2007]). However, in reality, many factors show negative skewness and excess kurtosis, which are precisely what we try to avoid. By taking skewness and kurtosis into account, we might be able to build a more robust alpha model that is less subject to downside surprises.

The challenge of higher moment optimization rests on two aspects. First, we need to estimate the co-skewness and co-kurtosis matrices. The number of parameters that need to be estimated increases exponentially as we start to include higher moments. However, in our previous research, we found even a naïve estimate of the co-skewness and co-kurtosis matrices using sample data can still yield satisfactory results.

The second challenge of higher moment optimization is how to solve the problem numerically. We could incorporate the higher moments in the objective function directly. However, because the objective function is non-convex, there is no guarantee that we can find the global optimal point. In our previous research, we found that polynomial goal programming, or PGP, algorithm can be used effectively in this setting.

Fama-MacBeth regression

Due to the popularity of asset pricing tests based on the Fama-MacBeth [1973] procedure, it is also widely used among practitioners in combining multiple factors. In the first step of Fama-MacBeth regression, a series of cross-sectional regressions of stock returns against factor scores are performed over time. In the second step, the time series of the regression coefficients are treated as the factor returns.

There are pros and cons of using the Fama-MacBeth procedure. On the one hand, the tools for regression are more widely available and mature than the tools for optimization. On the other hand, potential pitfalls like multicollinearity can have significant impact on the precision of factor return estimation.

Style rotation

In our opinion, there are two fundamental ways to improve alpha model performance, by searching for good factors and by accurately timing factor performance. The rest is just a variation of one of these two.

There are only so many new data sources. Similarly, there are only so many ways that analysts can build factors out of the existing databases. Because of the arbitrage forces in the market, eventually, most traditional alpha factors will or have become risk factors. Therefore, factor timing is an effective way to add alpha.

Style timing, like market timing, is not only very difficult, but also has limited breadth – there are only a handful of styles to choose from, compared to tens of thousands of stocks for a typical quantitative equity investor.

There are two common approaches in style timing strategies. The first approach is mostly based on the underlying time series properties of style factor returns and volatilities without using any exogenous variables, i.e., momentum in style returns. In Luo, Cahan, Jussa, and Alvarez [2010a], we found this approach has lost its predictive power in recent years. The second approach is conditional on exogenous variables like economic factors. The two most common statistical techniques in style timing strategies are either linear regression models (e.g., Zhang, Hopkins, Satchell, and Schwob [2009]) or logistic-type of classification regression algorithm (e.g., Clare, Sapuric, and Todorovic [2010]).

The static alpha model makes a rather unrealistic assumption that factor returns are constant over time. As we have shown in the previous sections, factor returns are not only not constant, but can be nonstationary.

In this research, we explore a very simple form of style rotation strategy, mostly using linear time series regression on capital market variables (e.g., VIX, put-call ratio, commodity price, currency, yield spread, and credit spread, etc.) and seasonality dummy variables (e.g., January effect, reporting month effect, December effect, etc.) A more in-depth research on style rotation strategies is forthcoming.

Our research suggests that factor timing is very difficult for the US market. The benefit mostly comes from reducing IC variability, rather than increasing the average IC.

The basic model setup is as follows:

$$\beta_{j,t} = \sum_{g=1}^{G} \delta_{j,g} E_{g,t-1} + \sum_{h=1}^{H} \rho_{j,h} C_{h,t-1} + \sum_{p=1}^{P} \theta_{j,p} A_{p,t-1} + \varsigma_{j,t-1}$$

where,

$\beta_{j,t}$ (as defined in the previous section) is the estimated factor return for style factor *j* in period *t*;

$E_{g,t-1}$ is the *g*th macroeconomic variable at period *t-1*;

$\delta_{j,g}$ is the estimated coefficient for the *j*th style factor with regard to the *g*th macroeconomic variable at period *t-1*;

$C_{h,t-1}$ is the *h*th capital market variable at period *t-1*;

$\rho_{j,h}$ is the estimated coefficient for the *j*th style factor with regard to the *h*th capital market variable at period *t-1*;

$A_{p,t-1}$ is the *p*th seasonal dummy variable at period *t-1*;

$\theta_{j,p}$ is the estimated coefficient for the *j*th style factor with regard to the *p*th dummy variable at period *t-1*;

$\varsigma_{j,t-1}$ is the regression residual, i.e., the random noise that can not be accounted for by the linear regression model;

j = 1 to J_t indicating the number of style factors in period *t*;

$g = 1$ to G indicating the number of macroeconomic variables;

$h = 1$ to H indicating the number of capital market variables; and

$p = 1$ to P indicating the number of seasonal dummy variables.

6. QCD model

QCD model methodology

We call our main stock-selection model, the QCD or Quantitative, Computation, and Dynamic, model, indicating the model rests on quantitative tools, computational engines, and dynamic factor selection and weighting schemes.

There are a few unique features of the QCD model.

- The QCD model is free from data mining and look-ahead bias. Not only are the data, factor, model estimation, and portfolio simulation purely out-of-sample, but also the entire model construction process is specified prior to the backtesting.
- We have access to high quality data sources and unique/less crowded databases.
- We emphasize new and innovative factors.
- Nonlinear *TREE* model is incorporated in a linear panel data econometric model.
- Top-down style rotation and industry timing models are incorporated in the bottom-up stock selection process.
- Industry specific data, factors, and models are incorporated for 11 industries: airlines, gaming, healthcare facilities, homebuilding, lodging, managed care, oil & gas exploration and production, oil & gas refining and marketing, retail, semiconductor, and bank & thrift.

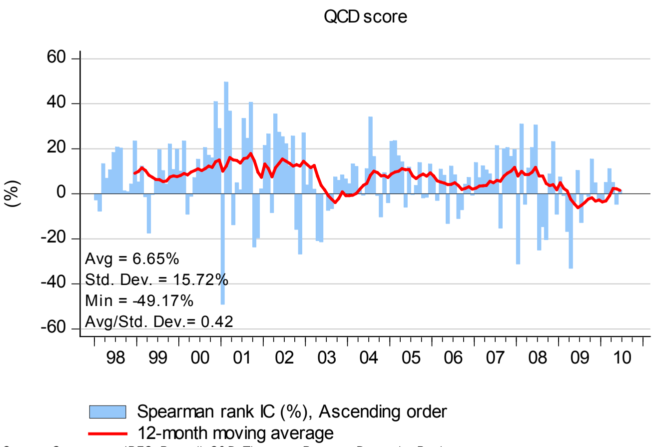
QCD model performance statistics

Over the entire backtesting period, from December 1997 to June 2010, the QCD model performs very well. The most challenging periods for the QCD model were in late 2003/early 2004 and 2009/early 2010. We have seen some recovery in recent months (Figure 48). We recommend using the QCD model in a sector-neutral context, as the model has stronger skill in selecting stocks than ranking sectors.

A more useful and realistic performance measurement is done at the portfolio level. In Section 10, we demonstrate the performance of five model portfolios (long-only large-cap core, long-only large-cap value, long-only large-cap growth, long-only small-cap, and long/short market neutral) with typical institutional constraints and transaction costs. The IR/Sharpe ratio for the five model portfolios ranges from 1.5 to 3.1 and stays positive almost every year since 1998. Even in 2008 and 2009, two of the most challenging years for quantitative investing, our market-neutral strategy produces Sharpe ratio of 0.85 and 1.24, respectively.

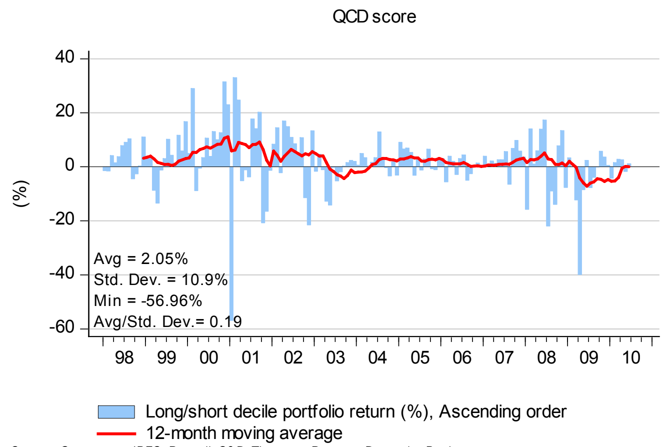
The model's forecasting horizon is about one quarter (Figure 49). The performance distribution is approximately normal with a heavier left tail, i.e., more downside than a normal distribution (Figure 50). The QCD score's serial correlation is reasonable (Figure 51), which suggests the model turnover should be slightly higher than value/quality type of factors, in line with growth/momentum/sentiment/technical and better than reversal factors.

Figure 46: Spearman rank IC



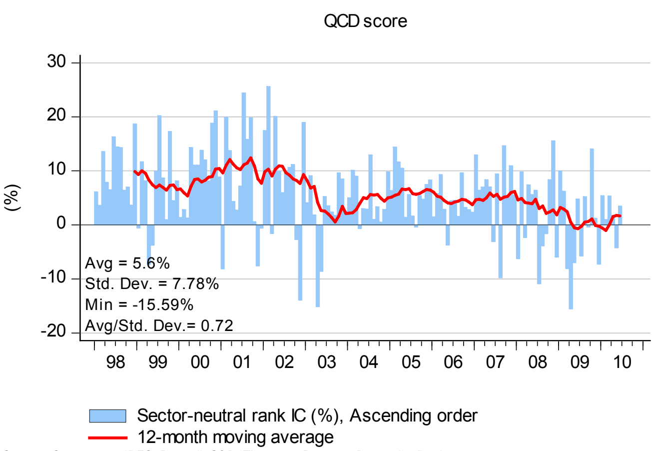
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 47: Long/short spread



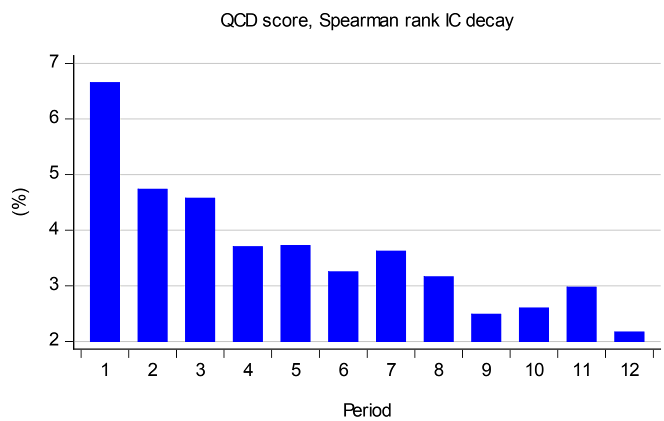
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 48: Sector-neutral rank IC



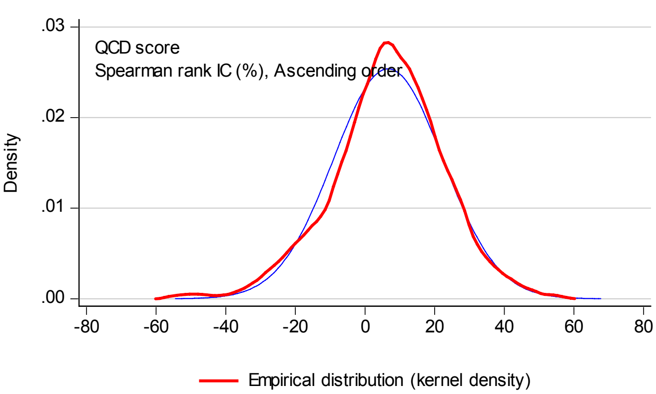
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 49: IC decay



