Quantitative Strategy

Global Markets Research

Deutsche Bank

19 September 2011

GTAA/Signal Processing

Quant Tactical Asset Allocation (QTAA)

Research summary
We develop a quantitative tactical asset allocation (QTAA) model by timing six asset classes: equity, fixed income, high yield bond, commodities, crude oil, and gold – using macroeconomic, capital market, seasonal, fundamental, and VRP factors.

Theme of the month – variance risk premium (VRP)

Global tactical asset allocation series
We plan to offer more global macro/GTAA-type research going forward, in addition to the bottom-up stock selection models we have traditionally been focusing on in the past.

Variance risk premium as a market timing factor
We find a new and unconventional factor, variance risk premium (VRP) has strong predictive power for future equity market returns in the US, Europe, France, Germany, and Canada. We also find VRP can predict future returns of fixed income, high yield bond, commodities, crude oil, and gold.

Macroeconomic, capital market, seasonal, and fundamental factors
We also test 40 economic, 12 capital market, six seasonal, and 80 aggregated fundamental variables in the context of predicting the returns of six asset classes (equity, fixed income, high yield bond, commodities, crude oil, and gold).

Quantitative tactical asset allocation (QTAA) model
In the end, we develop an integrated TAA model by dynamically weighting the six asset classes, using a realistic return predicting model, risk model, and optimizer. The optimized, monthly-rebalanced TAA strategy has generated a Sharpe ratio of 0.78, outperforming the benchmark model portfolio by 447%.

Source: gettyimages.com

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A letter to our readers

Global tactical asset allocation series

Traditionally, quantitative investing almost automatically means quantitative equity investing[1]. Over the years, equity quant investors have developed sophisticated models and tools, and are commanding a large percentage of institutional assets. Asset allocation, on the other hand, has traditionally followed discretionary/judgmental approaches. A search of "tactical asset allocation" on Amazon.com gives us only 494 hits with the only serious quantitative TAA book by Lee [2000][2].

We intend to provide more top-down global tactical asset allocation (GTAA) research in our *Signal Processing* and *Portfolios Under Construction* series. In the *Signal Processing* series, we will study both bottom-up stock selection factors, and factors that are useful in market timing or predicting returns for different asset classes. In the *Portfolios Under Construction* series, we will investigate risk and portfolio construction issues relevant to both portfolios of individual stocks and portfolios of asset classes.

The unique features of this research include:

- We test a new and unconventional signal for market timing – variance risk premium (VRP). VRP measures a purer form of risk premium, which has been rewarded over time.
- We include more asset classes than the typical TAA studies: namely equity, fixed income, high yield bonds, commodities, crude oil, gold, and cash. We also investigate the market timing ability of VRP in Europe, Germany, France, and Canada.
- We have done a comprehensive backtesting of 40 macroeconomic variables, 12 capital market factors, six seasonal indicators, and 80 aggregated fundamental signals in predicting returns of asset classes. This is substantially more than the number of variables studied in most published academic papers.
- We have tested a wide range of model building techniques.
- Our QTAA strategy uses realistic risk models and mean-variance optimization, while most academic research relies on naïve portfolio construction techniques (e.g., simply overweighting/underweighting assets by an arbitrary percentage point).

The fully optimized QTAA portfolio has generated a Sharpe ratio of 0.78, compared to the benchmark of 0.17 (or about 4.5x times higher), with lower drawdown and tail risk.

Yin, Rocky, Miguel, Javed, and John

Deutsche Bank Quantitative Equity Strategy Team

[1] There are significant regional differences. For example, in the US, quants are more likely to be in bottom-up stock selection, while in Europe, there is a decent community of top-down asset allocation quants. This has also changed in recent years, as we see more and more interest in GTAA-type of research. See Cahan, R., Luo, Y., Alvarez, M., Jussa, J., and Chen, Z. [2011]. "Emerging Issues: What's Hot in the World of Quant?", Deutsche Bank Quantitative Strategy, April 12, 2011, for more detailed discussion.

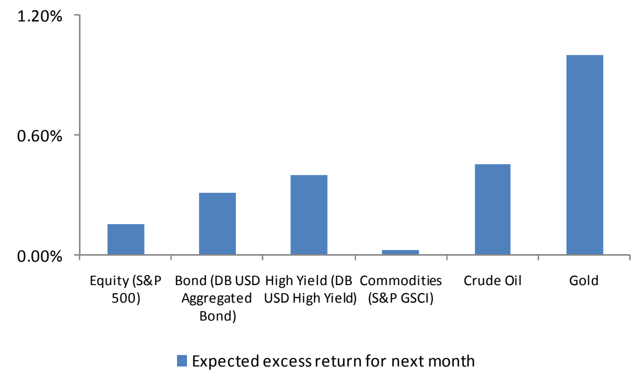
[2] The same search on SSRN gives us even less hits at 74. The amount of academic research in tactical asset allocation is somewhat limited. There is more research on market timing or predicting the equity risk premium. Our European quant team recently published a comprehensive survey of the equity risk premium – see Mesomeris, S., Salvini, M., and Avettand-Fenoel, J.R. [2011]. "Quantitative Musing: Road Map to the Equity Risk Premium", Deutsche Bank Quantitative Strategy, August 15, 2011.

Current recommendations

We recommend overweighting gold and underweighting equities

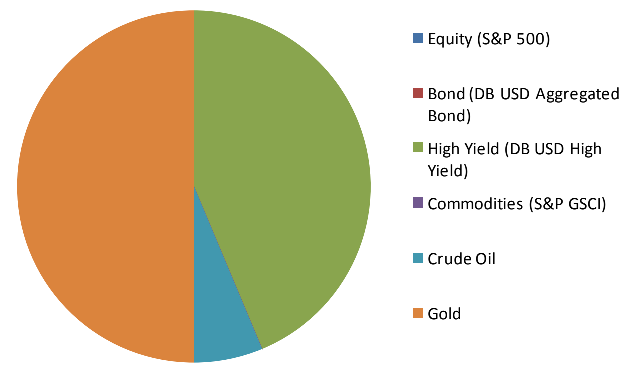
Currently, our QTAA model expects gold to outperform, while commodities and equity to underperform in September 2011 (see Figure 1). We recommend a portfolio with about 50.0% weight of gold, 43.7% of high yield bond, and 6.3% of crude oil (see Figure 2). Our benchmark holds mostly equity (48.3%), bond (26.9%), and crude oil (19.0%) – see Figure 3. Therefore, as shown in Figure 4, compared to our benchmark, we hold a large active position in gold (50%) and significant negative position in equity (-48.3%) and fixed income (-26.9%).

Figure 1: Ranking of expected returns for September 2011 for the six asset classes



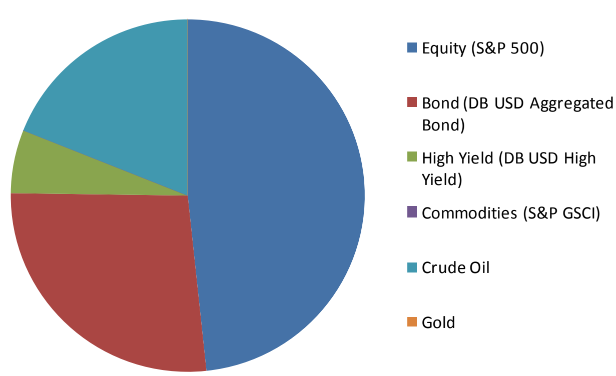
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 2: Recommended weight for September 2011 for the six asset classes



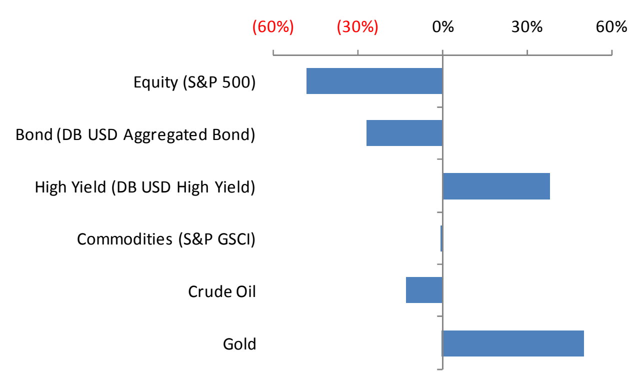
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 3: Benchmark weight



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 4: Active weight/position



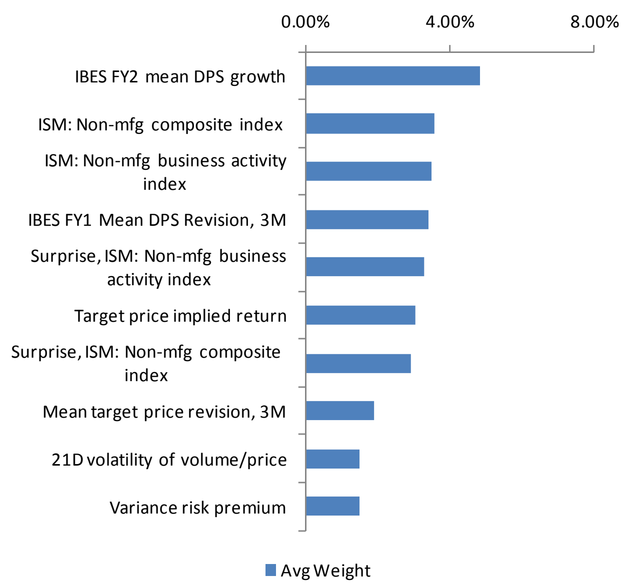
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

What's driving our recommendations?

As shown in Figure 5, in the long term, the most important determining factors behind our QTAA model are a blend of macroeconomic (ISM and ISM surprise), aggregated market fundamental (dividend growth, dividend revisions), and variance risk premium. Our current recommendation for next month is most driven by ISM surprise, S&P 500 earnings growth, and the long-term interest rate (see Figure 6).

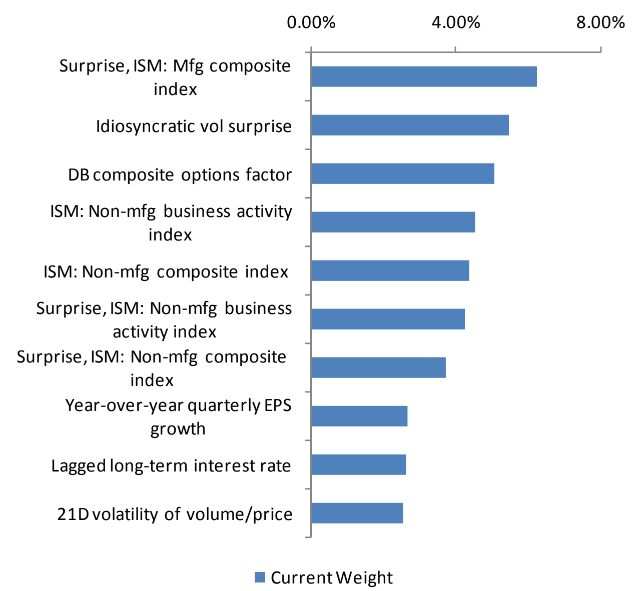
The direction of predictive variables on different asset classes can be different. Figure 7 shows the direction the top 10 factors in the long term and Figure 8 illustrates the direction of the top 10 variables for the current prediction.

Figure 5: Top 10 factors in the long term



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 6: Top 10 factors – current recommendation



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 7: The direction for the top 10 factors in the long term

	Avg Weight	Equity	Fixed Income	High Yield	Commodities	Crude Oil	Gold
IBES FY2 mean DPS growth	4.84%	Positive	Negative	Negative	Positive	Positive	Positive
ISM: Non-mfg composite index	3.56%	Negative	Negative	Negative	Positive	Positive	Positive
ISM: Non-mfg business activity index	3.51%	Positive	Positive	Negative	Positive	Positive	Positive
IBES FY1 Mean DPS Revision, 3M	3.42%	Negative	Negative	Negative	Negative	Negative	Negative
Surprise, ISM: Non-mfg business activity index	3.28%	Negative	Positive	Negative	Positive	Positive	Negative
Target price implied return	3.04%	Negative	Positive	Negative	Negative	Negative	Negative
Surprise, ISM: Non-mfg composite index	2.92%	Negative	Positive	Negative	Positive	Positive	Negative
Mean target price revision, 3M	1.88%	Positive	Negative	Negative	Positive	Positive	Negative
21D volatility of volume/price	1.51%	Positive	Positive	Positive	Negative	Negative	Negative
Variance risk premium	1.50%	Positive	Positive	Positive	Positive	Positive	Positive

Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 8: The direction for the top 10 factors in the current prediction

	Current Weight	Equity	Fixed Income	High Yield	Commodities	Crude Oil	Gold
Surprise, ISM: Mfg composite index	6.24%	Positive	Negative	Positive	Positive	Positive	Negative
Idiosyncratic vol surprise	5.48%	Positive	Negative	Positive	Positive	Positive	Negative
DB composite options factor	5.06%	Negative	Positive	Negative	Negative	Negative	Negative
ISM: Non-mfg business activity index	4.52%	Positive	Positive	Negative	Positive	Positive	Positive
ISM: Non-mfg composite index	4.37%	Negative	Negative	Negative	Positive	Positive	Positive
Surprise, ISM: Non-mfg business activity index	4.26%	Negative	Positive	Negative	Positive	Positive	Negative
Surprise, ISM: Non-mfg composite index	3.74%	Negative	Positive	Negative	Positive	Positive	Negative
Year-over-year quarterly EPS growth	2.65%	Positive	Negative	Negative	Positive	Positive	Positive
Lagged long-term interest rate	2.61%	Negative	Negative	Negative	Positive	Positive	Negative
21D volatility of volume/price	2.52%	Positive	Positive	Positive	Negative	Negative	Negative

Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Theme of the month – variance risk premium

In this research, we make an attempt to improve our equity market timing ability. We study a new and interesting concept called VRP, or variance risk premium. Bollerslev, Tauchen, and Zhou [2009] pioneered the study, and then Dreschsler and Yaron [2010] and Zhou [2011] further expanded the idea.

The central argument is that equity risk premia (or market risk premia for other asset classes) have a common short-run component – variance risk premium – that is not directly observable. However, an empirical proxy can be constructed from the difference between model-free options-implied variance and the conditional expectation of realized variance. VRP essentially measures the difference between expected and realized risk (variance) of an asset class.

The technical details of VRP

There are two raw ingredients to VRP, namely the model-free option-implied variance and the conditional expectation of realized variance. The derivation of the model-free option-implied variance, $IV_{t,t+1}$ is somewhat involved[3]. In a nutshell, however, it is as simple as the CBOE VIX index[4] for the US equity market and its variations in other countries.

In order to measure the actual return variance, academic research mostly replies on high frequency data. As shown in Anderson, Bollerslev, Diebold, and Ebens [2001], Barndorff-Nielsen and Shephard [2002], the sample variance ($RV_{t-1,t}$) calculated from high-frequency intraday data offers a much more accurate *ex post* observation of the true (unobserved) variance than the traditional ones using daily or lower frequency data.

VRP at time t is then defined as the difference between the ex ante expectation ($IV_{t,t+1}$) and the objective realized return variance ($RV_{t-1,t}$):

$$VRP_t = IV_{t,t+1} - RV_{t-1,t}$$

The monthly realized variance for the S&P 500 index ($RV_{t-1,t}$) is the summation of the 78 intra-day five minute squared log returns from 9:30AM to 4:00PM EST, including overnight returns[5].

An alternative calculation of VRP is to replace the realized variance ($RV_{t-1,t}$) with its expected value – we name this variable EVRP or expected variance risk premium.

$$EVRP_t = IV_{t,t+1} - E(RV_{t,t+1})$$

We can estimate $RV_{t,t+1}$ by the one-step ahead forecasts from a simple reduced form time series model for $RV_{t-1,t}$.

$$RV_{t,t+1} = \alpha + \beta \cdot IV_{t-1,t} + \gamma \cdot RV_{t-1,t} + \varepsilon_{t,t+1}$$

3 See, for example Zhou [2011], among others for detailed discussion.

4 The VIX index measures option-implied volatility. To convert volatility to variance, we need to calculate $VIX^2/12$.

5 The usage of high frequency data can be a challenge and requires sophisticated data management system. For a detailed discussion of our technology infrastructure on high frequency data, please refer to Cahan, R. Luo, Y., Jussa, J., and Alvarez, A. [2010].

The intuitions behind VRP

The economic rationale behind the VRP concept is that VRP is directly linked to the underlying volatility dynamics of consumption growth. Therefore, VRP serves as a useful predictor for the returns over horizons for which that risk factor is relatively more important.

The classical intertemporal CAPM (capital asset pricing model) model of Merton [1973] is often used as the theoretical foundation behind the risk-return tradeoff. The empirical evidence of CAPM model, however, has been particularly weak[6]. Most empirical analysis actually tends to support the opposite, i.e., a statistically significant and *negative* relationship between risk and return.

Our own words of intuition behind VRP is that when VRP is high, i.e., options-implied market volatility is higher than realized volatility, it suggests that investors are expecting higher volatility from the current level or rare event risk/tail risk. Because of the asymmetric nature of volatility (i.e., higher chance of having extremely high volatility levels), investors need to be compensated for taking the extra risk, at the aggregate level.

The perfect explanation of why VRP can predict future asset returns is still yet to be developed. The intuition is simple. VRP is a proxy for macroeconomic uncertainty or consumption volatility that varies independently with consumption growth. Investors demand higher returns for this consumption uncertainty; therefore, higher VRP predicts higher future returns.

What does it look like?

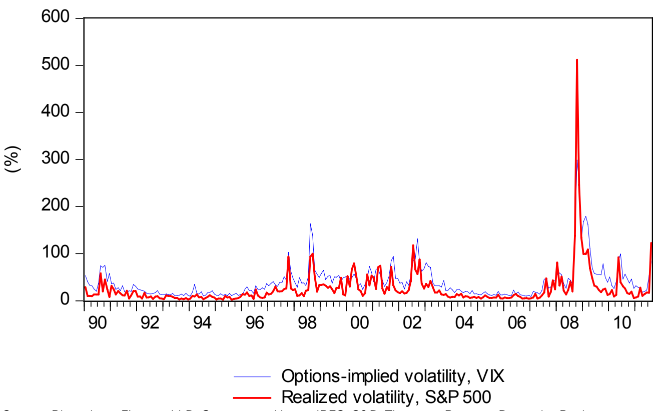
Figure 9 plots the options-implied volatility and the realized volatility for the S&P 500 index. The options-implied volatility is typically higher than the realized volatility – that's why it's typically called variance risk *premium* (Figure 10).