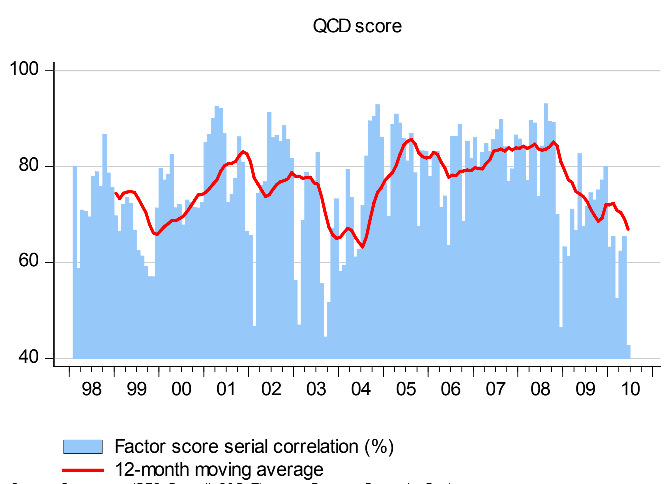
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 50: IC distribution



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 51: Factor score serial correlation



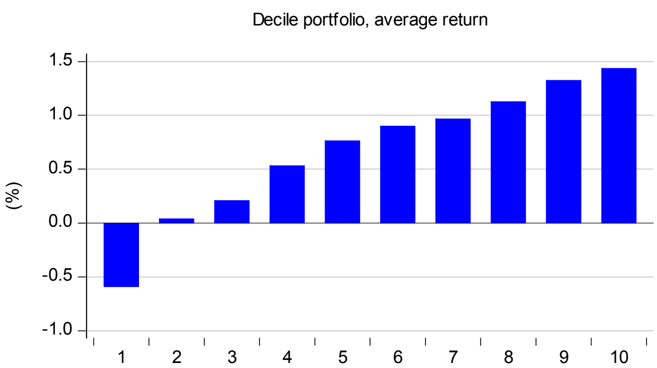
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Decile portfolio statistics

On a monthly basis, the best ranked stocks in decile 10 have outperformed the worst ranked stocks in decile one by approximately 2% (Figure 52), with lower volatility (Figure 53). The performance of the 10 decile portfolios is relatively monotonic based on Sharpe ratio, i.e., higher ranked stocks have been outperformed lower ranked stocks on a risk-adjusted basis (Figure 54).

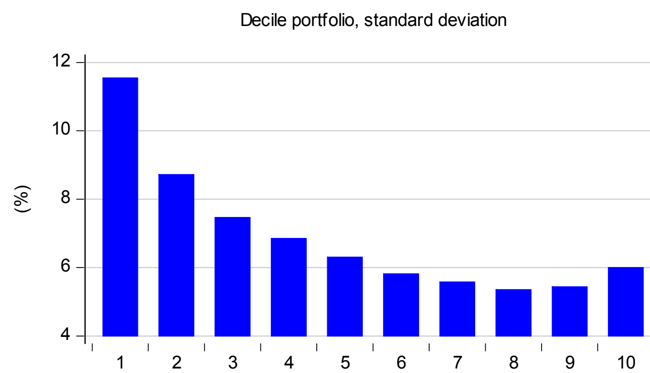
Outperforming stocks tend to have larger market cap, be more liquid, have lower beta, higher dividend yield, and higher share price (Figure 55 to Figure 59).

Figure 52: Decile portfolio, average monthly return



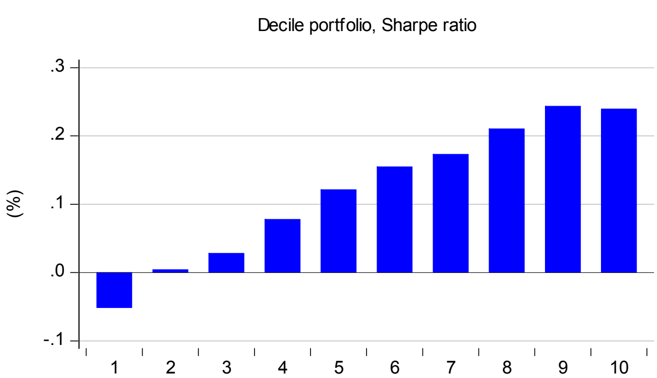
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 53: Decile portfolio, risk



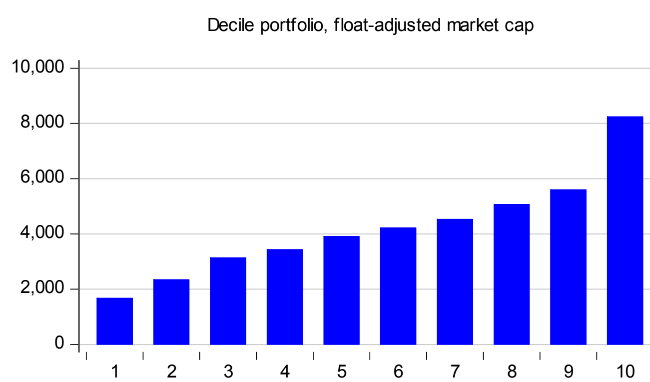
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 54: Decile portfolio, Sharpe ratio



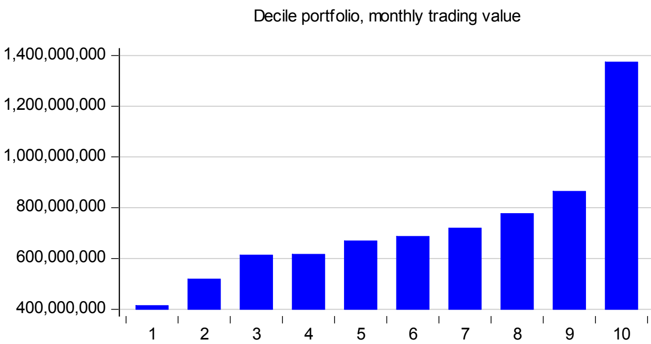
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 55: Decile portfolio, market cap



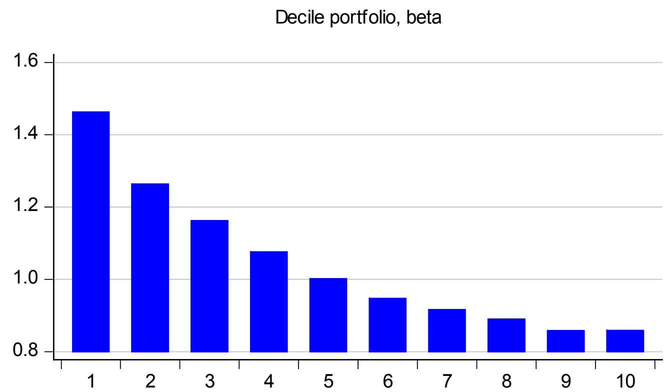
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 56: Decile portfolio, Liquidity



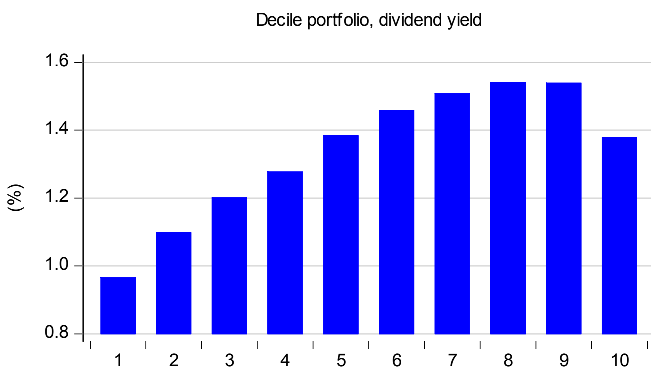
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 57: Decile portfolio, beta



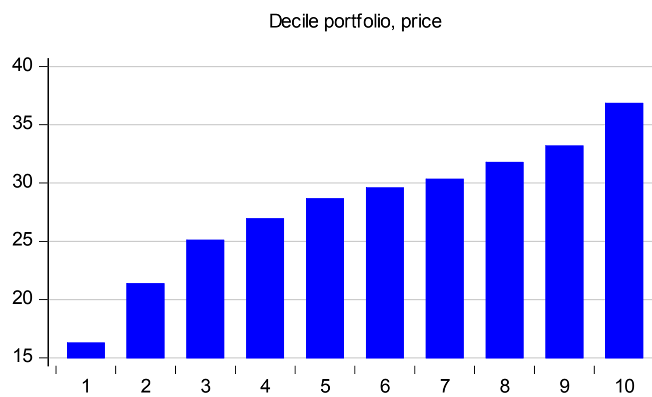
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 58: Decile portfolio, dividend yield



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 59: Decile portfolio, average share price

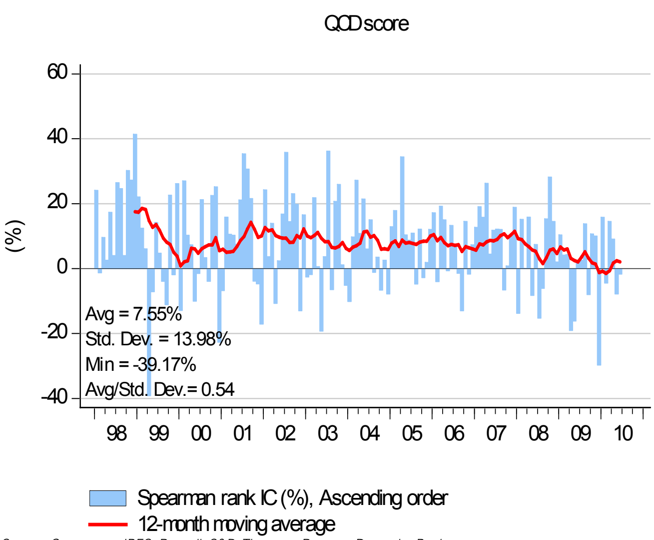


Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Selecting stocks within sectors

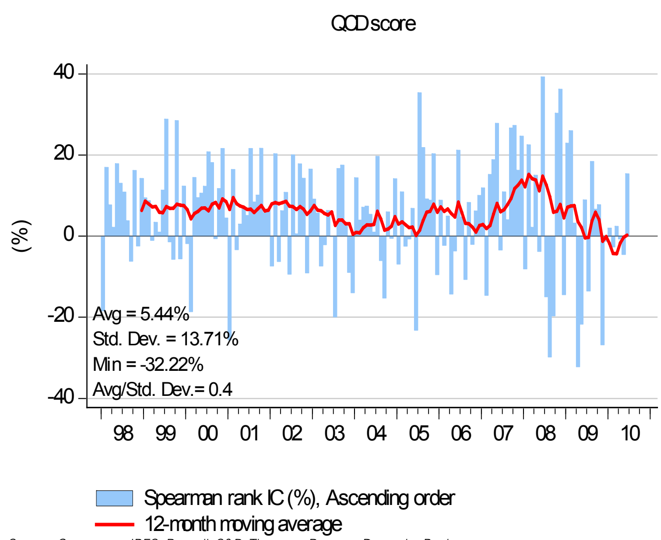
Our QCD model is most successful in ranking stocks within the energy, industrials, consumer discretionary, and info tech sectors. The recent performance in most sectors has been challenging, but has shown strong recovery in the industrials, health care, and financials sectors.

Figure 60: Rank IC, energy sector



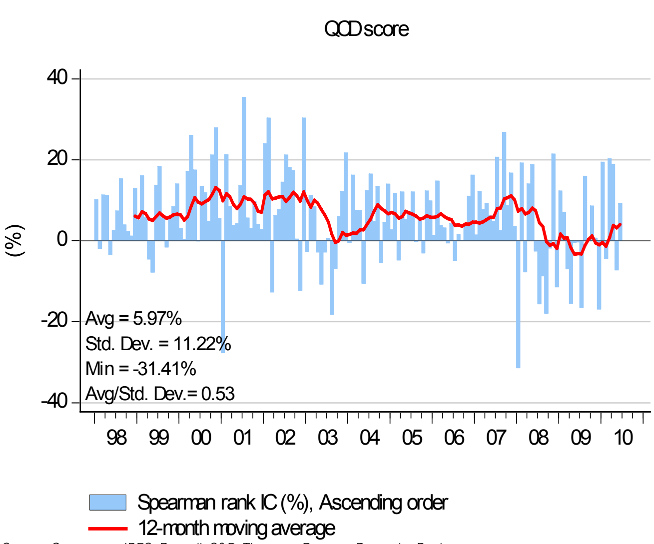
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 61: Rank IC, materials sector



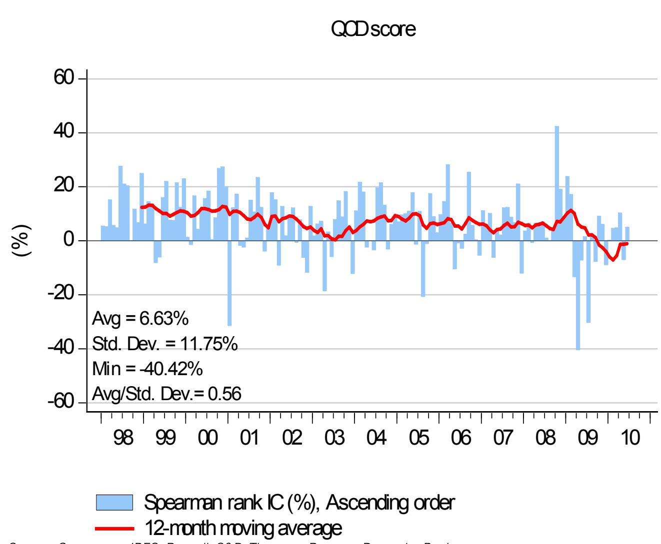
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 62: Ranked IC, industrials sector



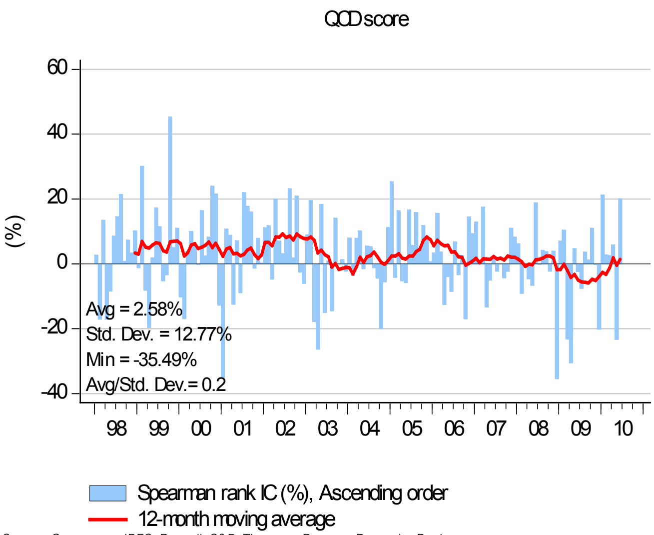
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 63: Rank IC, consumer discretionary sector



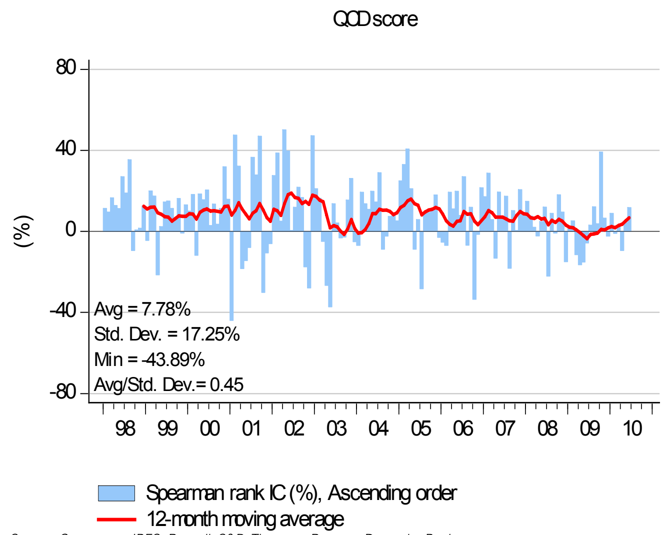
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 64: Ranked IC, consumer staples sector



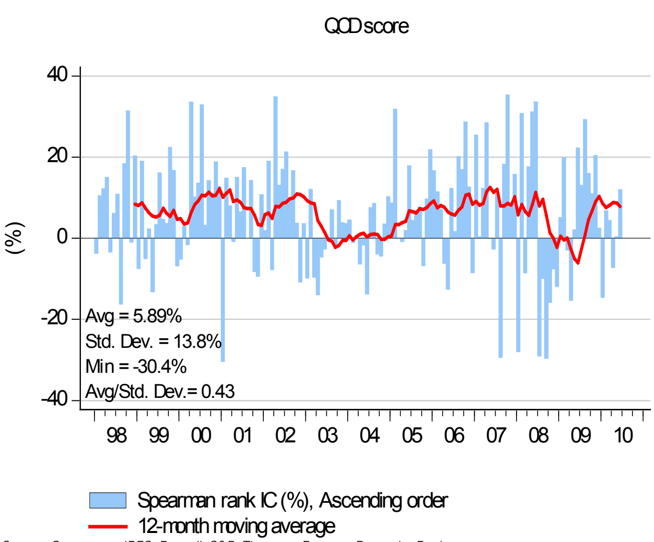
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 65: Rank IC, health care sector



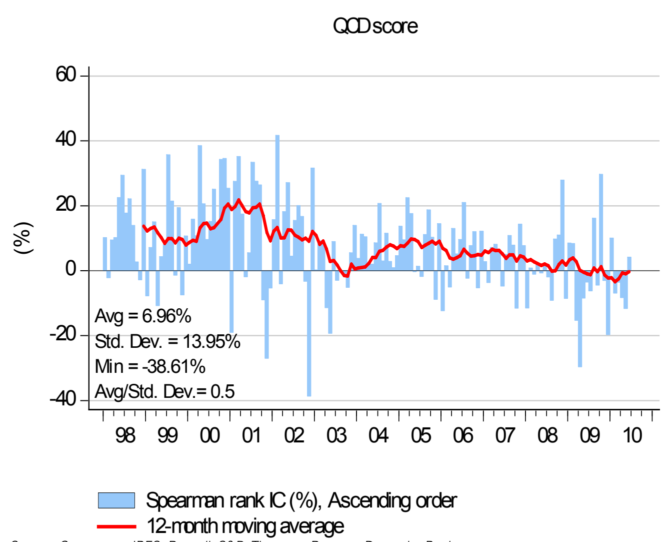
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 66: Ranked IC, financials sector



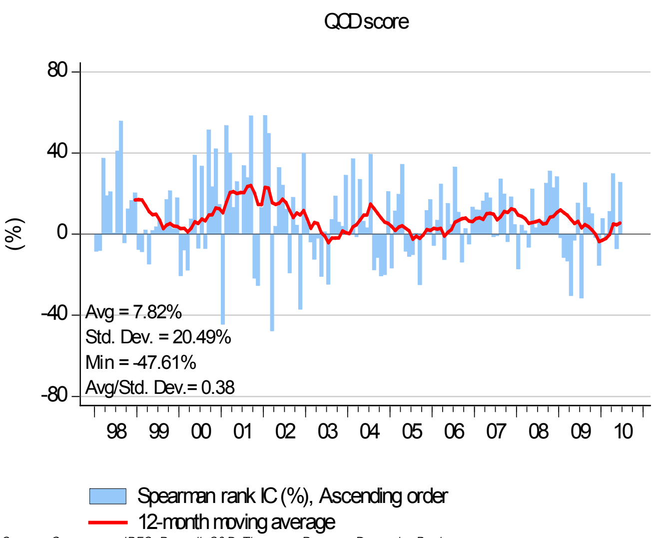
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 67: Rank IC, info tech sector



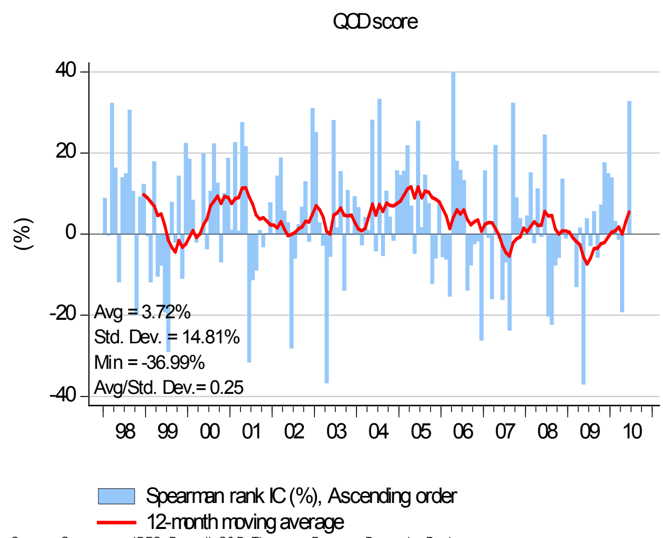
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 68: Ranked IC, telecom services sector



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 69: Rank IC, utilities sector

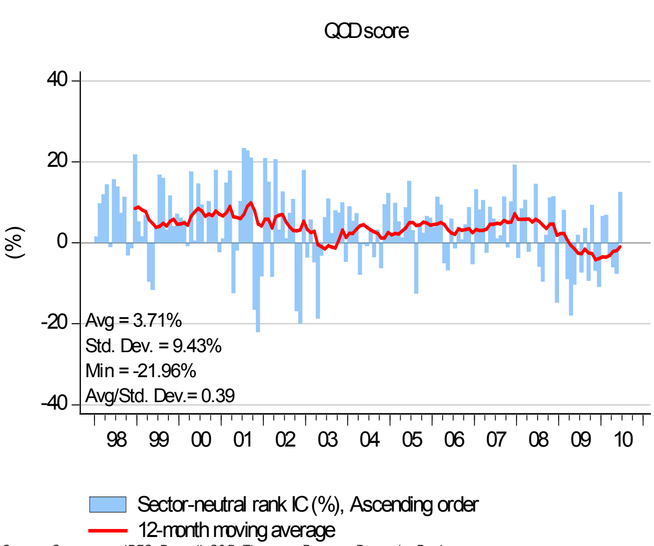


Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Selecting large, mid, and small-cap stocks