As shown in Figure 11, VRP does appear to lead the equity market, especially in crises. For example, VRP bottomed in October 2008, while the equity market bottomed in February 2009. On the other hand, VRP rose sharply in February 2009, which led a strong equity market recovery from March 2009 until April 2010.

The global equity markets are highly correlated. VRP's in different markets also appear to be highly correlated (see Figure 12). The average pairwise return correlation among five markets in our study is about 84%, while the average pairwise VRP correlation is about 86%.

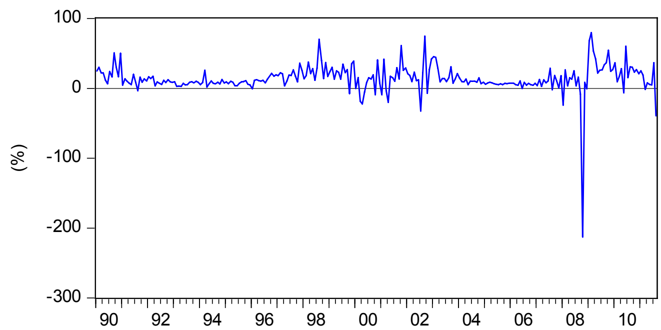
[6] For example, in Alvarez, Luo, Cahan, Jussa, and Chen. [2011], we found the negative relationship (statistically significant) between risk and future returns. Baker and Wurgler [2011] found similar evidence in most other countries as well.

Figure 9: Options-implied vol vs. realized vol, S&P 500



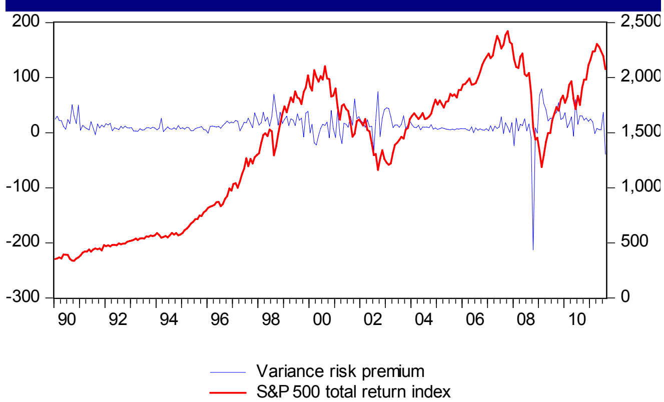
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 10: Variance risk premium, S&P 500



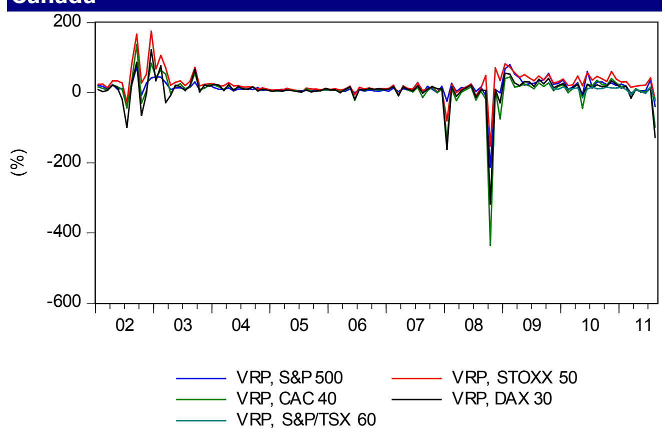
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 11: VRP and S&P 500



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 12: VRP for Europe, Germany, France, and Canada



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Empirical analysis

In this section, we perform some formal statistical backtesting on the predictive power of VRP. We test VRP in each of the five countries/regions (US, Europe, France, Germany, and Canada) on their respective country/region equity markets. Then, we apply VRP for the US equity market on other asset classes, i.e., fixed income, high yield bond, commodities, crude oil, and gold.

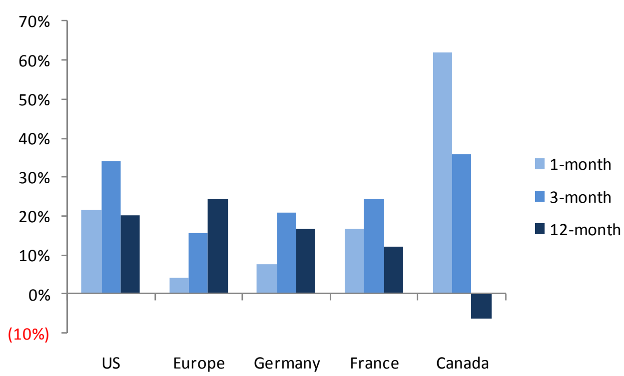
Variance risk premium is highly predictive of future equity market returns

First of all, we conduct a univariate backtesting on VRP for five equity market indices: S&P 500 (US), STOXX 50 (Europe), DAX 30 (Germany), CAC 40 (France), and S&P/TSX 60 (Canada).

Across the five markets, VRP is statistically significant in predicting up to 12 month ahead equity market excess returns (Figure 13). The correlation coefficients between VRP and forward 1-month and 3-month excess returns are positive for five markets. The correlation coefficients between VRP and forward 12-month excess returns are positive for all markets but Canada (S&P/TSX 60 index). VRP's predictive power seems to peak at approximately three-to-four month horizon for most markets.

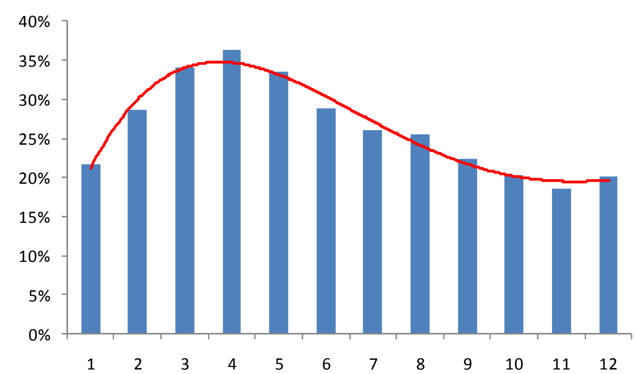
The history for Europe (Stoxx, DAX and CAC) is somewhat short (from early 2002) and is even worse for Canada (from 2009).

Figure 13: Summary



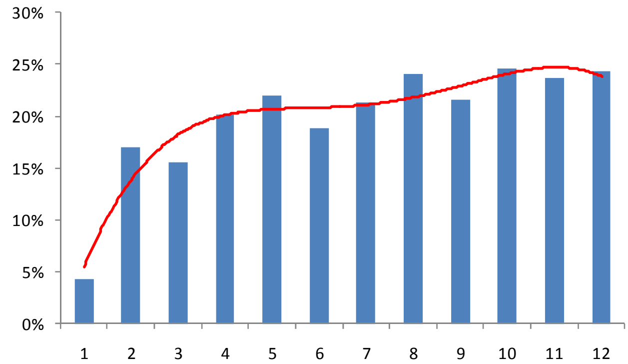
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 14: US – S&P 500



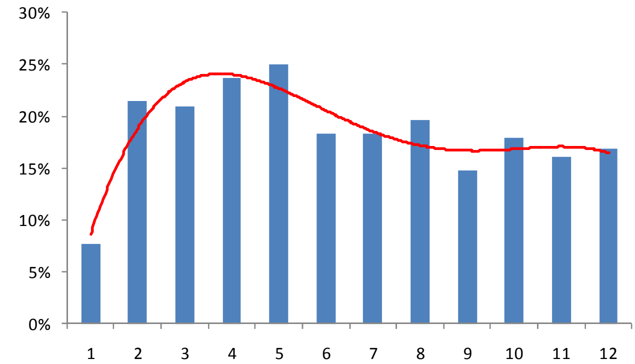
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 15: Europe – STOXX 50



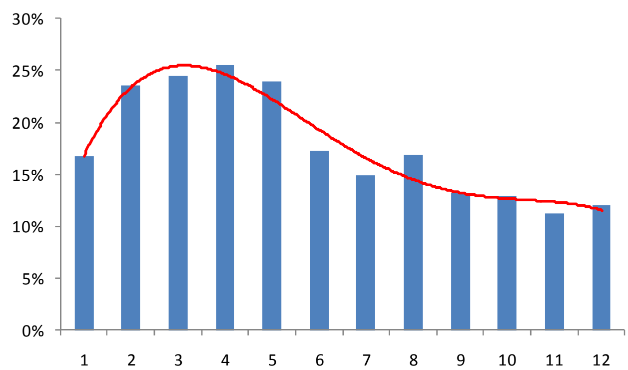
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 16: Germany – DAX 30



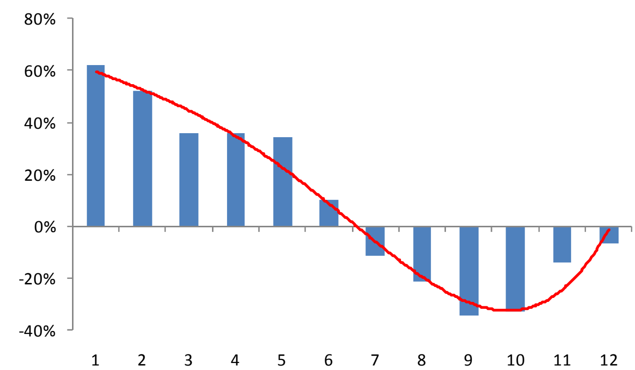
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 17: France – CAC 40



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 18: Canada – S&P/TSX 60



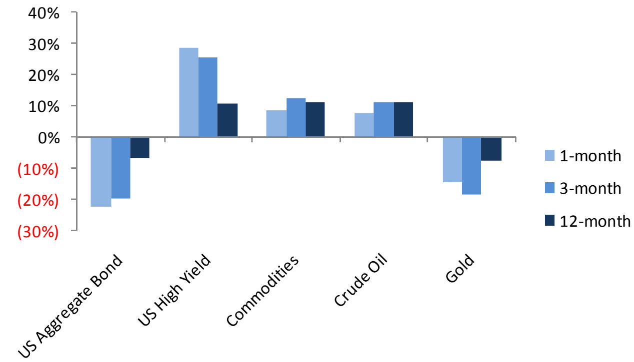
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Variance risk premium is also useful in predicting bond, credit, and commodity returns

If VRP truly represents the volatility of our consumption, it should also impact how investors view other risky assets like bonds or commodities. In this section, we calculate the time series IC of VRP (S&P 500 index) with five asset classes: aggregated US bonds, US high yield bonds, commodities (S&P GSCI index), crude oil (front-month futures), and gold.

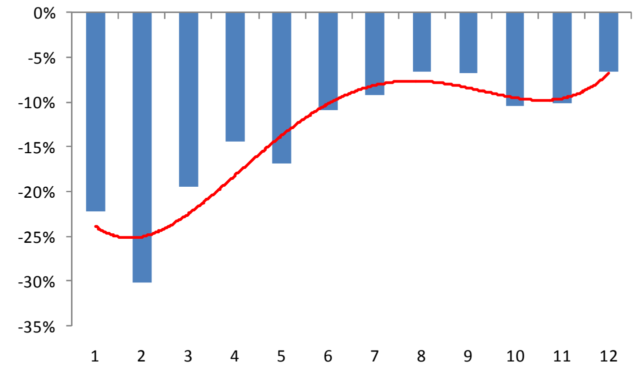
Interestingly, VRP also appears to be highly predictive of future returns for all five asset classes. The correlation coefficients are mostly negative for bonds and gold (as bonds and gold are perceived as less risky assets) and positive for high yield bonds, commodities, and crude oil. VRP's predictive power again seems to peak at the three-month horizon.

Figure 19: Summary – Other asset classes



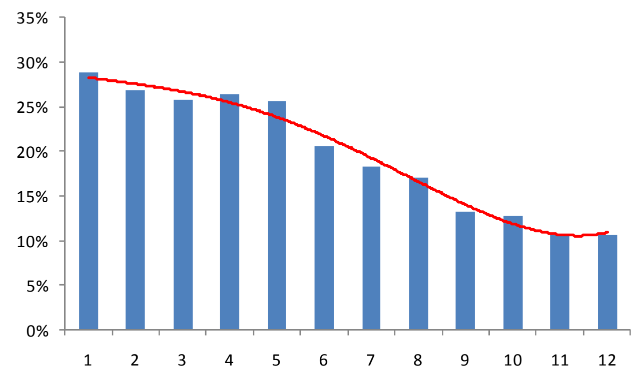
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 20: Fixed income



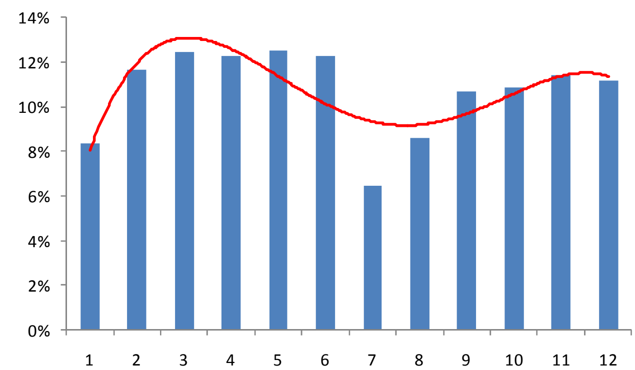
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 21: High yield bonds



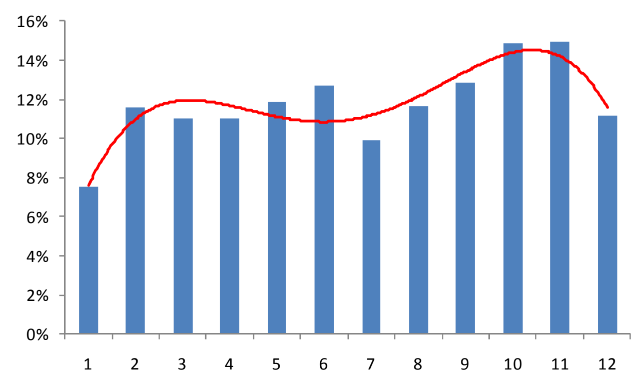
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 22: Commodities



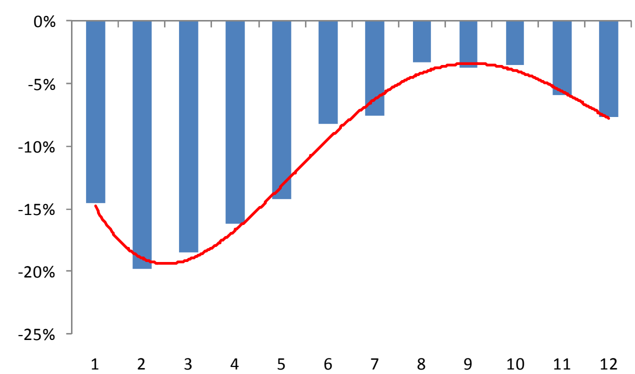
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 23: Crude oil



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 24: Gold

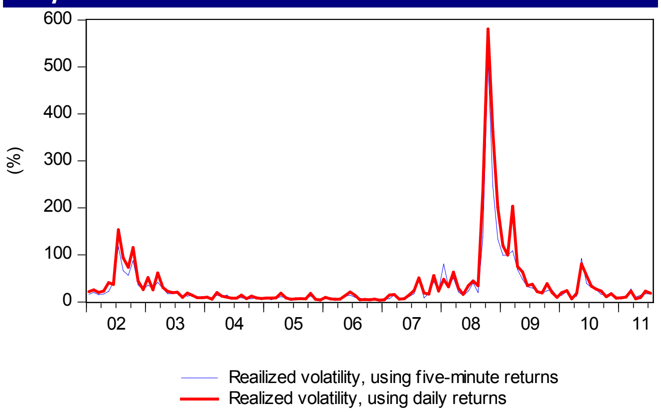


Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Robustness test – are high frequency data really that important?

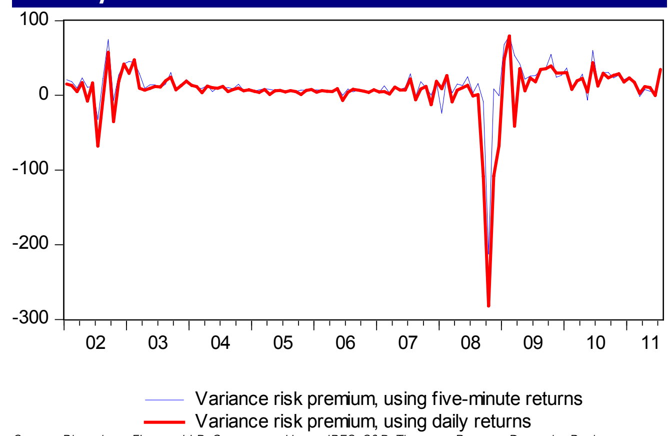
Academic research on VRP almost exclusively uses high frequency data to calculate realized volatility (see Bollerslev, Tauchen, Zhou [2009] and Dreschsler and Yaron [2010] and Zhou [2011]). However, we also know that the volatility estimates are highly correlated, regardless what frequency of data we use. For example, the correlation coefficient between five-minute return volatility and daily return volatility is about 98.6% (see Figure 25), while the VRP's calculated using five-minute return and daily return are about 84.8% (see Figure 26).