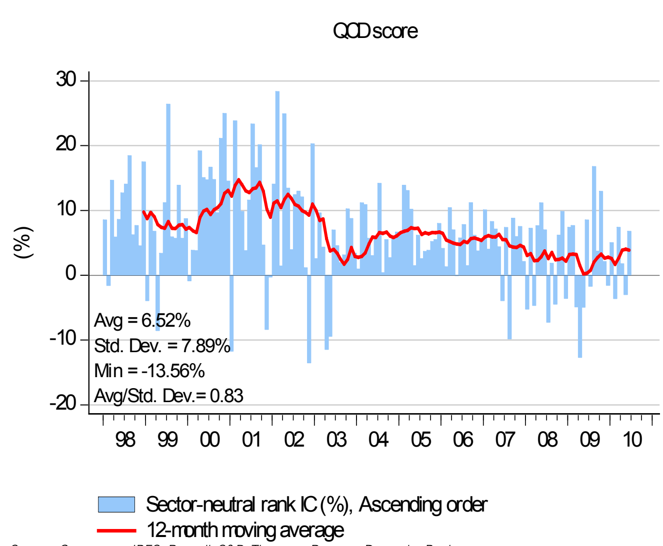
Similar to most other quant models, our QCD model also has much better stock-selection skill in the small cap universe (as measured by the Russell 2000) than in the large cap universe (as measure by the Russell 1000). The average IC is almost twice as high and the IR of the IC is more than twice as high. In recent years since 2009, the large cap model underperformed, while the small cap model still produced good performance.

Figure 70: Rank IC, Russell 1000



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 71: Rank IC, Russell 2000

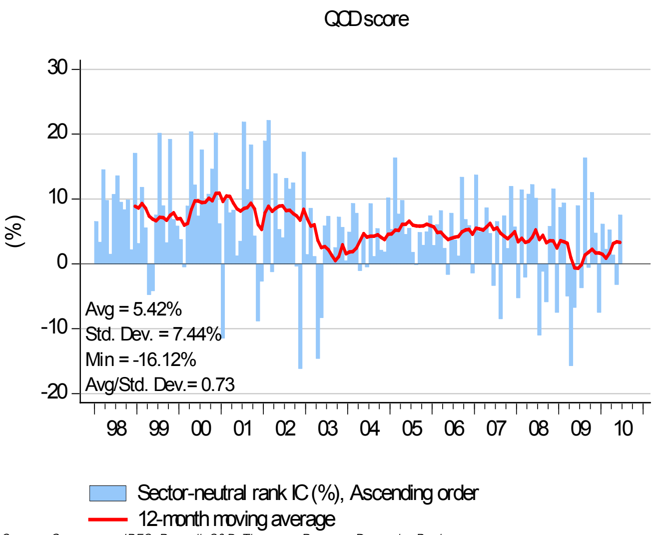


Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Selecting value vs. growth stocks

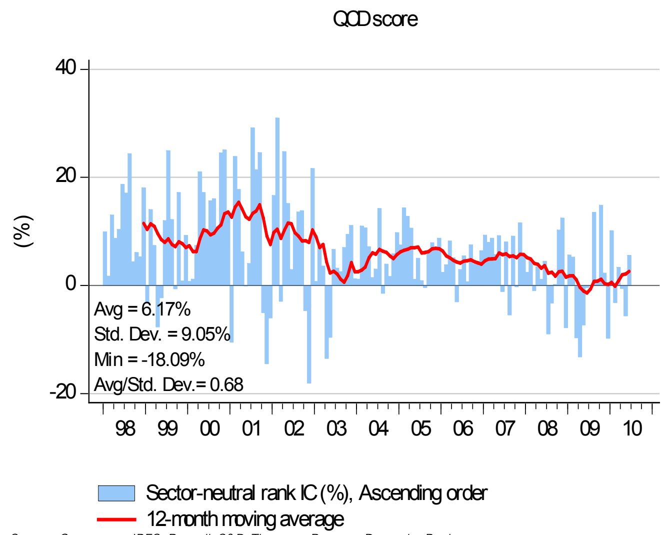
The QCD model works well for both value and growth universes. Prior to 2009, it appears that the QCD model was more effective in selecting growth stocks. Since 2009, the growth model seems to show faster decay than the value model. Both universes have seen some recovery in 2010.

Figure 72: Rank IC, Russell 3000 value



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 73: Rank IC, Russell 3000 growth

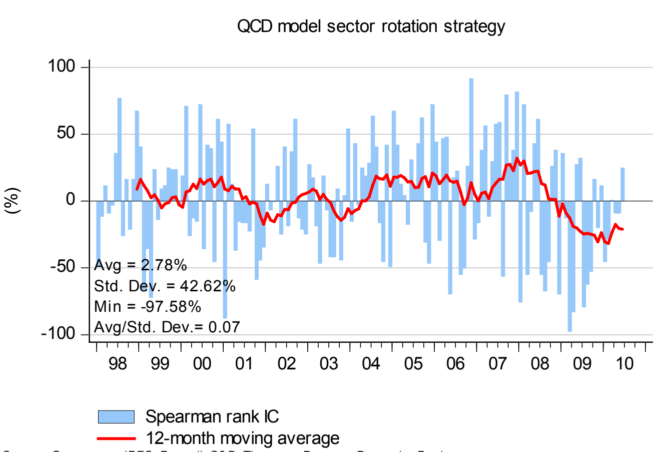


Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Stock selection vs. sector rotation

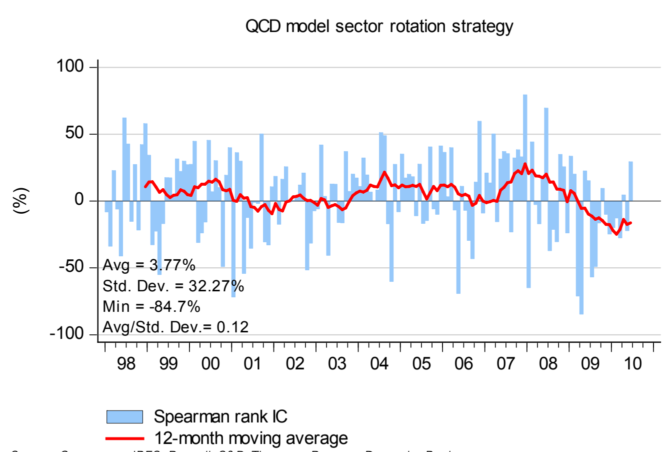
The QCD model is mainly designed as a stock-selection model. Nevertheless, we do find the model has certain sector and industry timing skills (Figure 74 and Figure 75). The sector rotation performance, however, is more cyclical than stock selection.

Figure 74: Rank IC, sector rotation



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 75: Rank IC, industry rotation

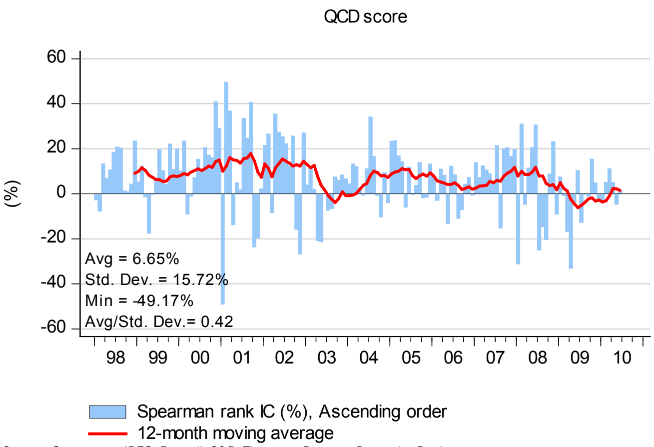


Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

QCD vs. change in QCD

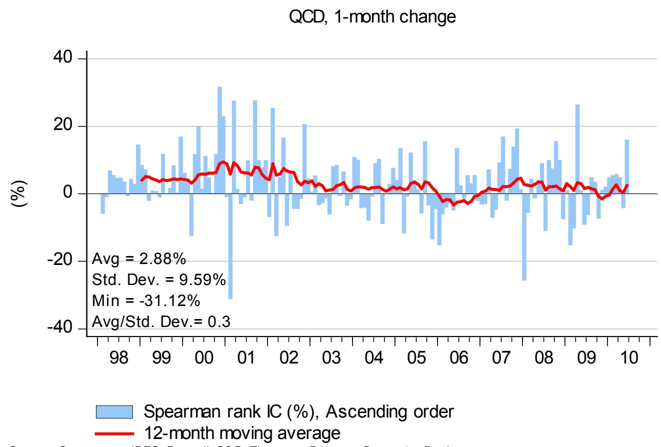
As shown in Figure 77 to Figure 79, the changes in QCD scores (monthly changes, quarterly changes, and annual changes) also have certain predictive power. However, the most effective usage of the model is still the absolute level of the model scores.

Figure 76: Rank IC, QCD



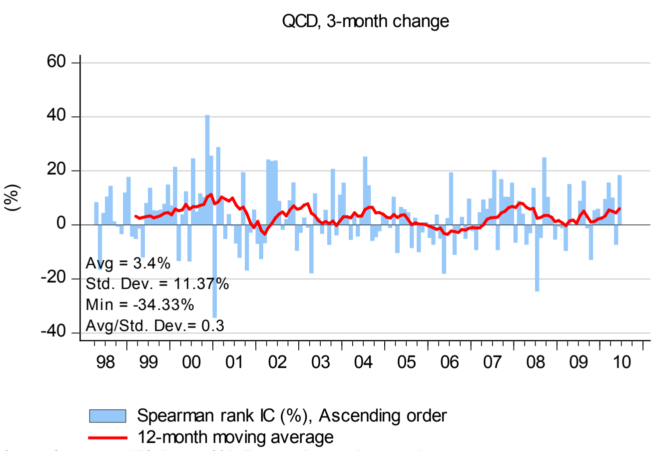
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 77: Rank IC, one-month change in QCD



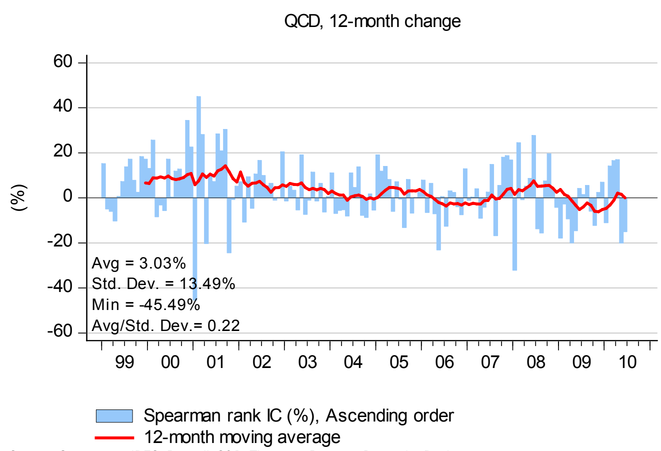
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 78: Rank IC, three-month change in QCD



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 79: Rank IC, one-month change in QCD



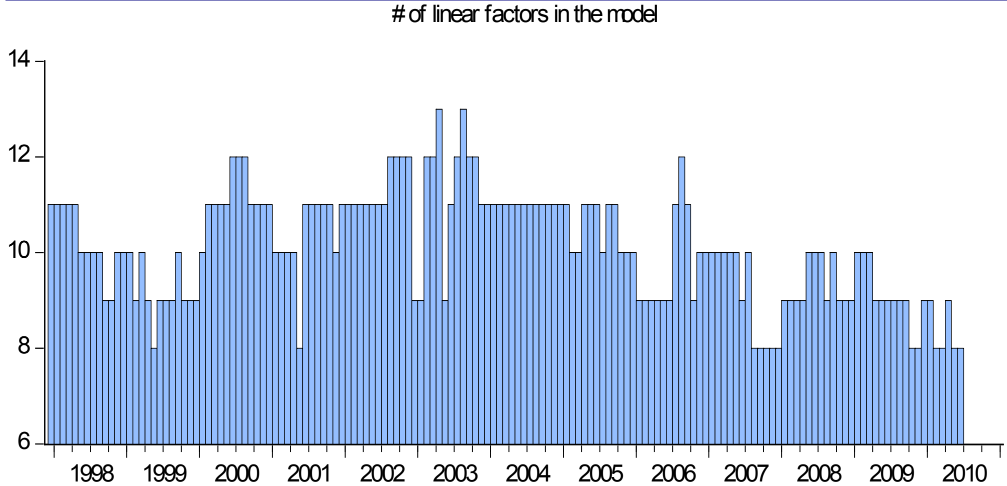
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Factor and factor weighting

On average, there are about 10 factors in the model at any given month (Figure 80). Figure 81 to Figure 86 show the QCD model weights in the six style categories: value, growth, momentum, sentiment, quality, and technical.

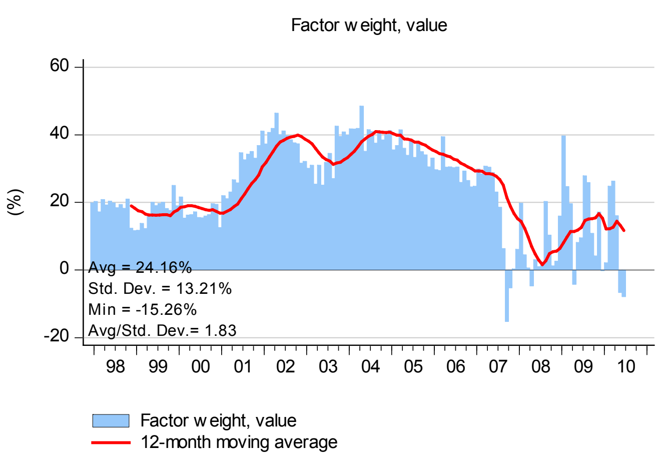
Over the entire backtesting period, the QCD model mostly overweights value (Figure 81) and quality (Figure 85) factors. The weights for growth, momentum/reversal, sentiment, and technical are about the same. In recent years, momentum/reversal (Figure 83) and quality (Figure 85) have seen some weight increases.

Figure 80: Number of factors in the QCD model



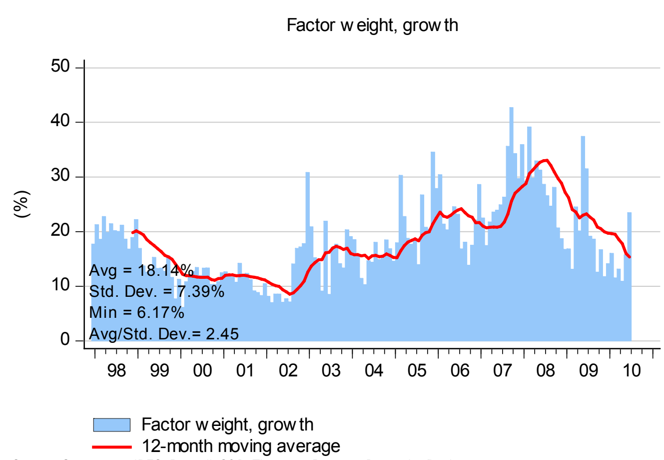
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 81: Factor weight, value



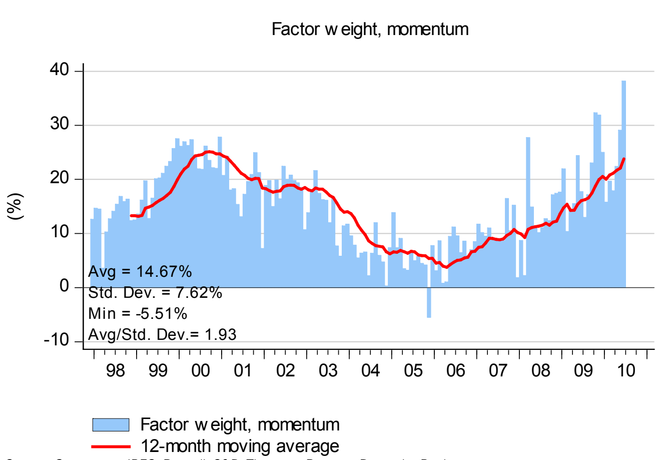
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 82: Factor weight, growth



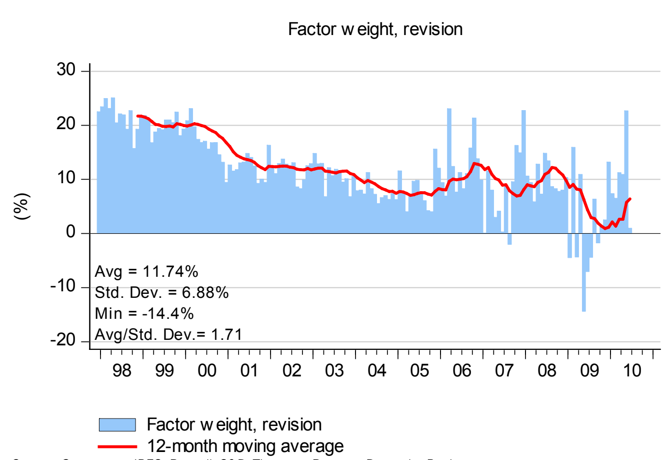
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 83: Factor weight, momentum/reversal



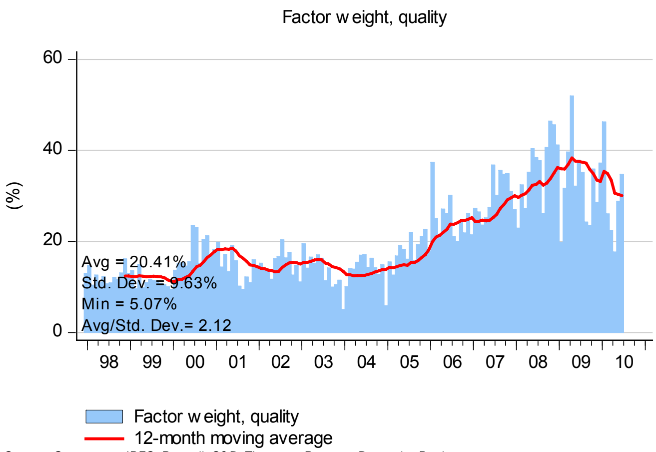
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 84: Factor weight, sentiment



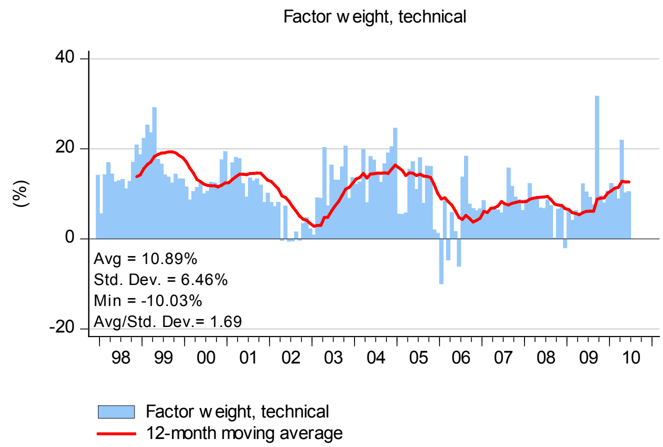
Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 85: Factor weight, quality



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 86: Factor weight, technical



Source: Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

7. Risk modeling

One of the most important inputs for portfolio construction is a risk estimate. In an optimized portfolio, stock weight is inversely related to estimated stock-specific risk. Generally speaking, the alpha model determines which stocks to invest in, while the risk model determines their weights.

Risk models are usually used for three purposes: 1) to predict future volatility before constructing a portfolio; 2) to understand the risk exposure and risk attribution of each asset, industry, and style; and 3) to evaluate the *ex post* portfolio performance.

Portfolio risk can not be estimated directly from historical returns. One problem is the curse of dimensionality. For a portfolio of N assets, we need to estimate $N \times (N+1)/2$ parameters, i.e., $N \times (N-1)/2$ of covariance parameters and N estimates of stock-specific risk. For the Russell 3000 universe, it means we have to estimate about 4.5 million parameters. There is also too much noise in risk forecast when estimated directly. More importantly, the risk also changes over time. In addition, it does not allow us to estimate risk for stocks without enough history.

In practice, some forms of factor-based risk models are used. There are three types of common risk models: macroeconomic factor based, fundamental factor based, and statistical factor based. In recent years, risk model vendors also developed a series of hybrid risk models by combining the three approaches. Some of the latest research focuses on extreme downside risk management and the misalignment of alpha and risk factors.

The basic structure of a risk model is almost identical to the alpha model described in the previous section:

$$r_{i,t+1} = \sum_{k=1}^{K} \beta_{k,t} F_{k,i,t} + \varepsilon_{i,t}$$

Where,

$r_{i,t+1}$ is the forward one-period ahead return for stock *i* in period *t+1*;

$F_{k,i,t}$ is the *k*th factor score for stock *i* in period *t*, e.g., where the *j*th factor is PE, then $F_{k,i,t}$ is the PE for stock *i* in period *t*);

$\beta_{k,t}$ is the estimated factor return for factor *k* in period *t*;

$\varepsilon_{i,t}$ is the regression residual, i.e., the random noise that can not be accounted for by the linear regression model;

i = 1 to N_t indicating the number of stocks in period *t*;

j = 1 to K indicating the number of factors in period *t*;

Given the equation above, the variance-covariance matrix of asset returns at time *t* is:

$$Cov_t = \Phi_t \Pi_t \Phi_t' + \Sigma_t$$

Where,

Φ_t is the $K \times K$ covariance matrix of the factor returns;

Π_t is the $N \times K$ factor exposure matrix; and

Σ_t is the $N \times N$ diagonal matrix of stock-specific risk (or idiosyncratic risk).