Figure 25: Realized volatility, five-minute returns vs. daily returns



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

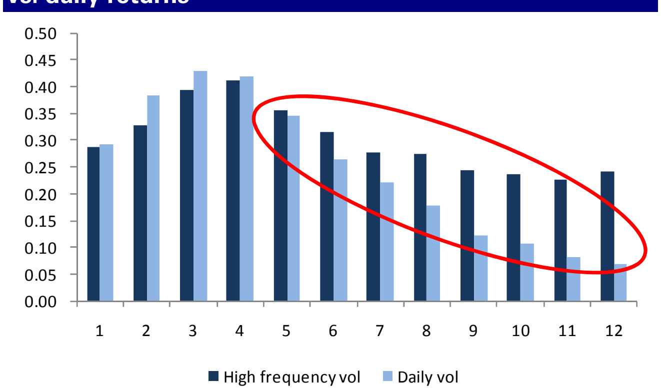
Figure 26: Variance risk premium, five-minute returns vs. daily returns



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

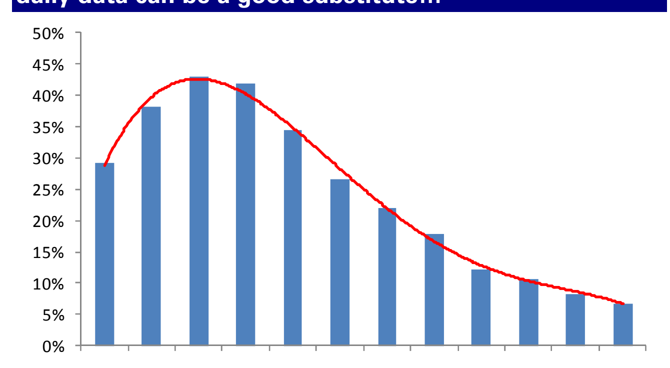
The key question is whether the superior predictive power of VRP is due to the fact we use high frequency data. Actually, in the period that we have both high frequency data and daily data, the performance is comparable in the short-term horizon. High-frequency based VRP wins only in forecasting horizon beyond four months (see Figure 27). In term of predictive power, using high frequency data does appear to have some incremental benefit, especially in cross-sectional prediction. Our tick database only has about 10 years of history. Prior to 2002, the VRP calculated using daily returns still shows strong predictive power of future equity market returns (see Figure 28). Therefore, in this research, we use high frequency VRP from 2002 to present; prior to 2002, we substitute with daily VRP.

Figure 27: Performance comparison, five-minute returns vs. daily returns



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 28: When we don't have high frequency data, daily data can be a good substitute…



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Backtesting of market timing models

In stock selection research, we mostly work with cross-sectional data. For example, we want to understand, at a given point in time, what stocks are expected to do well in the next period. Time series properties are of secondary importance[7].

In market timing research, the focus is exactly the opposite. We primarily care about time series predictability, i.e., is the S&P 500 index going up or down next month (or day, week, quarter, year, etc.) Cross sectional ranking becomes important only at a later stage when we construct a portfolio of different asset classes. The likely tools in market timing research are somewhat different and that is the goal of this section – to explain our backtesting methodology. We use VRP as an example to show how to conduct market timing research.

Model performance

There are a number of statistical measures in the academic literature to assess a model's performance. However, as shown in Campbell and Thompson [2008], statistical accuracy can be quite different from economic profit, i.e., whether we can build a profitable QTAA strategy.

In this research, we first evaluate our models based on two familiar concepts: time-series IC and cross-sectional IC. The time-series IC measures the correlation coefficient between our prediction and the subsequent realized return, for each of the asset classes. The cross-sectional IC, which is similar to the typical IC we use in our stock selection research, calculates the correlation coefficient between the predicted returns of the six assets and the subsequent realized returns of the same assets, at a given point in time. The ultimate test of our model performance will be presented in the subsequent section on portfolio excess returns.

Time series IC (TIC)

The time-series IC measures the correlation coefficient between our prediction and the subsequent realized return, for each of the asset classes. Time series IC can be useful to see if a potential factor has any predictive power for future returns. The downside of TIC is that it's not easy to see the evolution of a factor's efficacy over time, as it is calculated using the entire history[8].

As shown in Figure 29, compared to other common economic, capital market, seasonal, and fundamental factors, VRP has exhibited exceptional out-of-sample predictive power for future equity market returns. Across the six asset classes, VRP appears to be useful in predicting future equity, fixed income, high yield bond, and gold returns, but fails to show out-of-sample performance for commodities and crude oil (see Figure 30).

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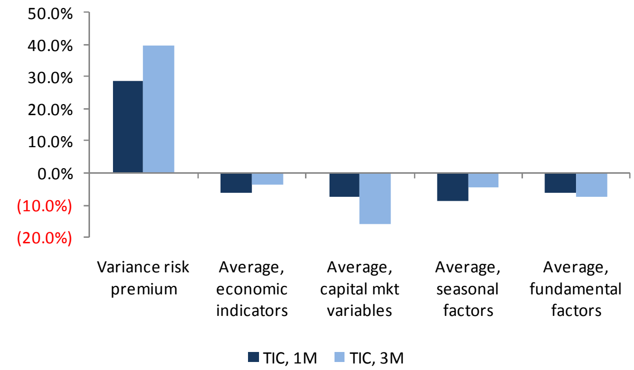
[7] See Luo, Cahan, Jussa, and Alvarez [2010a], for a detailed discussion of backtesting methodologies for stock selection research.

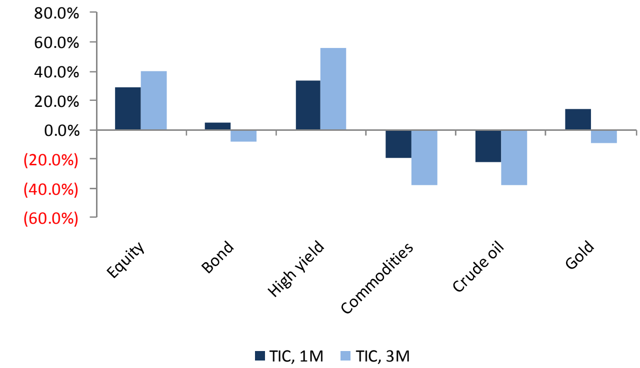
[8] We could potentially use a rolling or expanding window to calculate time series IC, to see the changes of TIC over time, but it still highly depends on the length of the rolling window or the choice of rolling versus expanding window.

Figure 29: Time series IC for the equity market



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 30: Time series IC, across different assets

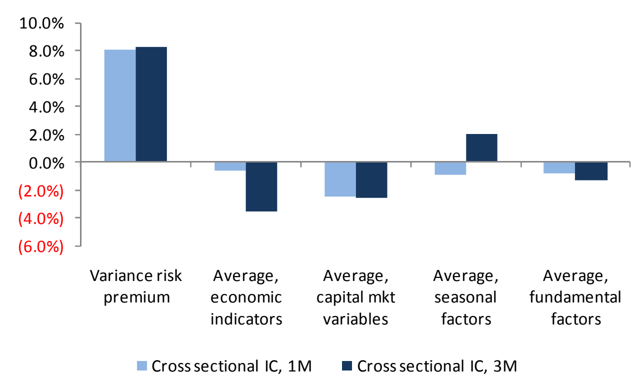


Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Cross sectional IC

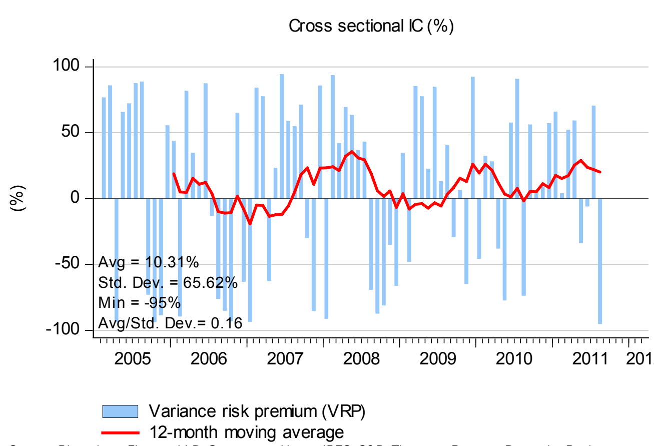
Cross-sectional IC is probably more interesting to us, since the ultimate goal is to compare the relative performance of various asset classes. The other benefit of cross-sectional IC is that it allows us to see the time evolution of a factor to assess its efficacy over time. The one-month-ahead prediction of the six asset classes (equity, fixed income, high yield bonds, commodities, crude oil, and gold) based on VRP is very strong and consistent over time (see Figure 31). In distinguishing the relative performance of the six asset classes, VRP also substantially outperforms other economic, capital market, seasonal, and aggregate fundamental variables (see Figure 32).

Figure 31: Compared to other variables



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 32: One-month ahead prediction



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

The importance of using Newey-West statistics

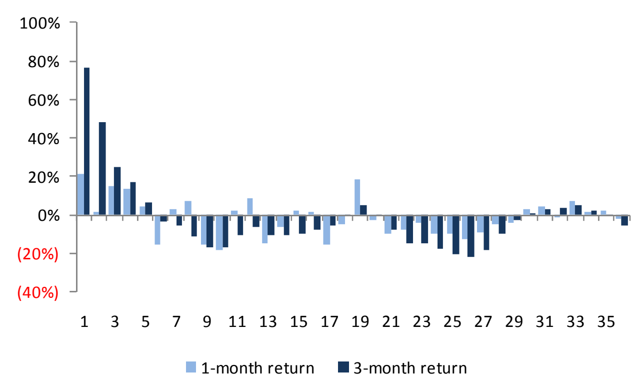
One of the problems dealing with time series data is that our data series and model residuals often violate the standard assumptions behind the standard ordinary least squares (OLS) regression. The error terms tend to have autocorrelation and heteroskedasticity. The statistical significance is often exaggerated. A Newey–West (Newey and West [1987]) estimator is used in econometrics to provide an estimate of the covariance matrix of the parameters that account for these issues.

As shown in Figure 33, the autocorrelation of one-month S&P 500 index return is minimal – we know the asset return series is close to a white noise series. If we repeat the exercise with *overlapping* three-month returns, autocorrelation is significant at up to three lags and shows some cyclical patterns[9].

The regular t-statistics tend to give overly optimistic relationships, as they do not take into account potential serial correlation. For example, based on the regular t-statistics (and p values), VRP appears to be highly predictive of future commodities returns from one month to six months. Based on the Newey-West p value, however, all these relationships prove to be insignificant (see Figure 34).

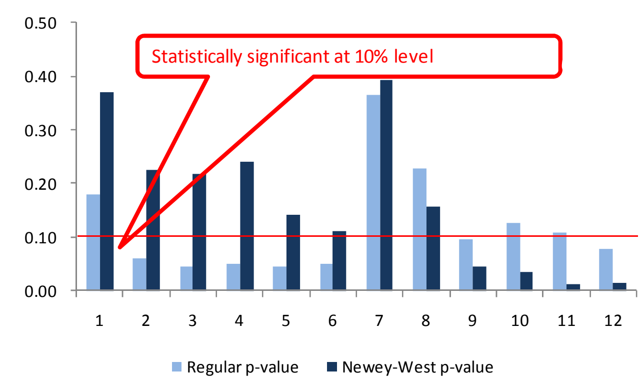
The difference between regular t-statistics and Newey-West is especially significant as we extend our forecasting horizon. For example, among the 140 market timing variables we test, 24 are statistically significant based on regular t-statistics (versus 23 based on the Newey-West test). For three-month horizon, 45 variables pass the regular t-statistics, but only 33 pass the Newey-West test.

Figure 33: S&P 500 return serial correlation



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 34: The impact of Newey-West statistics



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

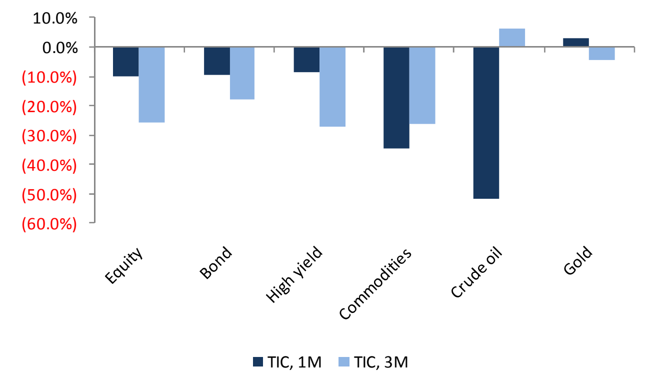
Benchmark

One of the most common approaches for estimating asset returns is based on historical averages[10]. In this research, the expected returns of each asset class in the benchmark model are based on the long-term average excess returns, using an expanding window from December 1987. As shown in Figure 35 and Figure 36, historical average return is a poor forecast of near-term future asset return. For the six asset classes, the one-month-ahead time series IC based on historical average is mostly negative, with the exception of gold. Cross sectionally, if we rank the six asset classes based on their predicted returns (using long-term averages), the correlation with subsequent performance is also slightly negative.

[9] This is not surprising, as we use three-month *overlapping* returns.

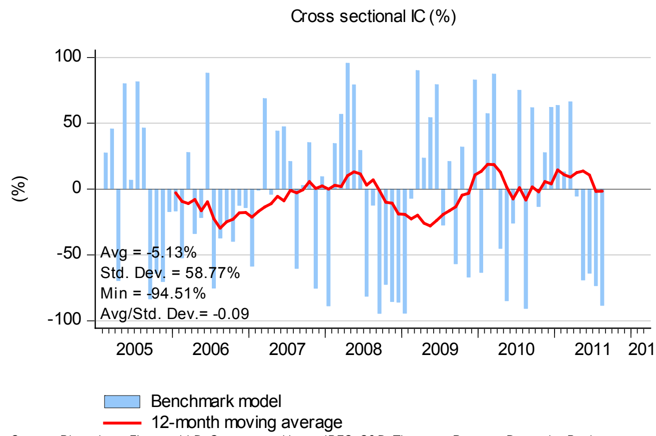
[10] Mesomeris, S., Salvini, M., and Avettand-Fenoel, J.R. [2011]. "Quantitative Musing: Road Map to the Equity Risk Premium", Deutsche Bank Quantitative Strategy, August 15, 2011, provides a detailed survey of different approaches of estimating equity risk premium.

Figure 35: Time series IC for various assets



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 36: Cross sectional IC

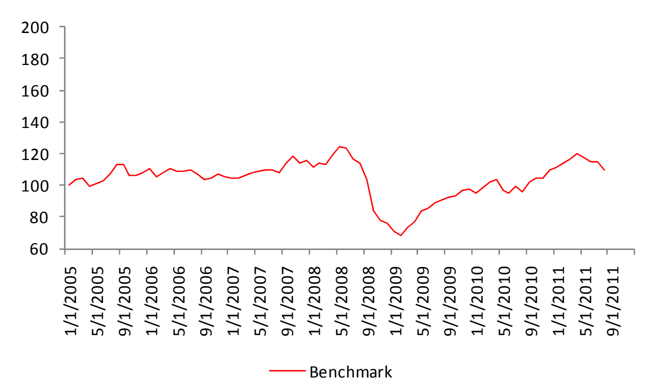


Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

The benchmark portfolio is formed with the above return expectation model and sample covariance matrix. The benchmark portfolio is then rebalanced every month, using a simple mean-variance optimization. The optimizer chooses a portfolio with a maximum expected return, subject to a risk budget. We do not allow shorting and set a maximum holding of any asset class to no more than 50% of the overall portfolio. The benchmark portfolio has a very low turnover of approximately 2.7% per month (one way).

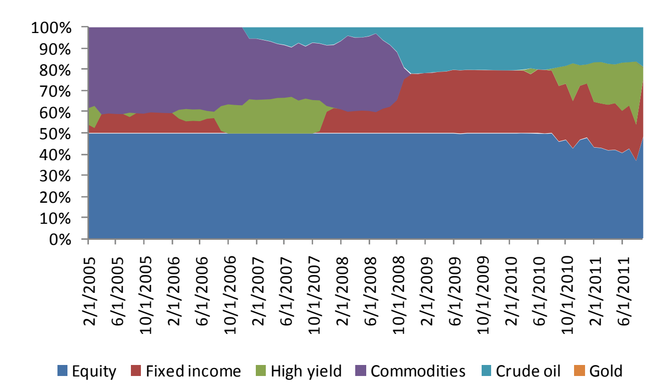
As shown in Figure 37, the performance of the benchmark portfolio was relatively flat until mid-2008. In the 2008 financial crisis, the benchmark portfolio fell 45% in nine months, then gradually recovered. The current market turmoil also causes significant volatility to the benchmark. Figure 38 shows the weights of the six asset classes over time. The benchmark portfolio holds a relatively stable equity position of approximately 50% (the upper holding limit). The benchmark portfolio mostly held commodities from early 2004 until 2008, then gave away to fixed income, high yield bonds, and crude oil in recent years.

Figure 37: Cumulative performance of the benchmark



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 38: Weighting of the six asset classes



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Asset return prediction models

In the academic literature, there appears ample evidence that asset returns are predictable in-sample. However, recent studies by Bossaerts and Hillion [1999], Goyal and Welch [2008] found poor out-of-sample predictability. As we will see in the later discussion, we find similar evidence that many factors have great in-sample predictive power, but most of them failed miserably in out-of-sample backtesting. Even more troubling, the in-sample and out-of-sample performance is inconsistent, i.e., the factors that do well in-sample are quite different from the factors that perform well out-of-sample, and vice versa.

Predictive variables

In addition to VRP, in this research, we study a wide range of macroeconomic, capital market, seasonal, and aggregated fundamental variables in market timing forecasting.

Macroeconomic variable

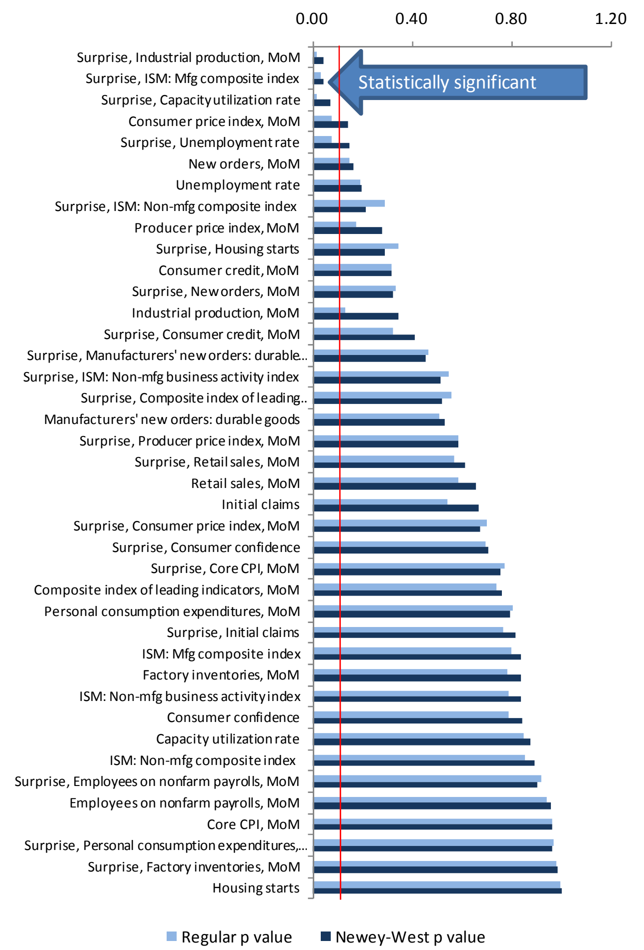
There is a long list of academic papers using macroeconomic variables in equity market timing research. For example, Campbell and Vuolteenaho [2004] addressed inflation; Lettau and Ludvigson [2001] covered the consumption-wealth ratio; Santos and Veronesi [2006] argued for labor income as a predictor; and Cooper and Priestly [2009] introduced GDP/output gap.

In Luo, Cahan, Jussa, and Alvarez [2010b], we studied the predictive power of a wide range of economic variables on equity style returns. We also find that most published research using economic factors suffers severe look-ahead bias. Economic time series are often re-stated, for correction or seasonal adjustment. Restatement introduces a significant source of look-ahead bias. We find restatement is common among many economic time series; restatement can be statistically significant; and restatement tends to be not random. For all our research, we use point-in-time non-restated economic data.

In Luo, Cahan, Jussa, and Alvarez [2010b], we also found that in some cases, the surprise component of an economic time series can be more predictive than the raw economic data itself. We define surprise as the difference between the first-reported economic data and the consensus estimate prior to the data release.

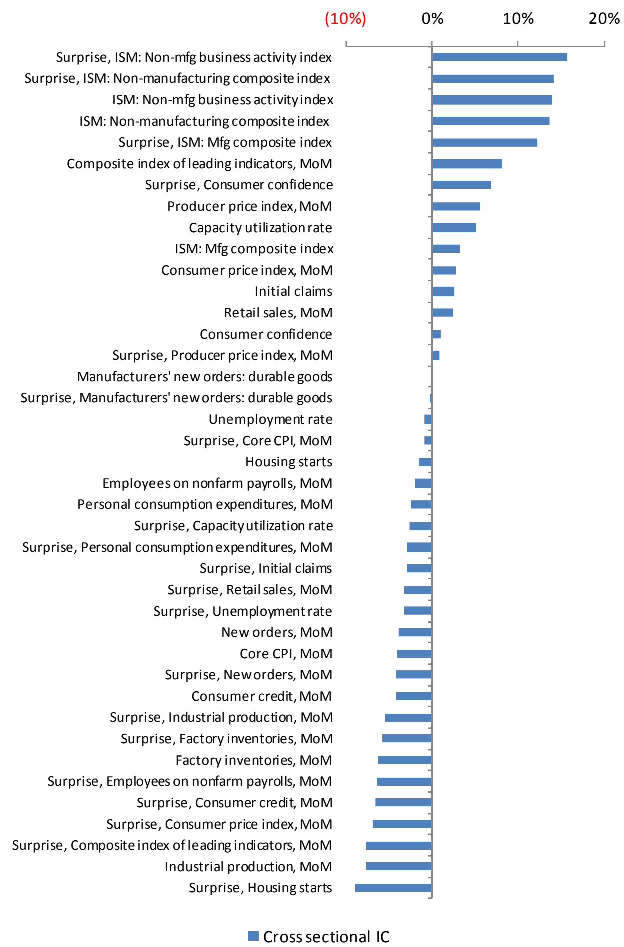
In this paper, we backtest 20 macroeconomic variables (all point-in-time non-restated) and 20 corresponding surprise versions. In-sample statistical testing suggests that five economic variables are potentially useful in predicting equity market returns (see Figure 39), while nine economic variables show some out-of-sample promise (see Figure 40). The surprise in ISM seems to be important based on both in-sample and out-of-sample backtesting. Most economic variables are statistically insignificant in-sample and have negative IC in out-of-sample backtesting.

Figure 39: In-sample statistical significance



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 40: Out-of-sample cross sectional IC

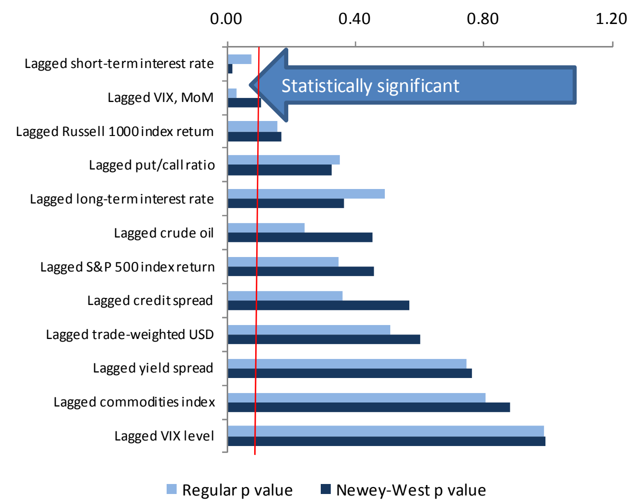


Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Capital market variables

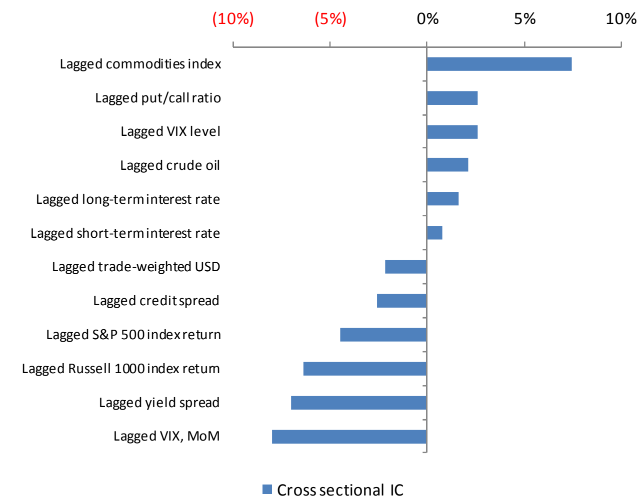
Capital market variables like VIX, yield spread, credit spread, currency, and commodities prices have been used extensively in our previous research (e.g., Luo, Cahan, Jussa, and Alvarez [2010b]). We prefer capital market variables for two main reasons: 1) they are not typically subject to revisions; and 2) they are typically available on a daily (or higher frequency) basis. Breen, Glosten and Jagannathan [1989] discussed nominal interest rates; Fama and French [1989] discussed yield spread in the market timing context. In our paper, we test 12 capital market variables. In-sample backtesting suggests that short-term interest rate and VIX have some predictive power for future equity market returns (see Figure 41), while out-of-sample backtesting favors lagged commodities index return and put/call ratio (see Figure 42).

Figure 41: In-sample statistical significance



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 42: Out-of-sample cross sectional IC

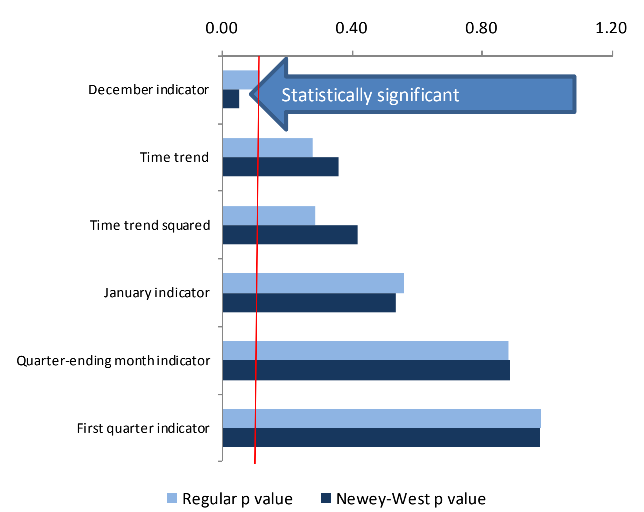


Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Seasonal variables

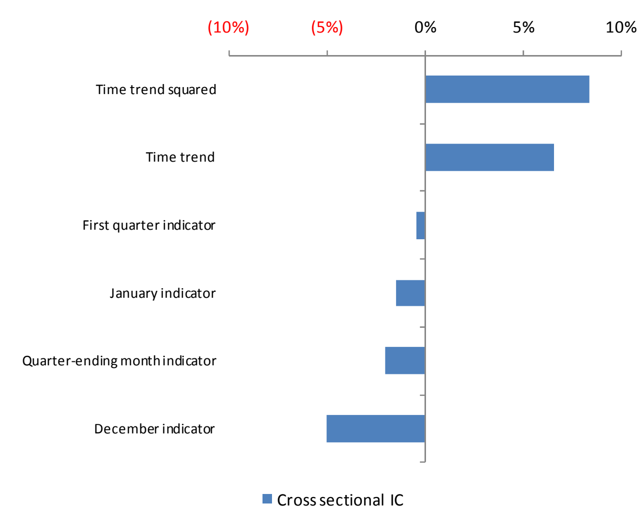
In Luo, Cahan, Jussa, and Alvarez [2010b], we studied four potential seasonal effects: January, December, quarter ending months, and first half of the year effect. The January effect is generally considered as the phenomenon in which small cap and low quality stocks outperform in January. The December effect is related to year-end window dressing, i.e., managers are likely to buy stocks that have been performing well towards year end to avoid showing losers on their investment holdings. Quarter-ending months follow similar arguments as the December effect, in that quarterly performance reporting is common for both mutual funds and personal accounts. The illusion of time diversification makes investors feel more comfortable investing in risky assets in the first half of the year, as their annual performance review is a little further away. In the second half, as year-end approaches, investors' risk appetite shrinks. The December effect seems to be strong in-sample, but disappears out-of-sample (see Figure 43 and Figure 44).

Figure 43: In-sample statistical significance



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 44: Out-of-sample cross sectional IC



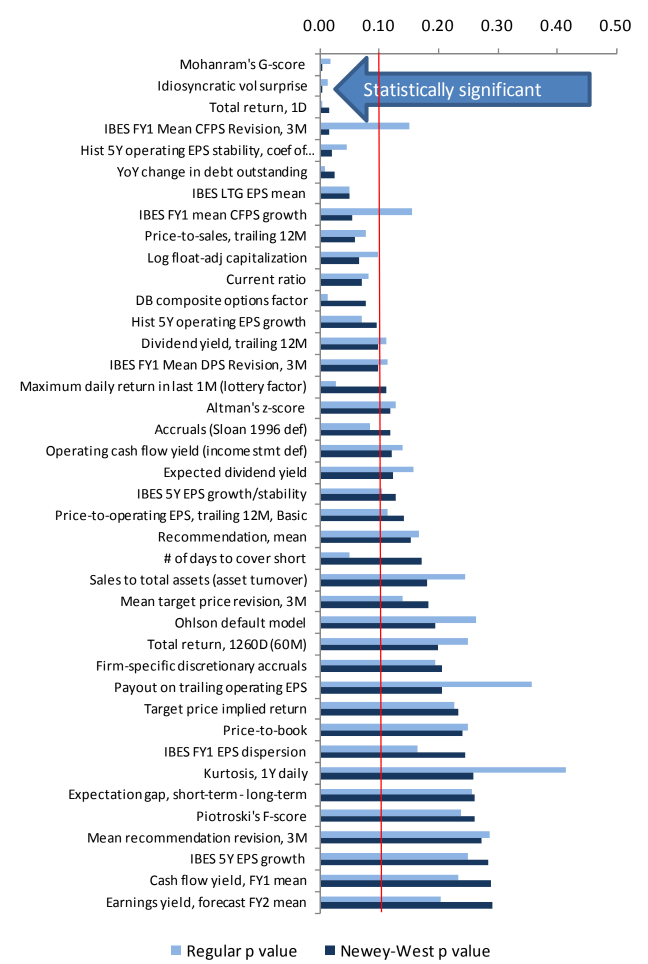
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Fundamental variables

Pastor and Stambaugh [2009] discussed dividend to price ratio; Campbell and Shiller [1998] covered earnings to price ratio; Pontiff and Schall [1998] addressed book-to-market ratio – all in the market timing context. We perform a much more comprehensive backtesting. We calculate a bottom-up aggregate market factor for each of the 80 standard quant factors in our factor library[11].

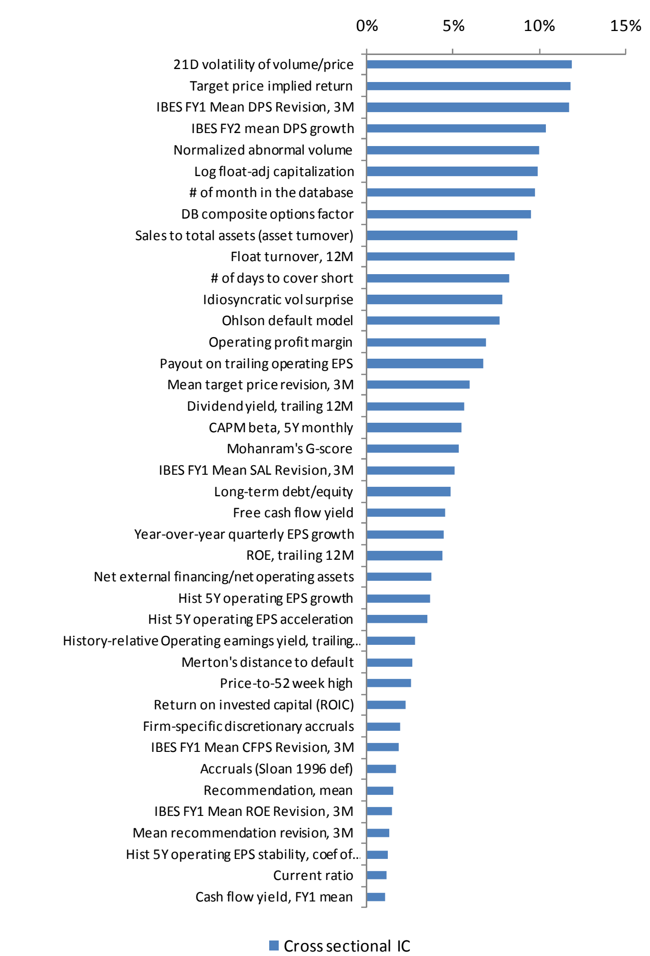
Using more recent data, however, it seems to suggest that the traditional earnings yield, book yield factors are statistically insignificant and have negative out-of-sample predictive power. Dividend yield does show some promise both in-sample and out-of-sample.

Figure 45: In-sample statistical significance



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 46: Out-of-sample cross sectional IC



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Modeling technique

There are probably as many modeling techniques as the number of potential predictors. In Luo, Cahan, Jussa, and Alvarez [2010], we test 10 modeling techniques from three categories (time series regression: linear model, robust regression, regime switching, and state-space/Kalman filter), naïve models (long-term moving average, short-term moving average,

[11] See Appendix II for a list of the 80 common fundamental factors.

exponentially weighted moving average), and machine learning techniques (classification and regression tree, random forest, and multivariate regression spline). We found reasonably sophisticated modeling techniques (i.e., regression based models) outperform both naïve strategies (i.e., moving averages) and overly complex models (i.e., machine learning techniques), when sample size is small.

Most models use multiple predictive variables. The focus is typically on variable selection. In Luo, Cahan, Jussa, and Alvarez [2010], we demonstrate variable selection using information criteria – we initially overfit the model with all potential variables, then we eliminate the redundant variables one at a time, all with a rolling window. The biggest problem to applying a similar approach here is that the variables mentioned above have very different length of history – some variables have over 20 years of data, while other factors have strong predictive power but limited history. If we use a 10-year window, then we essentially eliminate many of the new variables (which arguably have stronger predictive power and less crowded). If we use a shorter-window, e.g., a five-year window, then the data covers less than a full economic cycle.

Analysts and portfolio managers constantly search for the true model that predicts asset returns. Similarly, in academia, researchers have also invested significant time looking for the true asset pricing model. In our opinion, in social science such as finance, there is never a single real and true model. We subscribe Box's [1980] spirit that all models are false, but some are useful. Therefore, rather than selecting the best model, we could try to combine all potential models.

In this section, we pursue a model averaging approach, i.e., we try to pool the point estimates of each model at each given point in time, based on certain weighting schemes. The biggest benefit is that it can accommodate variables with different histories.

In a seminal paper by Bates and Granger [1969], the authors show combinations of individual forecasts can outperform the individual forecasts themselves, which promoted the wide spread of consensus estimates in economics and finance. Forecast combination has received attention in macroeconomic research, e.g., Stock and Watson [2003, 2004], but limited attention in finance. Two notable exceptions are Mamaysky, Spiegel, and Zhang [2007] and Rapach, Strauss, and Zhou [2010].

In this research, we design a unique model averaging approach, by weighting individual predictors on their most recent out-of-sample performance (as measured by cross sectional IC). The weight assigned to predictor k formed at time t is a function of the cross sectional IC calculated using the most recent three-year window. In particular, the weight to model k at time t is:

$$\omega_{k,t} = \sum_{time=t}^{t-L} IC_{k,time} \Bigg/ \sum_{i=1}^{I} \sum_{time=t}^{t-L} IC_{i,time}$$

Where,

$\omega_{k,t}$ is the weight for model k at time t;

$IC_{k,t}$ is the cross sectional IC for model k at time t

L is the length of look-back window; and

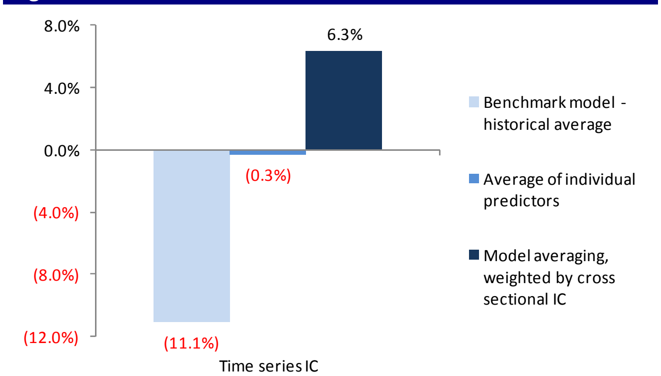
I is the total number of economic, capital market, seasonal, and fundamental factors.