Therefore, the factor model essentially translates the $N \times (N+1)/2$ parameter problem into a $K \times (K+1)/2 + (N \times K) + N$ problem. For the Russell 3000 universe, instead of estimating 4.5 million parameters, for a 10-factor model, we only need 33,055 estimates.

Madhavan and Yang [2003] provide a good overview of risk models and how to use risk models from a practitioner's point of view.

Common risk models

Macroeconomic factor based

In a macroeconomic risk model framework, the factor returns series, $\beta_{k,t}$ are pre-defined, e.g., industrial production, yield spread, or credit spread. Analysts pre-specify a set of macroeconomic factors that they believe can explain the cross-sectional stock return and risk. A set of time series regressions are then performed for each stock (or as a system of equations) against the common macroeconomic factors to estimate the factor exposure matrices, Φ_t.

Fundamental factor based

In a fundamental factor based risk model, the factor exposure matrices, Φ_t are given. For example, if we want to use earnings yield and price momentum as two fundamental risk factors, we know the earnings yield and price momentum for all stocks in our universe t time *t*. The trick is to estimate the factor return time series. Typically, a series of cross-sectional regressions are performed to estimate the $\beta_{k,t}$ series, i.e., Fama-MacBeth procedure.

Statistical risk model

Unlike the macroeconomic or fundamental risk models, in a statistical risk model, the factor exposure matrices and factor return series are estimated simultaneously from the data using principal component analysis or factor analysis. Statistical risk models generally fit the in-sample data better, but it does not guarantee it would perform well in out-of-sample risk forecasts. Statistical risk models are also difficult to interpret, as the factors extracted do not typically have any intuitive meaning.

Hybrid risk model

Fundamental factor models are widely used in the asset management industry to forecast portfolio volatility. As we all know, fundamental risk factors can not possibly capture all sources of risk, especially in market stress times. One solution to this problem was suggested by Miller [2006] and Menchero and Mitra [2008], by applying statistical factor analysis to the cross-sectional residuals in order to extract the omitted factor. In the so-called hybrid factor model, both fundamental and statistical factors are used to predict risk.

Development plan

In our research, we mostly use Axioma and Barra's risk models. In the future, we also plan to build two versions of our own risk models to supplement the vendor risk models: a fundamental risk model and a fundamental risk model that aligns with our QCD model.

8. Transaction cost analysis

Despite the importance of transaction cost analysis ("TCA") in quantitative equity investment, it has received relatively less attention than the other areas like alpha and risk modeling. TCA research has mostly been done by market microstructure researchers in academia (whom seem to form a separate and distinct group from the asset pricing researchers) and algorithmic trading researchers in practice (whom seem to be different from the traditional equity quant).

One reason is that the key input data for TCA research, high frequency or tick-by-tick data are more expensive to acquire than traditional financial databases like Compustat or Worldscope. In addition, the size of high frequency databases tends to be much larger (e.g., multiples of terabytes) than traditional databases (e.g., approximately 50-100 GB). Traditional relational database like Microsoft SQL Server or Oracle can not handle this size of data in real time. Specialized database like KDB or Vhayu are typically used.

Another reason is that unlike return and volatility, transaction cost is a more abstract concept that can never be accurately measured. Broadly speaking, there are two components of transaction costs, the fixed component (like commissions and bid/ask spreads) and variable component (like market impact and opportunity cost). The fixed component is relatively easy to model, but it accounts for a smaller percentage of the total costs. The variable component is more difficult to model and has been the focus of TCA research. Market impact is typically modeled as a function of trade size, ADV (average daily volume), volatility, execution horizon. A good overview of the topic is Kissell and Glantz [2003].

In theory, transaction costs should be integrated in the portfolio construction stage. For example, if two stocks have similar expected alpha, but one is substantially cheaper to trade (maybe because it is a large cap and liquid stock) than the other, we may want to trade the cheaper stock rather than the more expensive one (of course, it also depends on other parameters). Without taking into account transaction costs in the optimization, the optimizer may simply suggest trading equal amounts for both stocks.

In practice, many portfolio managers still do it separately. Typically, a trade list is generated by optimizing alpha adjusted for risk but without transaction costs. The trade list is then passed along to the traders, who then put the list into some trading algorithms to analyze the cost and determine a trading strategy accordingly.

We plan to further collaborate with our program trading and electronic trading desks on TCA research in the future.

9. Portfolio construction

The seminal work of Markowitz [1952] introduced modern finance and made finance a scientific discipline. Mean-variance optimization quantifies the trade-offs between risk and return.

The opponents of mean-variance optimization criticize that it is overly sensitive to the inputs (estimated mean and variance), which often contain errors.

Equally weighted

Equally weight all stocks in the potential "buy" basket is probably the simplest and also the most traditional approach. Similar to equal weighting scheme on factors, this is actually rather robust. DeMiguel, Garlappi, and Uppal [2009] found that naïve equally weighted portfolios outperformed most sophisticated portfolio construction techniques under certain conditions. Recently, the DeMiguel et al paper, however, was under attack by Kirby and Ostdiek [2010].

The downsides of equal weighting approach are two fold. First, it tends to have a small-cap bias, as small-cap stocks are weighted the same as large-cap stocks. Second, risk can not be explicitly quantified. For managers with an explicit benchmark and a target tracking error, the equal weighting scheme is difficult to implement in practice.

In Luo, Cahan, Jussa, and Alvarez [2010], we found that equally weighted top-minus-bottom decile portfolios pair well with mean-variance optimization. Depending on different factors and styles, the equal weighting scheme can be beneficial.

Capitalization weighted

To partially mitigate the issues with the equal weighting scheme, in practice, some managers adopt the cap-weighted approach. Stocks in the potential "buy" basket are invested based on their respective market capitalization. Small-cap bias is somewhat alleviated. However, risk can still not be explicitly quantified.

Stratified sampling

One way to better control for risk while still easy to implement is stratified sampling. In this approach, sector (and potentially size and country) weights are matched to the benchmark. Within each sector (and potentially size and country bucket), stocks are equally weighted. Stratified sampling approach still suffers the problem that risk is not explicated modeled.

Mean-variance optimization

Despite of all the critiques against mean-variance optimization, the most common approach used by quantitative portfolio managers to construct portfolios is still some variation of mean-variance optimization.

Bayesian approach

The Bayesian approach to deal with estimate errors ranges from pure statistical approach relying on diffuse-priors (Barry [1974] and Bawa, Brown, and Klein [1979]), to "shrinkage estimates" (Jobson and Korkie [1980] and Jorion [1985, 1986]), to the more recent approaches that rely on an asset pricing model for establishing a prior (Black and Litterman [1992], Pastor [2000] and Pastor and Stambaugh [2000]).

Robust optimization

One of the most common critiques of mean-variance optimization is error maximization, i.e., estimation errors in returns and risk can be magnified by optimizers. Robust optimization, in theory, takes estimation errors into account. Fabozzi, Kolm, Pachamanova, and Focardi [2007] provides a good overview of various robust optimization techniques.

Our approach

We prefer to keep the optimizer simple and push most of the issues to the factor construction stage. For example, in our research, we found it is very difficult to deal with factor decay and turnover in the portfolio construction stage, despite some promising theoretical research (e.g., Qian, Sorensen, and Hua [2007] and Sneddon [2008]).

Another example is how to account for extreme downside risk. Risk vendors like Barra and Axioma proposed various models to deal with extreme risks at the asset level with their risk models. In our opinion, it is very difficult to fit a non-normal return distribution at the asset level. We found, however, it is much easier and more promising to deal with extreme risk at the factor level.

10. Model portfolios

On a monthly basis, we build five standard model portfolios: 1) a long-only large-cap core portfolio benchmarked to the Russell 1000 index; 2) a long-only large-cap value portfolio benchmarked to the Russell 1000 Value index; 3) a long-only large-cap growth portfolio benchmarked to the Russell 1000 Growth index; 4) a long-only small-cap portfolio benchmarked to the Russell 2000 index; and 5) a long/short market neutral portfolio. We use Axioma's mid-term risk models and Axioma's optimizer to construct our model portfolios. We also keep track of a series of other portfolios for clients, e.g., large-cap value portfolio, large-cap growth portfolio, 130/30 portfolios. Please contact us for details.

The IR/Sharpe ratio for the five model portfolios ranges from 1.5 to 3.1 and stays positive almost every year since 1998. Even in 2008 and 2009, two of the most challenging years for quantitative investing, our market-neutral strategy produces Sharpe ratio of 0.85 and 1.24, respectively.

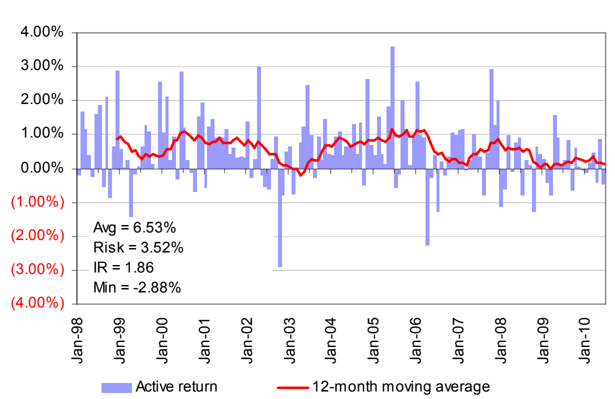
Long-only large-cap core portfolio

For the long-only large-cap core portfolio, we try to maximize expected return with the following constraints. Figure 87 to Figure 90 show the portfolio performance vs. the benchmark.

In the past 12 years, our large-cap portfolio outperforms the benchmark by 6.5% per year, with an active risk of about 3.5% per year, generating an annual IR of 1.86 after transaction costs. The realized active risk is higher than target tracking error, but stays in the range of 3% of 4%. The annual IR is positive for all years.