As a comparison, we could take the simple average of the forecasted returns from all the individual predictors[12]. Figure 47 and Figure 48 show the performance of the three models:

- **Benchmark:** we simply use the historical average return of each asset classes (expanding window) at a given point of time as the expected return for next period;
- **Naïve model:** we use the average of the forecasted returns from each individual predictor at a given point of time as the expected return for the next period; and
- **QTAA model:** we use a model averaging approach (weighted by a predictor's recent out-of-sample cross sectional IC).

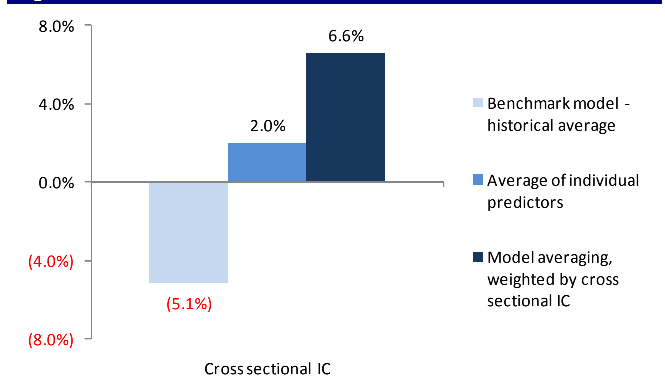
Historical average return is a poor predictor of future return. Both time series IC and cross sectional IC are negative. The naïve model is moderately positive (see Figure 49). Our QTAA model exhibits strong predictive power for future asset returns (see Figure 50).

Figure 47: One-month time series IC



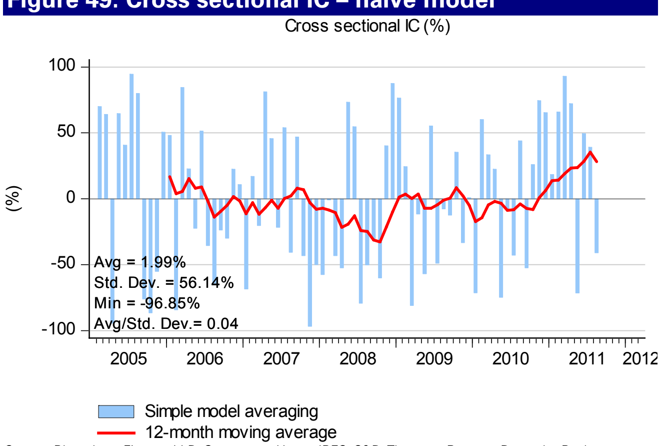
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 48: One-month cross sectional IC



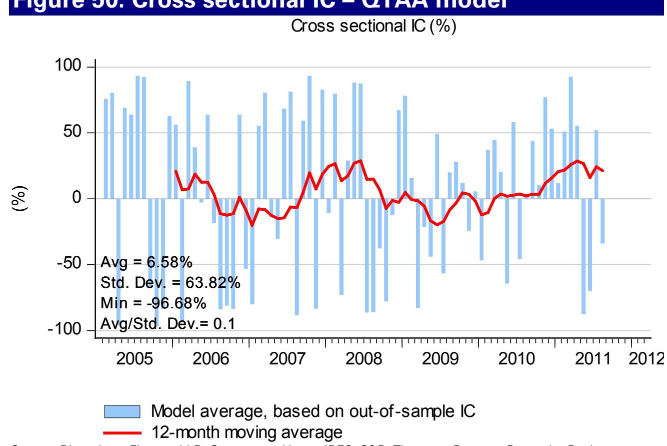
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 49: Cross sectional IC – naïve model



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 50: Cross sectional IC – QTAA model



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Model prediction – what does it look like?

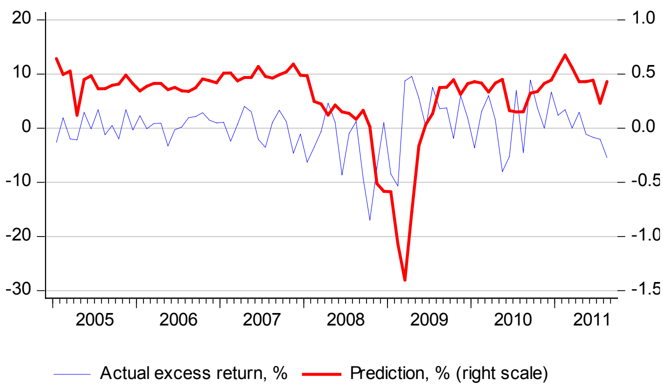
As shown in Figure 51 to Figure 56, the prediction of asset returns tends to be much less volatile than the actual realized returns. The reason is that, in the case of forecasting asset returns, the predictive power of most factors is low[13]; therefore, the intercept term (i.e., the

[12] We exclude those individual variables when they are statistically insignificantly using in-sample data.

[13] In most models, the typical R^2 is less than 5%.

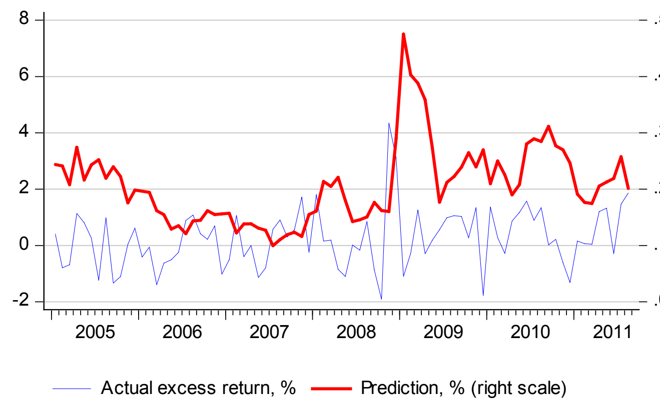
long-term average of asset returns, after controlling for the predictive variables) dominates the slope term.

Figure 51: Predictive returns vs. actual returns, S&P 500



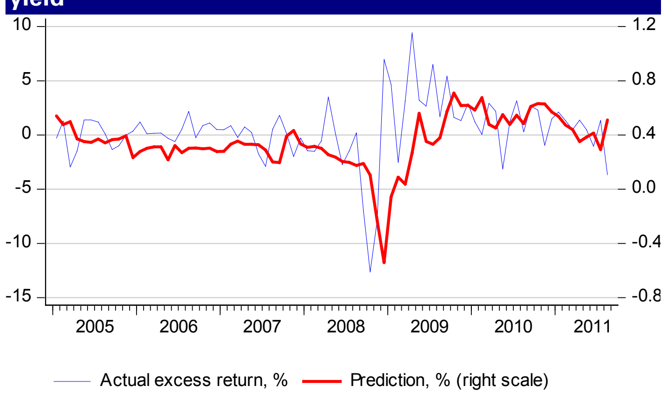
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 52: Predictive returns vs. actual returns, bond



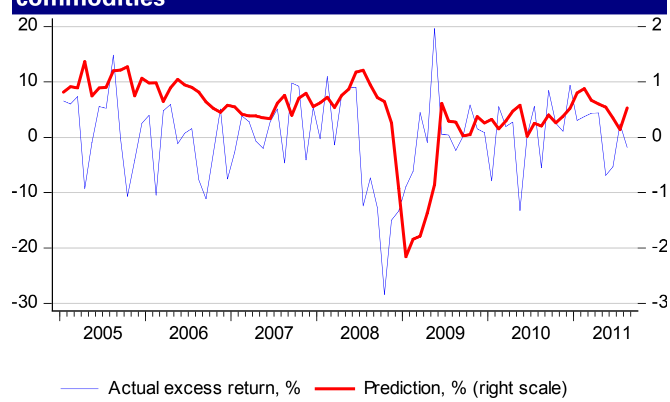
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 53: Predictive returns vs. actual returns, high yield



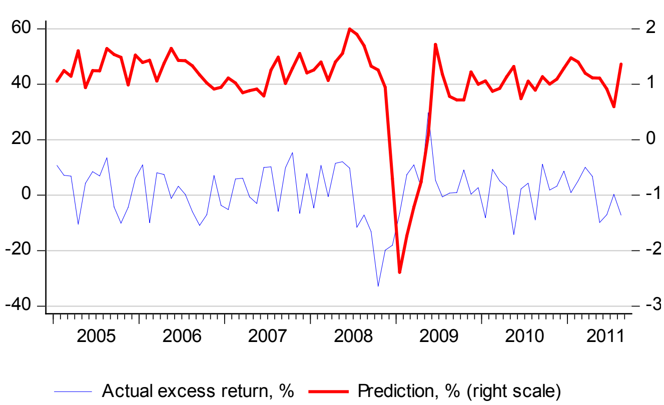
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 54: Predictive returns vs. actual returns, commodities



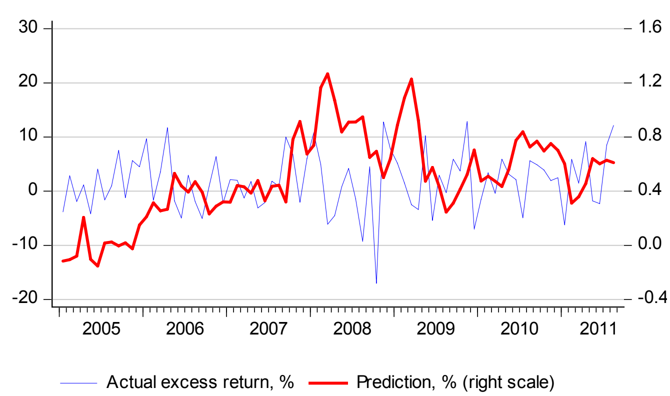
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 55: Predictive returns vs. actual returns, crude oil



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 56: Predictive returns vs. actual returns, gold



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Asset risk estimation models

As shown in Luo, Cahan, Alvarez, Jussa, and Chen [2011a], better risk models can help not only improve a portfolio's risk estimate, but also lift a portfolio's Sharpe ratio. The focus of this research paper is on asset return prediction. Therefore, for illustration purpose, we show two simple covariance matrices: 1) a sample covariance matrix using expanding window; and 2) a covariance matrix using the single index (SF) model as in Luo, Cahan, Alvarez, Jussa, and Chen [2011a].

Sample covariance matrix

For N asset classes, the sample covariance matrix is a $N \times N$ matrix. The ith row and jth column element of the covariance matrix is given by:

$$COV(i,j) = \frac{1}{T-1}\sum_{t=1}^{T}\left(R_{i,t} - \overline{R}_i\right)\left(R_{j,t} - \overline{R}_j\right)$$

where,

T is the sample period,

$R_{i,t}$ is the excess return of asset i in period t ,and

$\overline{R}_i$ is the sample mean of asset i .

The sample covariance matrix has $(N \times (N+1))/2$ parameters. In our case, for six asset classes, we need to estimate 21 parameters every month.

Single index (SF) model

The industry standard risk models are typically based on multiple factors rather than a single factor. Using multiple factors in our context is, however, problematic. We are not estimating a stock return covariance matrix where we typically have thousands of stocks; rather, we are estimating an asset covariance matrix where we tend to have only a handful of asset classes. We are essentially looking for a "hyper" index (or indices) that asset classes are built upon. The dimension of factor space is typically small – in our case, we have six asset classes. Therefore, rather than using multiple factors, we choose a single "hyper" factor for simplicity.

The single factor model (Sharpe [1963]) assumes a single-factor linear model for N asset returns:

$$R_{it} = c + \beta_i R_{Ft} + \varepsilon_{it}$$

where,

R_{it} is the return of asset i in period t ,

R_{Ft} is index return in period t , and

ε_{it} is the idiosyncratic error term of asset i in period t .

On the stock level, R_{Ft} is typically assumed to be a broad-based index, e.g., S&P 500. In our application, because we are modeling factor returns, there is no intuitive reason why a broad-based equity index should be the driver of factor returns. On the other hand, we can probably argue that market sentiment (as measured by the VIX index) is a common driver behind many asset classes (see Luo, Cahan, Jussa, and Alvarez [2010b]).

In the SF model, the regression residuals are assumed to be homoscedastic and cross-sectionally uncorrelated, i.e.,

$$\varepsilon \sim (0, \Psi)$$

All off-diagonal elements in Ψ are zero. The idiosyncratic risks of the assets are reflected by the diagonal elements of Ψ. Therefore, the covariance matrix S based on SF model can be calculated as:

$$S = \beta\beta' m_0^{(2)} + \Psi$$

Where,

β is the $N \times 1$ vector of the regression coefficients, and

$m_0^{(2)}$ is the variance of the single factor.

The structure of the $N \times N$ covariance matrix Ψ of residual returns is:

$\psi_{ii} = E\left(\varepsilon_i^2\right)$, and

$\psi_{ij} = 0$, when $i \neq j$

A sample estimate of ψ_{ii} is:

$$\hat{\psi}_{ii} = \frac{1}{T}\sum_{t=1}^{T}\hat{\varepsilon}_{it}^2$$

where,

$\hat{\varepsilon}_{it}$ is the regression residual of asset i in period t.

In the SF model, we need to estimate $2N+1$ parameters (N beta coefficients for the N factors, N idiosyncratic variance of the N factors, and 1 variance parameter for the single factor). In our six-asset example, we need to estimate 13 parameters (as oppose to 21 in the sample covariance case).

Figure 57 and Figure 58 show the current sample and SF covariance matrices. They are somewhat similar – the SF matrix seems to be a "shrunk" version of sample covariance matrix. The benefit of a structured model is probably limited in our example, as we have only six asset classes –dimensionality is already small.

Figure 57: Sample correlation matrix

	Equity	Bond	High Yield	Commodities	Crude Oil	Gold
Equity	100%					
Bond	(14.9%)	100%				
High Yield	71%	4%	100%			
Commodities	13%	(7.1%)	27%	100%		
Crude Oil	2%	(12.0%)	22%	88%	100%	
Gold	(8.5%)	37%	8%	24%	22%	100%

Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 58: Single-index (SF) correlation matrix

	Equity	Bond	High Yield	Commodities	Crude Oil	Gold
Equity	100%					
Bond	(6.5%)	100%				
High Yield	31%	(5.0%)	100%			
Commodities	8%	(1.3%)	7%	100%		
Crude Oil	4%	(0.7%)	3%	1%	100%	
Gold	(1.6%)	0%	(1.3%)	(0.3%)	(0.2%)	100%

Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

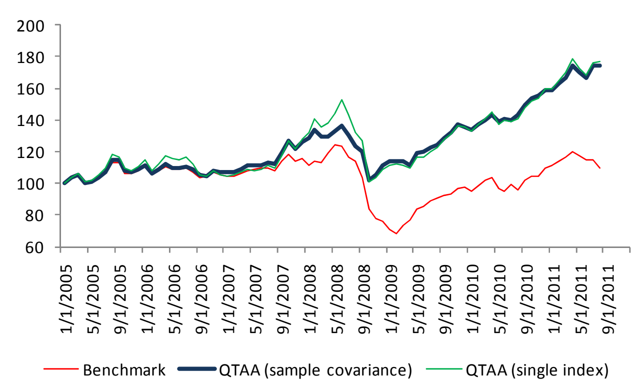
Portfolio construction for QTAA

We are currently working on a research project where we compare mean-variance optimization, minimum variance, and risk parity in the asset allocation decisions. For the purpose of this paper, we use a fairly simple mean-variance optimization to determine the optimal weighting of each asset in our portfolio. The benchmark portfolio is constructed using the same variance-covariance matrix and portfolio construction techniques.

While most academic research on TAA replies primarily on some naïve portfolio construction techniques, e.g., overweighting certain asset classes that are expected to outperform by a fixed percentage point, we construct our QTAA portfolio by mean-variance optimization. The objective is to maximize expected returns, subject to certain risk budget. We intentionally keep our constraints as simple as possible. The only constraint in our optimizer is maximum and minimum holding constraint – we do not short any asset class and the maximum we can hold for any particular asset class is no more than 50%.

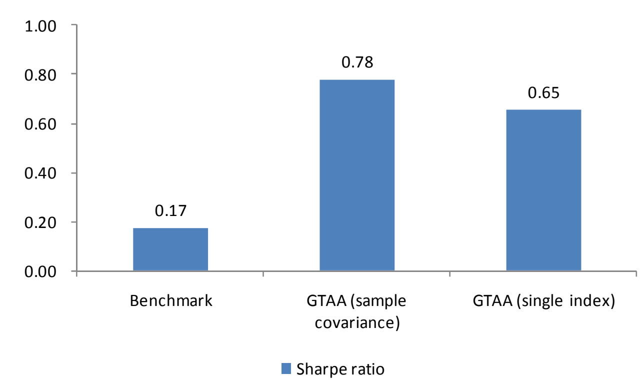
Figure 59 shows the cumulative performance of our QTAA strategy, compared to the benchmark. In our case, the choice of covariance matrix seems to make little difference. Return prediction largely determines our strategy performance. Our QTAA strategy outperforms the benchmark by the most in market turning points and performs in line with the benchmark in "normal" market environment. As shown in Figure 60, our QTAA model has a Sharpe ratio of 0.78, compared to the benchmark of 0.17, or more than 4.5x times higher than the benchmark. Our strategy also appears to outperform the benchmark in terms of Sortino ratio (see Figure 61) and has lower maximum drawdown (see Figure 62) and tail risk (measured by conditional VaR or expected shortfall). Our QTAA model has higher turnover (see Figure 63). On average, compared to the benchmark, our strategy holds less equity/fixed income/commodities, and more gold/high yield/crude oil (see Figure 64 to Figure 66).