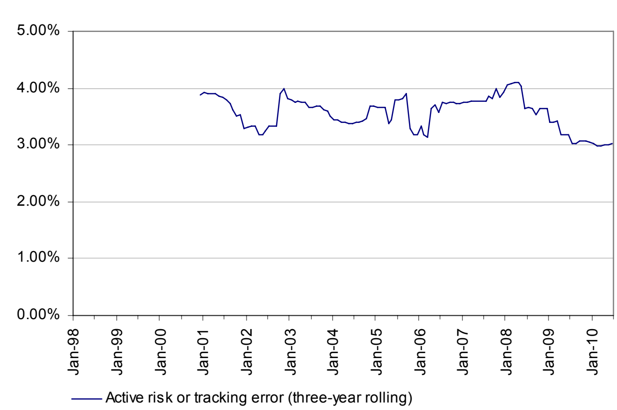
- Long only – no short sales are allowed
- No leverage
- Target annualized tracking error of 2.5% (relative to the Russell 1000 index)
- Beta neutral
- Sector neutral
- Turnover constrained at 20% one-way per month (or 240% one-way per year)

Figure 87: Active return



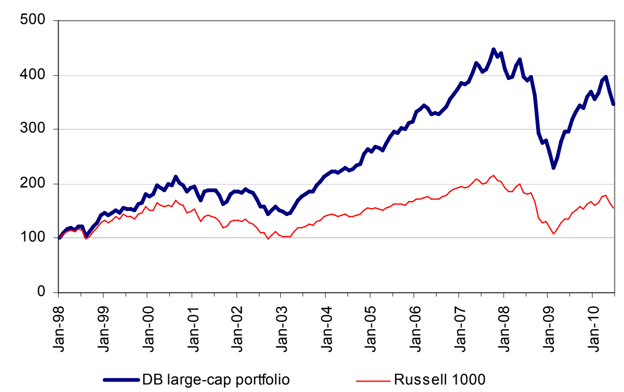
Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 88: Active risk



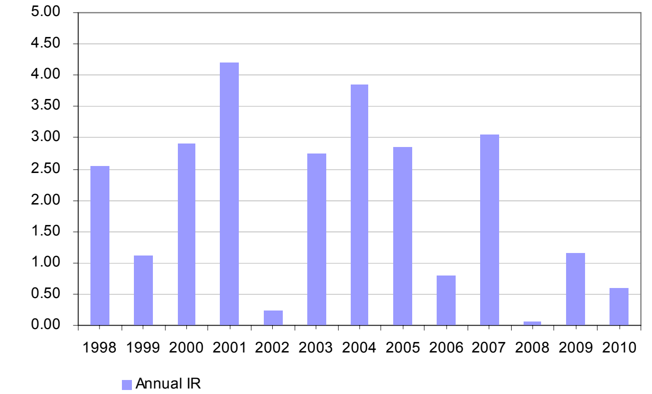
Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 89: Cumulative performance



Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 90: Annual IR



Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

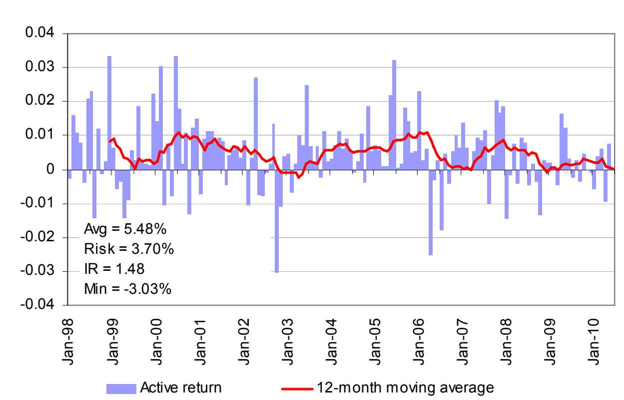
Long-only large-cap value portfolio

For the long-only large-cap value portfolio, we try to maximize expected return with the following constraints. Figure 91 to Figure 94 show the portfolio performance vs. the benchmark.

In the past 12 years, our large-cap portfolio outperforms the benchmark by 5.5% per year, with an active risk of about 3.7% per year, generating an annual IR of 1.48 after transaction costs. The realized active risk is higher than target tracking error, but stays in the range of 3% of 4% most of the time. The annual IR is positive for 11 of the 13 years.

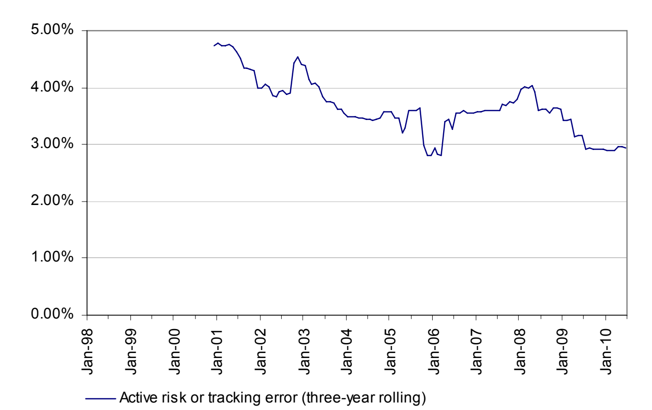
- Long only – no short sales are allowed
- No leverage
- Target annualized tracking error of 2.5% (relative to the Russell 1000 Value index)
- Beta neutral
- Sector neutral
- Turnover constrained at 20% one-way per month (or 240% one-way per year)

Figure 91: Active return



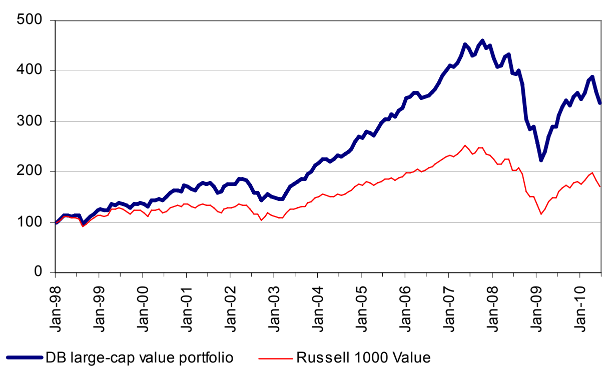
Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 92: Active risk



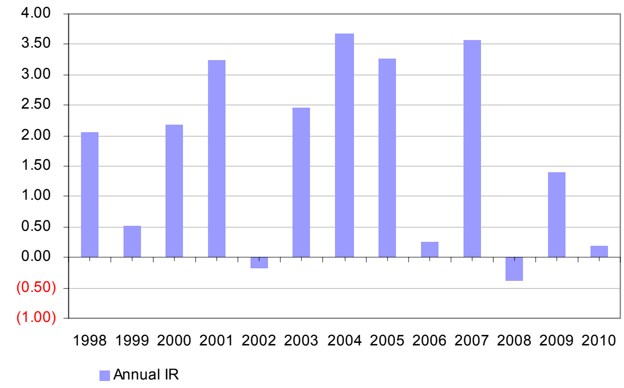
Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 93: Cumulative performance



Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 94: Annual IR



Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

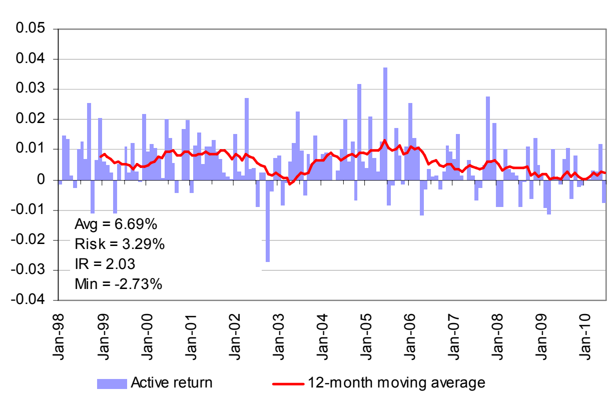
Long-only large-cap growth portfolio

For the long-only large-cap growth portfolio, we try to maximize expected return with the following constraints. Figure 95 to Figure 98 show the portfolio performance vs. the benchmark.

In the past 12 years, our large-cap portfolio outperforms the benchmark by 6.7% per year, with an active risk of about 3.3% per year, generating an annual IR of 2.03 after transaction costs. The realized active risk is higher than target tracking error, but stays in the range of 3% of 4%. The annual IR is positive for all years.

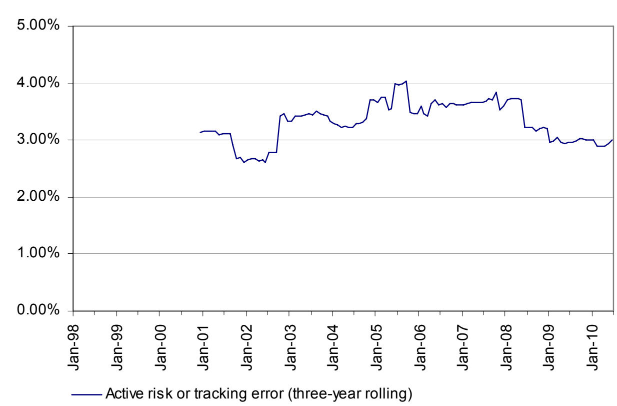
- Long only – no short sales are allowed
- No leverage
- Target annualized tracking error of 2.5% (relative to the Russell 1000 Growth index)
- Beta neutral
- Sector neutral
- Turnover constrained at 20% one-way per month (or 240% one-way per year)

Figure 95: Active return



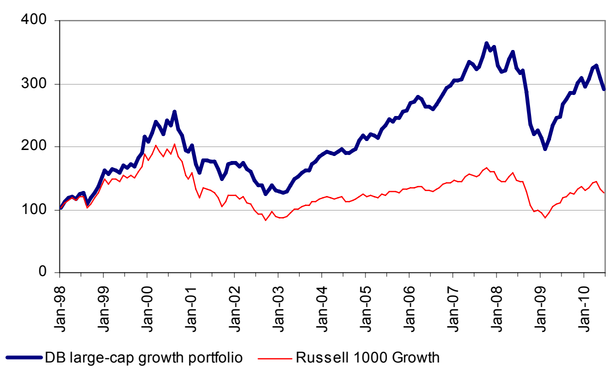
Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 96: Active risk



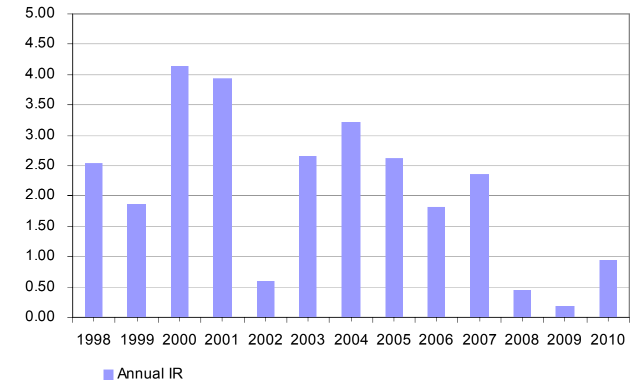
Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 97: Cumulative performance



Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 98: Annual IR



Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

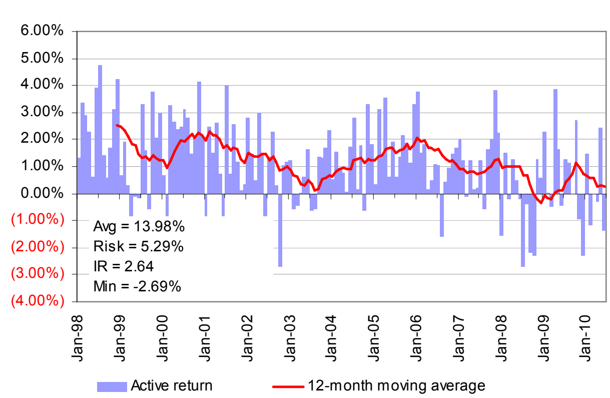
Long-only small-cap portfolio

For the small-cap long-only portfolio, we try to maximize expected return with the following constraints. Figure 99 to Figure 102 show the portfolio performance vs. the benchmark.

In the past 12 years, our large-cap portfolio outperforms the benchmark by 14.0% per year, with an active risk of about 5.3% per year, generating an annual IR of 2.64 after transaction costs. The realized active risk is higher than target tracking error, but stays in the range of 4% of 6%. The annual IR is positive for all years.

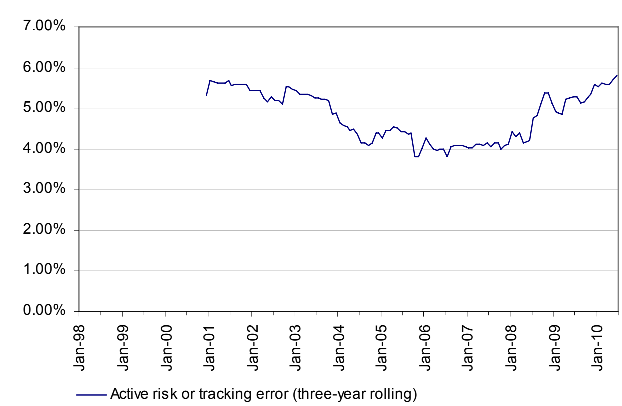
- Long only – no short sales are allowed
- No leverage
- Target annualized tracking error of 3% (relative to Russell 2000 index)
- Beta neutral
- Sector neutral
- Turnover constrained at 30% one-way per month (or 360% one-way per year)

Figure 99: Active return



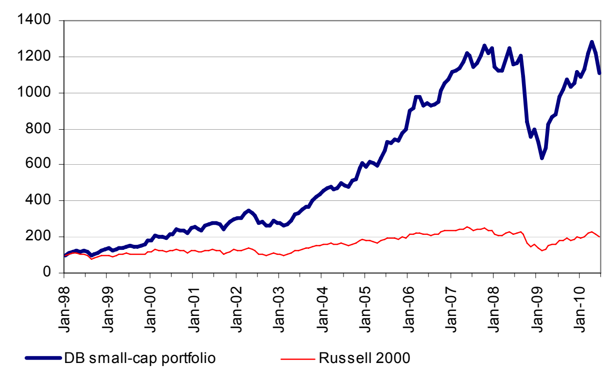
Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 100: Active risk



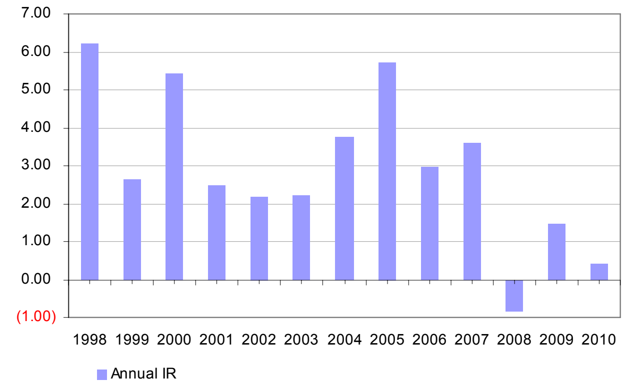
Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 101: Cumulative performance



Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 102: Annual IR



Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

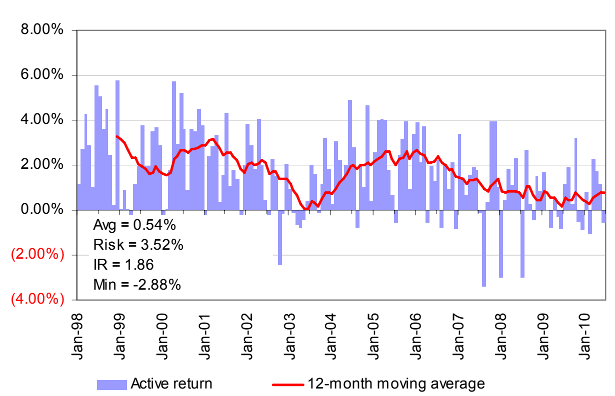
Long/short market-neutral portfolio

For the long/short market neutral portfolio, we try to maximize expected return with the following constraints. Figure 103 to Figure 106 show the portfolio performance vs. the benchmark.

In the past 12 years, our large-cap portfolio outperforms the benchmark by 19.5% per year, with an active risk of about 6.4% per year, generating an annual Sharpe ratio of 3.07 after transaction costs. The realized active risk is higher than target tracking error, but stays around 6%. The annual Sharpe ratio is positive for all years.

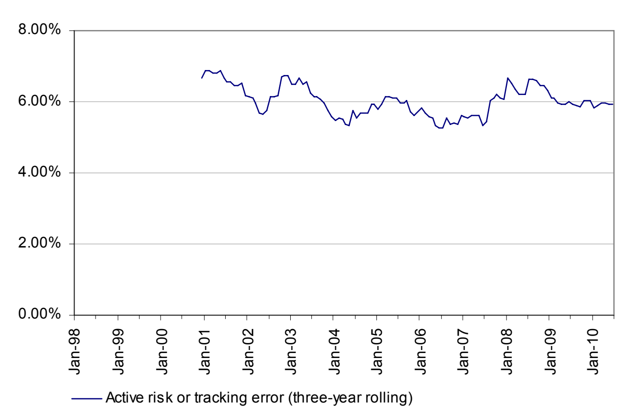
- Long/short market neutral strategy
- 2x leverage, i.e., for $1 capital, the strategy invests in $1 long and $1 short
- Target annualized volatility of 4%
- Beta neutral
- Sector neutral
- Turnover constrained at 30% one-way per month (or 360% one-way per year)

Figure 103: Active return



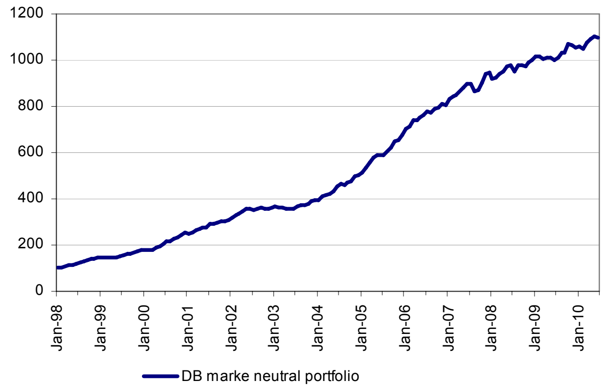
Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 104: Active risk



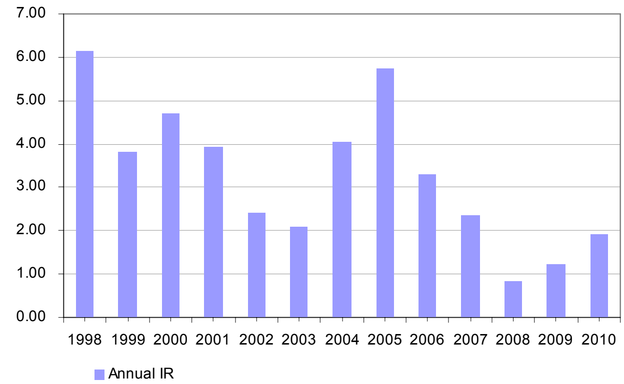
Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 105: Cumulative performance



Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 106: Annual Sharpe ratio



Source: Axioma, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

How can clients use our research

This paper summarizes the key elements of quantitative investing and our approaches. For more detailed background information, there are a number of books that provide a more elementary introduction to quantitative equity investing. The book, *Active Portfolio Management, A Quantitative Approach for Producing Superior Returns and Controlling Risk*, by Grinold and Kahn [1999] is probably the first book on this topic and remains the standard reference. Grinold and Kahn's book focuses on the more traditional linear multi-factor model approach, which has been widely adopted in the commercial risk models like BARRA, Northfield, and Axioma. The second book we would recommend is *Quantitative Equity Portfolio Management: An Active Approach to Portfolio Construction and Management* by Chincarini and Kim [2006], where the authors took a more econometric and empirical approach. The latest addition in this series is *Quantitative Equity Portfolio Management: Modern Techniques and Applications* by Qian, Hua, and Sorensen [2007], which remains our favorite.

The field of quantitative investing evolves quickly. Analysts need to stay abreast of the latest research. The above mentioned books provide a good starting point. In order to stay ahead of the curve, analysts need to keep up with the latest research in econometrics, statistics, accounting, finance, programming, and operation research. That is where we would hope our research would be able to help.

For quantitative investors, there are a few ways to use our research. First, they can read our research and see if there are any interesting ideas to be used in their own investment process. Second, we work closely with clients on customized research projects. Resources are scare; therefore, we hope we can save clients valuable time and investment on some preliminary research. Third, we provide regular data feeds on the factors we constructed and data items we collected. Last, some clients may find our stock-selection model, the QCD model, provides orthogonal information from their own models. Therefore, QCD model can be a stand-alone alpha signal.

For fundamental investors, there are also a few ways to use our research. First, understanding the driving forces behind quantitative investing is useful in its own right. Second, we can help clients build customized stock screens. This can be particularly useful to global asset managers, small and mid cap managers, or any managers interested in shrinking their investable universe before doing in-depth company specific research. Third, we have a series of industry-specific models, using industry-specific data and factors. Our quant models can help clients identify key investing trend in those industries of interest. Last, we provide a series of pre-built tools that clients can use to analyze the market, sectors, industries, and stocks.

Please contact us on customized research and data feed services.

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Appendix 1

Important Disclosures

Additional information available upon request

For disclosures pertaining to recommendations or estimates made on a security mentioned in this report, please see the most recently published company report or visit our global disclosure look-up page on our website at http://gm.db.com/ger/disclosure/DisclosureDirectory.eqsr**.**

Analyst Certification

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Deutsche Bank Securities Inc.

North American location

Deutsche Bank Securities Inc.
60 Wall Street
New York, NY 10005
Tel: (212) 250 2500

Deutsche Bank Securities Inc.
225 Franklin Street
25th Floor
Boston, MA 02110
Tel: (617) 988 6100

Deutsche Bank Securities Inc.
222 South Riverside Plaza
30th Floor
Chicago, IL 60606
Tel: (312) 537-3758

Deutsche Bank Securities Inc.
3033 East First Avenue
Suite 303, Third Floor
Denver, CO 80206
Tel: (303) 394 6800

Deutsche Bank Securities Inc.
1735 Market Street
24th Floor
Philadelphia, PA 19103
Tel: (215) 854 1546

Deutsche Bank Securities Inc.
101 California Street
46th Floor
San Francisco, CA 94111
Tel: (415) 617 2800

Deutsche Bank Securities Inc.
700 Louisiana Street
Houston, TX 77002
Tel: (832) 239-4600

International Locations

Deutsche Bank Securities Inc.
60 Wall Street
New York, NY 10005
United States of America
Tel: (1) 212 250 2500

Deutsche Bank AG London
1 Great Winchester Street
London EC2N 2EQ
United Kingdom
Tel: (44) 20 7545 8000

Deutsche Bank AG
Große Gallusstraße 10-14
60272 Frankfurt am Main
Germany
Tel: (49) 69 910 00

Deutsche Bank AG
Deutsche Bank Place
Level 16
Corner of Hunter & Phillip Streets
Sydney, NSW 2000
Australia
Tel: (61) 2 8258 1234

Deutsche Bank AG
Level 55
Cheung Kong Center
2 Queen's Road Central
Hong Kong
Tel: (852) 2203 8888

Deutsche Securities Inc.
2-11-1 Nagatacho
Sanno Park Tower
Chiyoda-ku, Tokyo 100-6171
Japan
Tel: (81) 3 5156 6701