Figure 59: Cumulative performance



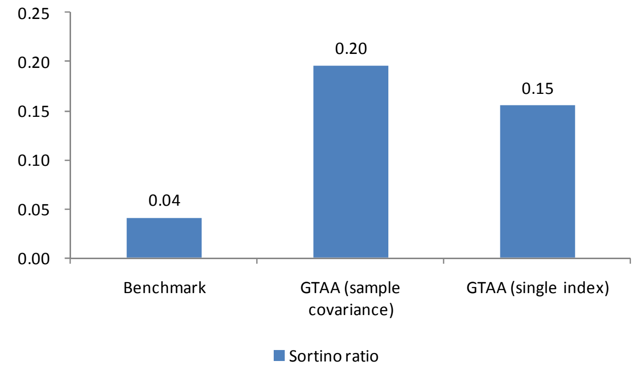
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 60: Sharpe ratio



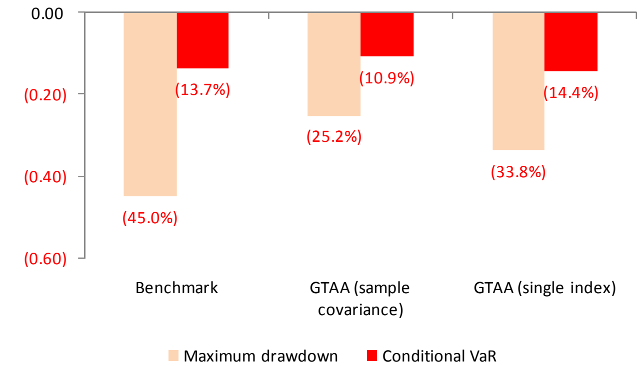
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 61: Sortino ratio



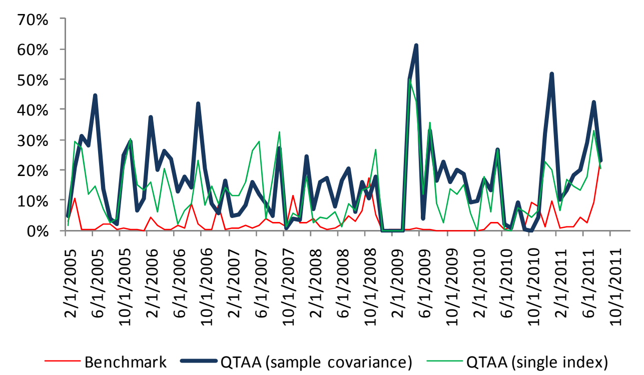
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 62: Maximum drawdown and conditional VaR



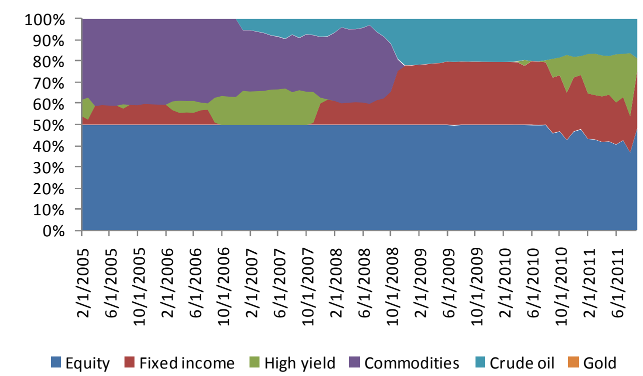
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 63: Turnover summary



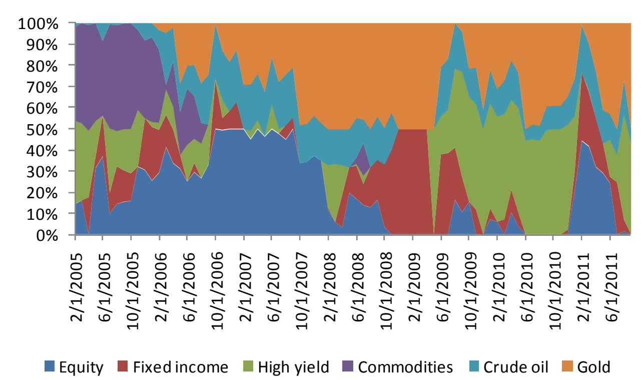
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 64: Asset weight – benchmark



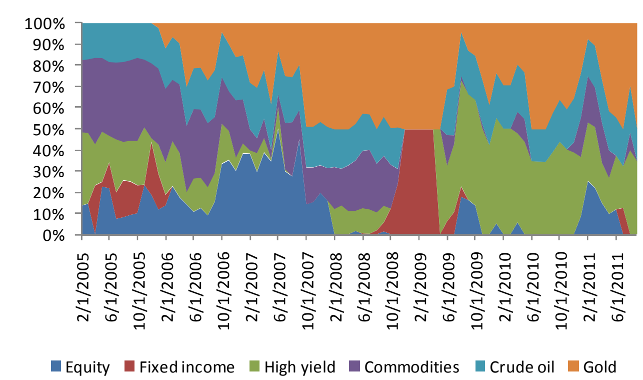
Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 65: Asset weight – sample covariance matrix



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Figure 66: Asset weight – single index covariance matrix



Source: Bloomberg Finance LLP, Compustat, Haver, IBES, S&P, Thomson Reuters, Deutsche Bank Quantitative Strategy

Future research

We intentionally leave out a few important areas for future research.

More asset classes

In this research, we have covered some limited space outside of the US market (European equity market, German equity market, French equity market, and Canadian equity market). We plan to include more countries (both equity and fixed income), more asset classes (e.g., REITs, TIPs), and style/sector/industry rotation strategies in the future[14].

More return prediction techniques

The current research focus primarily on time-series prediction of asset returns. In recent years, there are some interesting discussions on modeling GTAA strategies using cross-sectional models (see Blitz and van Vliet [2008] for example). We also exclusively rely on linear time series regression in this research. As shown in Luo, Cahan, Jussa, and Alvarez [2010], other nonlinear time series models or machine learning techniques can also be useful in return prediction.

Better risk models for asset allocation

As shown in Luo, Cahan, Alvarez, Jussa, and Chen [2011a], better risk models can help not only improve a portfolio's risk estimate, but also lift a portfolio's Sharpe ratio.

Better portfolio construction techniques

We are currently researching on comparing mean-variance optimization, minimum variance, and risk parity in asset allocation decisions. As shown in Luo, Cahan, Alvarez, Jussa, and Chen [2011b], incorporating tail risk in portfolio construction can not only effectively reduce a portfolio's downside risk, but also improve a portfolio's Sharpe ratio.

[14] Please note that we have a separate model for style rotation – see Luo, Y., Cahan, R., Jussa, J., and Alvarez, M. [2010b]. "GTAA/Signal Processing: Style Rotation", Deutsche Bank Quantitative Strategy, September 7, 2010 for details. Our European quant team also has a country rotation model – see Mesomeris, S., Salvini, M., and Kassam, A. [2010]. "Macromomentum Country Rotation", Deutsche Bank Quantitative Strategy, August 15, 2010 for details.

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Appendix A – List of factors

Figure 67: List of macroeconomic variables

Consumer credit, MoM	Surprise, Consumer credit, MoM
Personal consumption expenditures, MoM	Surprise, Personal consumption expenditures, MoM
Industrial production, MoM	Surprise, Industrial production, MoM
Capacity utilization rate	Surprise, Capacity utilization rate
Housing starts	Surprise, Housing starts
Consumer price index, MoM	Surprise, Consumer price index, MoM
Core CPI, MoM	Surprise, Core CPI, MoM
Producer price index, MoM	Surprise, Producer price index, MoM
Employees on nonfarm payrolls, MoM	Surprise, Employees on nonfarm payrolls, MoM
Unemployment rate	Surprise, Unemployment rate
Initial claims	Surprise, Initial claims
New orders, MoM	Surprise, New orders, MoM
Manufacturers' new orders: durable goods	Surprise, Manufacturers' new orders: durable goods
Factory inventories, MoM	Surprise, Factory inventories, MoM
Retail sales, MoM	Surprise, Retail sales, MoM
Consumer confidence	Surprise, Consumer confidence
Composite index of leading indicators, MoM	Surprise, Composite index of leading indicators, MoM
ISM: Mfg composite index	Surprise, ISM: Mfg composite index
ISM: Non-mfg composite index	Surprise, ISM: Non-mfg composite index
ISM: Non-mfg business activity index	Surprise, ISM: Non-mfg business activity index

Source: Deutsche Bank Quantitative Strategy

Figure 68: List of capital market and seasonal variables

Capital market variables	Seasonal variables
Lagged S&P 500 index return	January indicator
Lagged Russell 1000 index return	Quarter-ending month indicator
Lagged VIX level	December indicator
Lagged VIX, MoM	First quarter indicator
Lagged put/call ratio	Time trend
Lagged short-term interest rate	Time trend squared
Lagged long-term interest rate	Variance risk premium
Lagged yield spread	
Lagged credit spread	
Lagged commodities index	
Lagged crude oil	
Lagged trade-weighted USD	

Source: Deutsche Bank

Figure 69: List of fundamental variables

Dividend yield, trailing 12M	IBES FY1 Mean DPS Revision, 3M
Expected dividend yield	IBES FY1 Mean ROE Revision, 3M
Price-to-operating EPS, trailing 12M, Basic	Recommendation, mean
Operating earnings yield, trailing 12M, Basic	Mean recommendation revision, 3M
Earnings yield, forecast FY1 mean	Target price implied return
Earnings yield, forecast FY2 mean	Mean target price revision, 3M
Earnings yield x IBES 5Y growth	ROE, trailing 12M
Sector-relative Operating earnings yield, trailing 12M, Basic	Return on invested capital (ROIC)
History-relative Operating earnings yield, trailing 12M, Basic	Sales to total assets (asset turnover)
Operating cash flow yield (income stmt def)	Operating profit margin
Cash flow yield, FY1 mean	Current ratio
Free cash flow yield	Long-term debt/equity
Price-to-sales, trailing 12M	Altman's z-score
Price-to-book	Merton's distance to default
EBITDA/EV	Ohlson default model
Price-to-book adj for ROE, sector adj	Campbell, Hilscher, and Szilagyi model
Hist 5Y operating EPS growth	Accruals (Sloan 1996 def)
Hist 5Y operating EPS acceleration	Firm-specific discretionary accruals
IBES 5Y EPS growth	Hist 5Y operating EPS stability, coef of determination
IBES 5Y EPS growth/stability	IBES 5Y EPS stability
IBES LTG EPS mean	IBES FY1 EPS dispersion
IBES FY2 mean DPS growth	Payout on trailing operating EPS
IBES FY1 mean EPS growth	YoY change in # of shares outstanding
Year-over-year quarterly EPS growth	YoY change in debt outstanding
IBES FY1 mean CFPS growth	Net external financing/net operating assets
IBES SUE, amortized	Piotroski's F-score
Total return, 1D	Mohanram's G-score
Total return, 21D (1M)	# of days to cover short
Maximum daily return in last 1M (lottery factor)	CAPM beta, 5Y monthly
21D volatility of volume/price	CAPM idosyncratic vol, 1Y daily
Total return, 252D (12M)	Realized vol, 1Y daily
12M-1M total return	Skewness, 1Y daily
Price-to-52 week high	Kurtosis, 1Y daily
Total return, 1260D (60M)	Idiosyncratic vol surprise
IBES LTG Mean EPS Revision, 3M	Normalized abnormal volume
IBES FY1 Mean EPS Revision, 3M	Float turnover, 12M
IBES FY1 EPS up/down ratio, 3M	Moving average crossover, 15W-36W
Expectation gap, short-term - long-term	Log float-adj capitalization
IBES FY1 Mean CFPS Revision, 3M	# of month in the database
IBES FY1 Mean SAL Revision, 3M	DB composite options factor

Source: Deutsche Bank

Appendix B – Factor performance review

In this section we present our standard factor performance tables

Every month, we review the performance of about 80 factors from our factor library. Please note that this is only a tiny fraction of our factor library, which includes over 1,200 factors for the US market. We choose these 80 factors to provide a balanced view for each broad factor category.

We measure factor performance in five standard analyses: long/short hedged portfolio, Pearson information coefficient, Spearman rank IC, sector-neutral IC, and risk-adjusted IC. For simplicity, we only present Spearman rank IC in this report.

Due to space limitation, we will only present the results for the broad investable universe, two size (Russell 1000 and Russell 2000), two style (Russell 3000 Value and Russell 3000 Growth) universes, and 10 GICS sectors on a monthly basis. However, we perform factor backtesting for more sub-universes on a daily basis, e.g., S&P index family, GICS industry groups, etc. We plan to publish a factor performance review on our research website in the next few months. In the meantime, please contact us for customized factor backtesting.

The tables in the next few pages reveal a large amount of useful information. Not only do we summarize recent factor performance (last month, last year, last three years), but also provide factor distribution (standard deviation, skewness, kurtosis, percent positive, performance in up and down markets), along with factor turnover (factor score serial correlation).

Figure 70: US factor performance, Spearman rank IC

Factor Name	Direction[1]	Current # of Stocks	Average (%) Last M	Average (%) 12M Avg	Average (%) 3Y Avg	Since Inception Avg	Std Dev	Max	Min	p-value[2]	# of Months	Avg # of Stocks	%Positive	Avg in Up Mkt (%)	Avg in Dn Mkt (%)	Serial Corr (%)[3]
1. Value																
1 Dividend yield, trailing 12M	Ascending	2,955	26.46	(0.37)	1.47	2.73	14.80	42.92	(32.80)	0.00	284	2,813	54.93	(2.62)	12.00	99.29
2 Expected dividend yield	Ascending	2,955	27.00	0.03	1.63	2.98	15.13	43.91	(33.31)	0.00	284	2,813	54.23	(2.58)	12.61	99.30
3 Price-to-operating EPS, trailing 12M, Basic	Descending	2,334	2.95	(0.81)	1.60	2.91	10.75	30.95	(31.06)	0.00	199	2,376	59.30	0.93	6.33	95.13
4 Operating earnings yield, trailing 12M, Basic	Ascending	2,935	19.63	3.18	2.80	4.79	13.51	46.11	(33.51)	0.00	199	2,884	60.80	(0.29)	13.54	96.21
5 Earnings yield, forecast FY1 mean	Ascending	2,789	12.79	2.96	1.85	4.41	12.52	47.77	(34.46)	0.00	284	2,530	63.03	0.93	10.43	94.99
6 Earnings yield, forecast FY2 mean	Ascending	2,791	0.01	2.33	1.99	3.98	12.01	45.95	(33.92)	0.00	284	2,427	63.73	1.74	7.86	94.23
7 Earnings yield x IBES 5Y growth	Ascending	1,824	(11.46)	1.55	0.95	1.77	10.35	41.21	(27.88)	0.02	199	1,966	60.30	4.15	(2.34)	93.48
8 Sector-rel Operating earnings yield, trailing 12M, Basic	Ascending	2,935	15.83	3.49	2.70	4.09	8.61	28.32	(15.77)	0.00	199	2,884	66.83	1.16	9.15	95.73
9 Hist-rel Operating earnings yield, trailing 12M, Basic	Ascending	2,618	0.55	(1.11)	(0.03)	0.72	6.99	17.07	(17.53)	0.19	164	2,501	52.44	0.47	1.09	93.31
10 Operating cash flow yield (income stmt def)	Ascending	2,937	8.13	3.38	2.02	4.10	11.33	46.10	(32.95)	0.00	284	2,768	65.14	0.98	9.50	95.70
11 Cash flow yield, FY1 mean	Ascending	1,601	(7.48)	1.51	1.16	1.66	13.60	35.60	(48.02)	0.08	206	872	56.80	1.01	2.80	96.32
12 Free cash flow yield	Ascending	2,884	5.29	2.64	2.23	4.84	8.16	32.78	(19.42)	0.00	247	2,522	73.68	2.45	9.09	94.46
13 Price-to-sales, trailing 12M	Descending	2,901	(11.30)	0.48	1.61	1.95	11.10	40.35	(29.56)	0.00	284	2,746	56.69	1.70	2.37	99.06
14 Price-to-book	Descending	2,847	(5.12)	(3.25)	(0.06)	0.98	10.92	34.65	(25.64)	0.13	284	2,729	50.35	(0.14)	2.92	97.49
15 EBITDA/EV	Ascending	2,571	10.57	3.16	1.80	4.17	10.43	40.18	(27.79)	0.00	284	2,430	65.49	1.22	9.29	95.18
16 Price-to-book adj for ROE, sector adj	Descending	2,695	(11.66)	(1.90)	0.27	0.59	8.82	32.65	(21.81)	0.26	284	2,454	50.00	1.04	(0.18)	95.32
2. Growth																
17 Hist 5Y operating EPS growth	Descending	2,813	17.98	2.73	1.18	0.73	7.57	20.16	(20.78)	0.18	192	2,651	53.65	(1.12)	3.75	97.11
18 Hist 5Y operating EPS acceleration	Ascending	2,813	(10.50)	(2.83)	(1.97)	0.92	6.32	14.08	(17.05)	0.05	192	2,651	58.33	0.19	2.10	94.32
19 IBES 5Y EPS growth	Ascending	1,896	22.26	4.10	1.26	0.75	8.93	23.00	(30.49)	0.16	284	1,884	54.23	1.97	(1.35)	98.23
20 IBES 5Y EPS growth/stability	Ascending	1,896	22.66	3.96	1.62	1.22	8.21	22.66	(21.21)	0.01	284	1,884	55.63	0.97	1.67	98.60
21 IBES LTG EPS mean	Descending	2,130	12.79	(3.23)	(0.48)	1.83	16.25	52.30	(37.37)	0.06	284	2,157	48.94	(3.85)	11.66	97.98
22 IBES FY2 mean DPS growth	Ascending	2,049	14.39	(0.31)	0.97	0.76	8.53	23.79	(20.93)	0.35	111	1,405	52.25	(3.03)	7.24	87.99
23 IBES FY1 mean EPS growth	Ascending	2,083	(14.28)	1.44	(1.96)	0.71	8.41	21.40	(29.20)	0.15	284	2,140	58.80	2.19	(1.84)	88.75
24 Year-over-year quarterly EPS growth	Ascending	2,926	0.27	3.71	0.06	2.32	7.13	24.40	(21.05)	0.00	199	2,893	67.84	2.29	2.38	81.15
25 IBES FY1 mean CFPS growth	Descending	1,471	3.94	(0.33)	1.90	0.19	10.73	41.86	(26.89)	0.83	156	565	51.28	(0.36)	1.15	92.50
26 IBES SUE, amortized	Ascending	2,495	2.45	2.16	(0.07)	1.31	6.20	20.01	(15.76)	0.00	222	2,283	59.91	2.00	0.12	73.49
3. Price momentum and reversal																
27 Total return, 1D	Descending	2,955	4.92	3.89	3.33	5.06	7.09	34.06	(15.49)	0.00	284	2,770	78.87	5.05	5.09	1.67
28 Total return, 21D (1M)	Descending	2,955	(3.83)	0.46	0.74	2.09	10.74	41.84	(27.50)	0.00	284	2,769	59.15	3.84	(0.93)	0.21
29 Maximum daily return in last 1M (lottery factor)	Descending	2,949	27.86	1.30	2.73	5.00	14.97	55.32	(38.37)	0.00	284	2,647	64.08	(1.13)	15.61	51.94
30 21D volatility of volume/price	Descending	2,949	8.08	1.90	1.50	0.39	6.91	17.88	(24.64)	0.34	284	2,647	51.06	1.18	(0.98)	55.60
31 Total return, 252D (12M)	Ascending	2,862	3.24	2.99	(1.54)	2.82	14.02	38.82	(55.90)	0.00	284	2,691	61.62	1.31	5.43	89.08
32 12M-1M total return	Ascending	2,862	2.22	3.28	(0.81)	3.71	13.19	37.32	(48.47)	0.00	284	2,691	65.14	2.75	5.36	87.65
33 Price-to-52 week high	Ascending	2,890	26.41	2.91	(0.69)	3.16	16.47	48.47	(58.28)	0.00	284	2,707	62.68	(2.44)	12.86	82.71
34 Total return, 1260D (60M)	Ascending	2,475	23.68	4.86	(0.03)	0.90	10.81	23.93	(34.21)	0.17	272	2,137	55.51	0.27	1.99	97.18

Note

1 Direction indicates how the factor scores are sorted. Ascending order means higher factor scores are likely to be associated with higher subsequent stock returns, and vice versa for descending order.
2 P-value indicates the statistical significance of a factor's performance. A smaller p-value suggests that it is more likely the factor's performance is different from zero.
3 This is the autocorrelation of a factor's scores over time. Higher serial correlation is likely to have lower portfolio turnover based on the factor.

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

Figure 70: US factor performance, Spearman rank IC (cont'd)

		Current	Average (%)			Since Inception										
Factor Name	Direction[1]	# of Stocks	Last M	12M Avg	3Y Avg	Avg	Std Dev	Max	Min	p-value[2]	# of Months	Avg # of Stocks	%Positive	Avg in Up Mkt (%)	Avg in Dn Mkt (%)	Serial Corr (%)[3]
4. Sentiment																
35 IBES LTG Mean EPS Revision, 3M	Ascending	1,968	1.14	0.96	(0.23)	0.84	3.90	12.24	(12.34)	0.00	284	2,080	61.62	0.62	1.21	59.24
36 IBES FY1 Mean EPS Revision, 3M	Ascending	2,724	3.04	2.71	0.02	2.84	8.59	26.35	(32.95)	0.00	284	2,468	66.20	2.51	3.40	76.11
37 IBES FY1 EPS up/down ratio, 3M	Ascending	2,710	4.15	3.12	0.61	3.09	7.93	24.00	(24.67)	0.00	284	2,327	65.85	3.38	2.59	79.68
38 Expectation gap, short-term - long-term	Ascending	2,083	(8.44)	1.27	(1.35)	1.22	5.17	15.55	(22.92)	0.00	284	2,137	65.49	1.32	1.04	87.32
39 IBES FY1 Mean CFPS Revision, 3M	Ascending	1,430	5.52	2.12	(0.14)	0.89	10.29	29.49	(37.12)	0.22	198	804	62.12	(0.10)	2.60	65.27
40 IBES FY1 Mean SAL Revision, 3M	Ascending	2,696	0.82	2.86	0.11	1.08	7.90	27.89	(24.31)	0.07	182	2,141	60.44	0.61	1.80	71.39
41 IBES FY1 Mean FFO Revision, 3M	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
42 IBES FY1 Mean DPS Revision, 3M	Ascending	1,120	0.75	2.52	0.53	0.57	5.35	15.47	(16.80)	0.27	108	971	58.33	0.34	0.97	61.59
43 IBES FY1 Mean ROE Revision, 3M	Ascending	2,040	1.22	1.97	0.69	0.73	6.73	21.19	(21.55)	0.26	108	1,693	59.26	0.06	1.92	66.39
44 Recommendation, mean	Descending	2,128	(9.00)	4.32	0.63	0.83	8.39	21.84	(23.50)	0.15	213	2,274	56.34	2.63	(2.28)	94.27
45 Mean recommendation revision, 3M	Descending	1,971	(8.95)	0.09	0.31	1.27	4.31	11.94	(19.67)	0.00	210	2,196	63.81	1.19	1.42	60.07
46 Target price implied return	Ascending	2,122	(30.36)	2.40	1.95	0.80	16.57	61.59	(38.29)	0.56	149	2,093	54.36	8.79	(10.43)	78.35
47 Mean target price revision, 3M	Ascending	1,962	14.38	2.33	(0.24)	2.00	13.59	30.54	(43.72)	0.08	146	2,003	62.33	(0.59)	5.60	75.67
5. Quality																
48 ROE, trailing 12M	Ascending	2,833	21.13	4.78	2.84	4.19	11.20	35.70	(31.83)	0.00	199	2,813	63.82	0.28	10.93	97.90
49 Return on invested capital (ROIC)	Ascending	2,920	22.02	5.05	3.05	4.04	10.24	31.79	(29.65)	0.00	199	2,875	64.32	0.54	10.08	98.09
50 Sales to total assets (asset turnover)	Ascending	2,936	(2.74)	5.03	3.29	1.60	8.92	22.87	(22.20)	0.00	284	2,766	57.39	2.50	0.04	99.43
51 Operating profit margin	Ascending	2,879	8.50	1.34	1.25	1.12	5.37	16.03	(14.20)	0.00	284	2,601	60.21	0.69	1.87	98.43
52 Current ratio	Descending	2,339	1.18	(0.57)	0.00	1.92	10.51	38.59	(31.29)	0.00	284	2,230	54.93	(0.99)	6.96	97.85
53 Long-term debt/equity	Ascending	2,809	(0.62)	(0.52)	(0.07)	0.64	9.71	35.17	(27.71)	0.26	284	2,705	47.18	(1.24)	3.90	98.49
54 Altman's z-score	Ascending	2,307	12.11	2.66	0.89	0.08	9.36	31.81	(30.14)	0.88	284	2,160	49.65	0.72	(1.01)	98.21
55 Merton's distance to default	Ascending	2,147	32.36	3.97	2.19	3.12	11.61	32.36	(42.82)	0.00	284	2,125	65.49	(0.83)	9.95	94.73
56 Ohlson default model	Descending	2,277	15.64	3.63	1.41	2.13	6.24	18.39	(15.67)	0.00	247	2,108	65.99	1.47	3.29	98.09
57 Campbell, Hilscher, and Szilagyi model	Descending	2,597	19.91	4.55	1.90	2.57	11.78	26.12	(36.73)	0.00	200	2,535	57.00	(1.13)	9.01	97.01
58 Accruals (Sloan 1996 def)	Descending	1,559	(2.67)	0.05	0.09	0.60	4.36	13.91	(11.24)	0.02	284	1,405	56.69	0.66	0.49	89.08
59 Firm-specific discretionary accruals	Descending	1,467	3.32	1.06	0.95	0.50	4.21	13.84	(11.48)	0.11	191	1,350	51.83	0.03	1.25	98.54
60 Hist 5Y operating EPS stability, coef of determination	Ascending	2,813	1.54	0.48	(0.73)	0.51	4.92	13.29	(12.22)	0.15	192	2,651	53.13	0.32	0.82	96.62
61 IBES 5Y EPS stability	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
62 IBES FY1 EPS dispersion	Descending	2,605	28.69	5.75	2.45	2.37	10.42	28.69	(35.89)	0.00	284	2,309	61.27	(0.60)	7.51	84.86
63 Payout on trailing operating EPS	Ascending	2,260	24.44	(1.81)	0.26	0.72	13.78	38.96	(30.80)	0.38	284	2,197	50.35	(4.22)	9.26	99.22
64 YoY change in # of shares outstanding	Descending	2,886	16.89	2.83	2.38	2.59	9.02	45.66	(18.80)	0.00	284	2,716	58.80	(0.88)	8.58	93.87
65 YoY change in debt outstanding	Descending	2,187	(7.06)	(0.56)	(0.53)	0.29	4.12	10.47	(12.60)	0.24	284	2,173	55.99	1.03	(1.01)	89.68
66 Net external financing/net operating assets	Ascending	2,873	6.30	1.56	1.73	2.83	10.20	47.77	(27.56)	0.00	284	2,462	58.10	(0.31)	8.27	94.73
67 Piotroski's F-score	Ascending	2,186	5.90	2.30	(0.21)	3.01	10.97	36.04	(30.75)	0.00	199	2,150	59.80	(1.24)	10.36	90.35
68 Mohanram's G-score	Ascending	584	16.31	2.61	2.14	2.12	8.80	23.29	(28.58)	0.00	199	449	57.79	(0.06)	5.86	94.88
6. Technicals																
69 # of days to cover short	Descending	2,955	0.91	1.95	1.93	2.54	9.50	25.27	(33.83)	0.01	101	2,891	55.45	3.37	0.98	93.05
70 CAPM beta, 5Y monthly	Descending	2,646	33.80	(0.38)	(0.84)	0.96	17.24	47.46	(46.59)	0.41	224	2,280	47.32	(7.41)	15.44	98.69
71 CAPM idosyncratic vol, 1Y daily	Descending	2,889	33.80	3.13	2.92	4.78	17.93	57.92	(39.71)	0.00	284	2,664	60.92	(2.00)	16.50	99.14
72 Realized vol, 1Y daily	Descending	2,889	37.13	2.63	2.52	4.68	18.58	59.23	(40.14)	0.00	284	2,664	60.21	(2.69)	17.44	99.07
73 Skewness, 1Y daily	Descending	2,889	5.94	0.24	0.28	1.13	5.40	20.19	(14.38)	0.00	284	2,664	56.69	0.55	2.13	89.56
74 Kurtosis, 1Y daily	Descending	2,889	3.87	1.50	0.96	1.34	5.69	16.79	(15.27)	0.00	284	2,664	62.32	0.92	2.06	91.23
75 Idiosyncratic vol surprise	Descending	2,875	19.26	4.51	2.30	2.82	7.51	26.30	(26.53)	0.00	283	2,651	66.43	0.90	6.12	86.57
76 Normalized abnormal volume	Ascending	2,955	10.96	2.42	2.00	1.08	6.88	20.03	(20.63)	0.01	284	2,807	59.15	2.45	(1.29)	81.56
77 Float turnover, 12M	Descending	2,955	16.36	0.88	(0.70)	2.09	15.97	55.05	(36.72)	0.03	284	2,818	50.35	(5.00)	14.36	99.19
78 Moving average crossover, 15W-36W	Ascending	2,857	11.10	0.46	(1.09)	2.06	13.22	44.24	(52.53)	0.01	284	2,398	59.15	0.67	4.47	90.75
79 Log float-adj capitalization	Ascending	2,955	18.01	3.51	2.73	3.00	10.94	26.56	(38.42)	0.00	284	2,813	60.92	2.55	3.78	99.35
80 # of month in the database	Ascending	2,955	11.46	1.16	1.64	2.20	8.19	35.34	(21.02)	0.00	259	2,818	59.07	(0.35)	6.60	88.46
81 DB composite options factor	Ascending	1,573	(0.30)	1.74	1.53	1.91	4.67	14.68	(18.88)	0.00	121	1,467	67.77	0.91	3.49	2.25

Note

1 Direction indicates how the factor scores are sorted. Ascending order means higher factor scores are likely to be associated with higher subsequent stock returns, and vice versa for descending order.
2 P-value indicates the statistical significance of a factor's performance. A smaller p-value suggests that it is more likely the factor's performance is different from zero.
3 This is the autocorrelation of a factor's scores over time. Higher serial correlation is likely to have lower portfolio turnover based on the factor.

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

Figure 71: Factor performance by size and style index

Factor Name	Last Month					Three-year				
	Universe	Russell 1000	Russell 2000	Russell 3K Value	Russell 3K Growth	Universe	Russell 1000	Russell 2000	Russell 3K Value	Russell 3K Growth
1. Value										
1 Dividend yield, trailing 12M	26.46	28.07	23.90	32.46	22.99	1.47	1.62	0.87	1.88	2.12
2 Expected dividend yield	27.00	28.87	24.47	33.36	22.97	1.63	1.26	1.18	2.03	2.06
3 Price-to-operating EPS, trailing 12M, Basic	2.95	(0.51)	4.46	4.13	1.29	1.60	1.07	1.55	2.49	1.05
4 Operating earnings yield, trailing 12M, Basic	19.63	6.61	22.56	21.87	16.40	2.80	0.94	3.10	2.90	2.64
5 Earnings yield, forecast FY1 mean	12.79	(2.83)	16.52	15.13	7.67	1.85	(1.36)	2.66	2.15	1.69
6 Earnings yield, forecast FY2 mean	0.01	(17.89)	5.21	1.14	(3.71)	1.99	(0.80)	2.76	2.66	1.67
7 Earnings yield x IBES 5Y growth	(11.46)	(22.11)	(3.85)	(16.25)	(4.80)	0.95	0.03	1.48	1.33	0.72
8 Sector-rel Operating earnings yield, trailing 12M, Basic	15.83	(0.90)	19.83	17.65	12.77	2.70	0.71	3.14	2.46	2.97
9 Hist-rel Operating earnings yield, trailing 12M, Basic	0.55	0.16	0.96	1.40	(0.72)	(0.03)	(1.01)	0.16	0.36	0.69
10 Operating cash flow yield (income stmt def)	8.13	(4.58)	10.89	9.89	3.73	2.02	0.70	2.25	2.32	1.57
11 Cash flow yield, FY1 mean	(7.48)	(9.38)	(9.26)	(5.33)	(11.28)	1.16	0.65	1.41	1.95	0.38
12 Free cash flow yield	5.29	(5.05)	7.44	4.14	9.69	2.23	0.32	2.81	1.30	3.57
13 Price-to-sales, trailing 12M	(11.30)	(11.92)	(10.73)	(14.98)	(9.08)	1.61	1.66	1.75	2.22	1.81
14 Price-to-book	(5.12)	(11.39)	(0.18)	(7.27)	(6.66)	(0.06)	(0.34)	0.44	0.11	0.80
15 EBITDA/EV	10.57	0.87	11.88	11.13	8.13	1.80	0.58	1.95	1.69	1.46
16 Price-to-book adj for ROE, sector adj	(11.66)	(12.45)	(9.46)	(18.55)	(9.46)	0.27	0.25	0.61	0.89	0.32
2. Growth										
17 Hist 5Y operating EPS growth	17.98	(21.05)	14.30	18.55	18.53	1.18	(0.04)	1.28	1.05	0.13
18 Hist 5Y operating EPS acceleration	(10.50)	(16.52)	(8.47)	(12.40)	(5.83)	(1.97)	(2.94)	(1.46)	(1.96)	(2.32)
19 IBES 5Y EPS growth	22.26	19.80	22.03	24.06	23.52	1.26	0.69	1.33	1.08	(0.08)
20 IBES 5Y EPS growth/stability	22.66	22.33	20.31	23.05	26.04	1.62	0.94	1.70	1.38	0.38
21 IBES LTG EPS mean	12.79	16.56	8.22	20.43	9.71	(0.48)	(0.10)	(1.02)	0.23	0.27
22 IBES FY2 mean DPS growth	14.39	(7.74)	15.79	14.75	18.33	0.97	0.07	1.29	1.21	0.61
23 IBES FY1 mean EPS growth	(14.28)	(21.48)	(9.73)	(15.59)	(12.63)	(1.96)	(3.27)	(1.42)	(1.83)	(2.19)
24 Year-over-year quarterly EPS growth	0.27	(7.20)	2.74	0.67	(1.95)	0.06	(1.87)	0.81	0.17	(0.33)
25 IBES FY1 mean CFPS growth	3.94	0.12	(7.30)	(1.94)	(4.90)	1.90	3.09	(0.94)	(1.95)	(2.32)
26 IBES SUE, amortized	2.45	(4.45)	2.79	(0.33)	4.77	(0.07)	(1.85)	0.47	(0.84)	0.19
3. Price momentum and reversal										
27 Total return, 1D	4.92	5.71	3.18	3.02	4.98	3.33	3.42	3.32	3.41	3.34
28 Total return, 21D (1M)	(3.83)	(6.52)	(3.08)	(6.58)	(1.23)	0.74	(0.22)	1.01	0.68	1.62
29 Maximum daily return in last 1M (lottery factor)	27.86	34.80	21.88	30.65	24.06	2.73	0.04	3.37	2.58	3.04
30 21D volatility of volume/price	8.08	(8.36)	(1.91)	6.92	8.71	1.50	0.26	(1.11)	1.45	1.31
31 Total return, 252D (12M)	3.24	(1.02)	3.90	6.45	(2.22)	(1.54)	(1.81)	(1.36)	(1.46)	(2.08)
32 12M-1M total return	2.22	(2.81)	2.92	4.88	(3.22)	(0.81)	(1.36)	(0.54)	(0.76)	(1.04)
33 Price-to-52 week high	26.41	30.73	22.42	30.86	22.64	(0.69)	(2.34)	(0.19)	(1.27)	(0.53)
34 Total return, 1260D (60M)	23.68	(20.09)	22.93	28.36	18.02	(0.03)	0.97	(0.13)	(0.32)	(1.01)
4. Sentiment										
35 IBES LTG Mean EPS Revision, 3M	1.14	(0.31)	0.87	(0.26)	2.93	(0.23)	(0.81)	0.38	(0.51)	0.39
36 IBES FY1 Mean EPS Revision, 3M	3.04	(5.28)	4.77	2.11	3.73	0.02	(2.24)	0.85	(0.25)	(0.00)
37 IBES FY1 EPS up/down ratio, 3M	4.15	(1.05)	4.14	2.87	6.34	0.61	(1.22)	1.19	0.18	0.92
38 Expectation gap, short-term - long-term	(8.44)	(11.03)	(6.90)	(8.42)	(7.76)	(1.35)	(2.32)	(0.95)	(0.91)	(1.75)
39 IBES FY1 Mean CFPS Revision, 3M	5.52	(0.20)	6.37	12.31	1.35	(0.14)	(1.57)	1.05	(0.21)	(0.34)
40 IBES FY1 Mean SAL Revision, 3M	0.82	4.15	2.18	1.17	(2.52)	0.11	1.67	0.89	(0.31)	0.56
41 IBES FY1 Mean FFO Revision, 3M	NA	NA	NA	11.16	NA	NA	NA	NA	4.93	NA
42 IBES FY1 Mean DPS Revision, 3M	0.75	(5.82)	6.21	2.16	(2.49)	0.53	(0.80)	1.90	0.84	0.56
43 IBES FY1 Mean ROE Revision, 3M	1.22	(2.65)	2.23	0.96	0.89	0.69	(1.25)	2.12	0.62	0.47
44 Recommendation, mean	(9.00)	(13.53)	(5.14)	(8.03)	(12.55)	0.63	(0.77)	1.43	1.08	(0.25)
45 Mean recommendation revision, 3M	(8.95)	(15.11)	(5.36)	(10.82)	(9.21)	0.31	(1.21)	0.98	0.22	0.07
46 Target price implied return	(30.36)	(35.74)	(26.16)	(35.05)	27.36	1.95	1.28	2.33	2.56	(1.40)
47 Mean target price revision, 3M	14.38	14.36	12.98	18.53	9.80	(0.24)	(0.74)	0.34	(0.38)	0.05
5. Quality										
48 ROE, trailing 12M	21.13	13.35	21.59	24.56	21.15	2.84	1.64	2.79	2.78	2.39
49 Return on invested capital (ROIC)	22.02	12.27	23.19	23.23	23.44	3.05	1.62	3.14	2.84	2.59
50 Sales to total assets (asset turnover)	(2.74)	0.11	(4.01)	(7.22)	3.33	3.29	3.23	3.37	3.49	2.60
51 Operating profit margin	8.50	5.16	10.00	8.96	11.75	1.25	0.36	1.62	0.08	1.94
52 Current ratio	1.18	3.93	(4.51)	6.76	(1.37)	0.00	(0.73)	(0.50)	(0.02)	(0.18)
53 Long-term debt/equity	(0.62)	1.77	(3.44)	3.85	(1.92)	(0.07)	0.39	(0.66)	0.37	0.17
54 Altman's z-score	12.11	6.41	15.28	4.83	18.68	0.89	0.92	1.17	0.28	1.23
55 Merton's distance to default	32.36	44.07	24.20	32.82	31.16	2.19	0.78	2.04	1.80	1.85
56 Ohlson default model	15.64	(4.04)	16.86	10.78	19.22	1.41	0.64	2.02	0.10	2.16
57 Campbell, Hilscher, and Szilagyi model	19.91	16.19	19.27	20.07	22.64	1.90	1.09	2.04	1.63	1.20
58 Accruals (Sloan 1996 def)	(2.67)	(2.96)	(2.96)	(0.91)	(1.70)	0.09	(0.57)	0.39	(0.49)	0.24
59 Firm-specific discretionary accruals	3.32	(2.93)	1.79	2.19	4.07	0.95	(0.88)	0.87	0.40	1.08
60 Hist 5Y operating EPS stability, coef of determination	1.54	4.24	(0.00)	(5.46)	9.89	(0.73)	(1.10)	(0.70)	(1.72)	(0.30)
61 IBES 5Y EPS stability	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
62 IBES FY1 EPS dispersion	28.69	30.60	24.80	29.25	30.91	2.45	1.27	2.74	2.08	2.30
63 Payout on trailing operating EPS	24.44	(27.89)	22.05	30.81	19.56	0.26	(0.70)	(0.38)	0.88	0.85
64 YoY change in # of shares outstanding	16.89	10.92	15.20	16.95	18.33	2.38	2.02	2.09	1.87	2.75
65 YoY change in debt outstanding	(7.06)	(6.74)	(3.78)	(6.99)	(6.48)	(0.53)	(0.09)	(0.10)	(0.80)	(0.38)
66 Net external financing/net operating assets	6.30	0.91	5.62	4.40	9.94	1.73	1.23	1.58	1.26	2.36
67 Piotroski's F-score	5.90	(0.90)	6.67	7.45	4.13	(0.21)	(0.86)	(0.12)	(0.48)	(0.06)
68 Mohanram's G-score	16.31	10.98	14.48	14.05	16.18	2.14	0.93	2.21	1.41	2.32
6. Technicals										
69 # of days to cover short	0.91	(8.97)	(9.02)	0.85	1.51	1.93	(0.19)	1.33	2.59	1.27
70 CAPM beta, 5Y monthly	33.80	(44.16)	28.38	(36.40)	30.82	(0.84)	1.34	(0.78)	1.05	0.11
71 CAPM idosyncratic vol, 1Y daily	33.80	37.57	30.71	38.69	29.33	2.92	0.59	3.18	2.60	3.20
72 Realized vol, 1Y daily	37.13	46.39	32.65	42.38	32.47	2.52	0.52	2.91	2.10	2.95
73 Skewness, 1Y daily	5.94	6.40	4.48	7.07	5.49	0.28	(2.08)	1.00	0.09	0.48
74 Kurtosis, 1Y daily	3.87	(3.18)	5.18	7.35	2.02	0.96	0.38	1.20	1.06	1.06
75 Idiosyncratic vol surprise	19.26	13.51	17.66	19.55	19.68	2.30	0.72	2.46	1.80	2.39
76 Normalized abnormal volume	10.96	8.51	(5.45)	10.97	11.12	2.00	(1.23)	(1.96)	1.92	2.02
77 Float turnover, 12M	16.36	31.13	16.30	17.37	13.59	(0.70)	0.41	(0.44)	(0.81)	(0.26)
78 Moving average crossover, 15W-36W	11.10	16.95	7.31	13.44	8.63	(1.09)	(1.91)	(0.46)	(1.67)	(0.73)
79 Log float-adj capitalization	18.01	(14.05)	13.61	16.86	21.17	2.73	1.88	2.26	2.56	2.76
80 # of month in the database	11.46	4.68	9.70	10.07	13.92	1.64	(0.47)	1.48	1.87	2.02
81 DB composite options factor	(0.30)	(8.53)	8.14	0.80	(1.80)	1.53	0.76	1.37	1.59	1.62

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

Figure 72: Factor performance by GICS sector

	Last Month										
Factor Name	Universe	Energy	Materials	Industrial	Consumer Disc	Consumer Staples	Health Care	Financials	Info Tech	Telecom Services	Utilities
1. Value											
1 Dividend yield, trailing 12M	26.46	22.32	8.19	17.42	15.65	30.05	21.72	25.14	25.39	32.68	33.51
2 Expected dividend yield	27.00	26.88	8.17	18.12	16.85	34.11	22.56	23.47	23.23	33.03	35.06
3 Price-to-operating EPS, trailing 12M, Basic	2.95	10.76	(15.16)	1.39	(12.08)	(6.56)	5.50	5.72	(0.87)	(13.43)	8.79
4 Operating earnings yield, trailing 12M, Basic	19.63	25.98	(5.12)	15.38	8.64	16.73	26.70	19.77	9.57	16.81	20.23
5 Earnings yield, forecast FY1 mean	12.79	23.25	(7.05)	6.05	7.22	(6.60)	23.71	12.10	4.05	17.64	9.75
6 Earnings yield, forecast FY2 mean	0.01	15.88	(19.07)	(15.45)	(0.80)	(21.55)	21.62	3.30	(7.69)	7.41	7.84
7 Earnings yield x IBES 5Y growth	(11.46)	1.36	(28.09)	0.61	(6.96)	(2.15)	(9.76)	(2.78)	(7.07)	(16.60)	11.98
8 Hist-rel Operating earnings yield, trailing 12M, Basic	0.55	2.40	12.79	18.59	(10.12)	7.35	7.22	(1.03)	5.77	(6.09)	(38.64)
9 Operating cash flow yield (income stmt def)	8.13	(0.82)	(7.76)	(0.48)	0.26	(1.28)	19.97	12.75	3.31	1.38	10.30
10 Cash flow yield, FY1 mean	(7.48)	(13.01)	(7.81)	(8.00)	(12.67)	(22.77)	0.71	(18.28)	(3.50)	(7.39)	(13.52)
11 Free cash flow yield	5.29	8.82	9.43	11.56	1.84	5.14	20.80	(15.80)	3.72	21.35	1.86
12 Price-to-sales, trailing 12M	(11.30)	(7.06)	(28.85)	(30.74)	(24.37)	(28.35)	4.04	(20.05)	(9.51)	(17.56)	(0.94)
13 Price-to-book	(5.12)	(8.54)	(12.25)	(18.38)	14.15	(25.93)	1.91	(16.50)	7.50	39.16	(17.54)
14 EBITDA/EV	10.57	1.14	2.97	8.15	6.91	(1.83)	19.27	16.47	6.40	(7.38)	9.41
2. Growth											
15 Hist 5Y operating EPS growth	17.98	16.11	18.42	(30.93)	8.29	(39.32)	11.01	28.96	(9.00)	12.91	(29.21)
16 Hist 5Y operating EPS acceleration	(10.50)	12.44	(23.72)	8.32	(13.54)	6.66	(4.69)	(18.77)	6.50	(1.90)	(21.49)
17 IBES 5Y EPS growth	22.26	25.98	37.43	32.87	20.16	(31.00)	9.39	33.30	8.67	(18.35)	(33.25)
18 IBES 5Y EPS growth/stability	22.66	24.08	36.06	33.66	23.72	38.12	9.45	24.48	11.63	(6.61)	(34.60)
19 IBES LTG EPS mean	12.79	(4.19)	(11.13)	5.03	(3.95)	6.67	6.42	5.09	8.70	19.16	5.78
20 IBES FY2 mean DPS growth	14.39	13.37	(23.24)	6.53	15.52	18.78	29.63	(12.08)	(17.13)	15.38	4.17
21 IBES FY1 mean EPS growth	(14.28)	(13.17)	19.83	(21.99)	2.22	2.80	(9.06)	(20.93)	(4.70)	(15.54)	20.46
22 Year-over-year quarterly EPS growth	0.27	4.02	(22.86)	(10.38)	5.30	24.87	6.35	1.51	(0.34)	(0.23)	12.59
23 IBES FY1 mean CFPS growth	3.94	(3.84)	(15.15)	(2.87)	2.80	(3.81)	(2.56)	(6.39)	7.30	(31.23)	(11.18)
24 IBES SUE, amortized	2.45	11.83	(21.20)	8.52	(1.79)	8.52	13.52	(0.00)	1.44	4.88	9.77
3. Price momentum and reversal											
25 Total return, 1D	4.92	11.02	15.92	(2.33)	2.12	6.57	12.14	4.85	(3.40)	9.11	(1.55)
26 Total return, 21D (1M)	(3.83)	(2.11)	(3.01)	1.21	5.79	(17.99)	(6.04)	(11.14)	(8.63)	(15.95)	6.61
27 Maximum daily return in last 1M (lottery factor)	27.86	23.26	3.06	13.45	28.53	27.52	18.85	22.93	18.89	22.16	35.56
28 21D volatility of volume/price	8.08	0.78	(1.67)	(1.73)	9.50	31.98	8.27	0.85	(6.52)	12.63	7.43
29 Total return, 252D (12M)	3.24	1.46	(5.04)	4.45	9.28	(26.93)	12.63	20.39	(3.68)	(22.89)	(0.16)
30 12M-1M total return	2.22	1.26	(6.86)	4.71	12.05	25.96	10.91	18.90	(6.27)	(23.86)	2.84
31 Price-to-52 week high	26.41	19.68	(3.39)	24.95	19.49	(35.45)	25.35	(27.89)	18.30	24.51	(1.64)
32 Total return, 1260D (60M)	23.68	(33.43)	17.79	(30.85)	28.07	34.57	10.60	45.40	7.34	(44.51)	(30.13)
4. Sentiment											
33 IBES LTG Mean EPS Revision, 3M	1.14	8.58	(4.88)	5.61	5.31	7.71	5.26	2.83	(4.93)	(14.03)	(2.83)
34 IBES FY1 Mean EPS Revision, 3M	3.04	22.19	(8.96)	10.49	4.11	(8.58)	6.39	(2.02)	1.21	(10.20)	22.06
35 IBES FY1 EPS up/down ratio, 3M	4.15	14.10	(14.70)	13.46	8.02	(5.45)	7.98	(0.35)	4.55	(12.12)	(0.53)
36 Expectation gap, short-term - long-term	(8.44)	(11.00)	(16.37)	(20.36)	3.36	(1.72)	(7.91)	(19.30)	(4.51)	(10.45)	19.02
37 IBES FY1 Mean CFPS Revision, 3M	5.52	11.86	(16.03)	(10.72)	(2.13)	5.62	5.71	12.63	(11.27)	(21.85)	(10.64)
38 IBES FY1 Mean SAL Revision, 3M	0.82	4.47	20.68	1.17	13.17	(1.45)	(3.51)	12.76	(2.83)	(12.35)	(8.04)
39 IBES FY1 Mean FFO Revision, 3M	NA	NA	NA	NA	NA	NA	NA	15.36	NA	NA	NA
40 IBES FY1 Mean DPS Revision, 3M	0.75	(2.98)	(13.01)	21.36	7.19	12.02	(20.14)	0.58	1.02	(6.92)	16.80
41 IBES FY1 Mean ROE Revision, 3M	1.22	20.25	14.87	(9.33)	1.89	18.41	(5.31)	(2.18)	4.70	27.66	(4.52)
42 Recommendation, mean	(9.00)	(7.03)	(12.29)	(7.58)	6.80	15.93	18.14	2.60	(10.09)	24.15	(16.59)
43 Mean recommendation revision, 3M	(8.95)	(24.27)	4.26	1.83	(5.06)	6.00	(9.46)	(6.34)	(8.82)	7.39	(14.26)
44 Target price implied return	(30.36)	(35.59)	(29.55)	(26.74)	(9.53)	(18.28)	(34.47)	(30.38)	(26.14)	9.96	(12.06)
45 Mean target price revision, 3M	14.38	21.08	(7.60)	9.30	19.62	(11.04)	21.08	23.72	4.21	(50.00)	5.04
5. Quality											
46 ROE, trailing 12M	21.13	22.87	3.72	24.44	17.59	41.87	29.02	22.90	13.05	18.09	25.78
47 Return on invested capital (ROIC)	22.02	24.63	10.59	29.11	23.01	43.12	29.88	22.95	14.98	22.48	(27.85)
48 Sales to total assets (asset turnover)	(2.74)	5.52	(17.29)	(6.21)	1.29	(6.36)	6.06	7.83	(0.66)	9.25	6.74
49 Operating profit margin	8.50	(1.00)	32.86	13.34	5.96	19.18	27.55	(7.98)	2.37	25.27	4.64
50 Current ratio	1.18	4.52	0.37	(10.85)	11.25	21.76	(3.11)	(12.32)	(3.96)	10.94	28.06
51 Long-term debt/equity	(0.62)	5.51	(20.88)	10.82	9.00	0.80	(4.62)	10.65	(3.19)	30.35	1.55
52 Altman's z-score	12.11	16.86	24.82	24.88	18.93	(12.62)	(19.41)	3.42	13.35	2.11	(4.17)
53 Merton's distance to default	32.36	26.36	30.26	29.43	37.97	43.57	28.05	22.36	18.94	37.47	30.23
54 Ohlson default model	15.64	18.92	19.22	26.28	27.87	21.36	27.90	1.79	10.56	(10.00)	12.74
55 Campbell, Hilscher, and Szilagyi model	19.91	22.92	27.84	34.31	30.87	(32.35)	28.31	(31.24)	15.60	(14.48)	(8.10)
56 Accruals (Sloan 1996 def)	(2.67)	15.38	2.00	5.73	(4.19)	11.57	(2.26)	NA	(0.49)	(20.37)	6.83
57 Firm-specific discretionary accruals	3.32	9.33	(13.58)	6.05	1.33	(11.73)	(2.88)	NA	(5.95)	(27.24)	(3.41)
58 Hist 5Y operating EPS stability, coef of determination	1.54	(7.03)	(3.96)	4.35	(1.82)	(30.64)	15.67	(6.03)	6.93	(4.53)	(18.21)
59 IBES 5Y EPS stability	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA	NA
60 IBES FY1 EPS dispersion	28.69	20.63	18.95	33.62	28.63	46.99	33.22	16.85	15.14	29.53	(39.53)
61 Payout on trailing operating EPS	24.44	24.89	(8.13)	12.31	13.10	22.88	18.09	(27.03)	23.10	28.78	(25.46)
62 YoY change in # of shares outstanding	16.89	31.30	(0.37)	15.14	15.25	16.35	23.66	11.21	21.53	10.39	(13.84)
63 YoY change in debt outstanding	(7.06)	(7.75)	11.69	(2.95)	(9.76)	6.01	(5.84)	(9.69)	(5.07)	(0.81)	6.72
64 Net external financing/net operating assets	6.30	12.71	3.52	7.36	(1.39)	27.48	11.35	(3.35)	9.83	17.82	3.93
65 Piotroski's F-score	5.90	15.42	(8.88)	5.66	6.27	7.03	6.66	(26.97)	3.50	25.55	(28.67)
66 Mohanram's G-score	16.31	NA	NA	9.10	32.36	22.01	14.27	NA	12.53	NA	NA
6. Technicals											
67 # of days to cover short	0.91	4.62	(6.71)	1.51	12.02	24.58	11.03	(8.61)	2.96	12.50	(18.63)
68 CAPM beta, 5Y monthly	33.80	(25.19)	(43.43)	35.49	33.71	(29.41)	18.52	(27.00)	20.90	16.05	54.81
69 CAPM idosyncratic vol, 1Y daily	33.80	30.17	6.96	28.05	36.46	43.62	27.03	29.82	20.34	47.73	27.46
70 Realized vol, 1Y daily	37.13	31.53	14.70	31.40	40.94	46.26	27.15	35.61	21.17	49.40	30.39
71 Skewness, 1Y daily	5.94	1.88	3.06	8.46	(1.37)	(1.83)	0.79	7.57	1.92	36.42	14.07
72 Kurtosis, 1Y daily	3.87	6.19	(3.07)	8.64	(1.13)	9.92	4.39	(4.54)	(7.55)	39.26	(22.72)
73 Idiosyncratic vol surprise	19.26	30.76	4.06	23.35	26.05	43.31	24.16	15.28	15.57	39.57	29.23
74 Normalized abnormal volume	10.96	8.89	2.43	4.82	11.57	34.98	18.14	(0.17)	9.51	44.99	(8.99)
75 Float turnover, 12M	16.36	15.25	9.44	14.52	12.57	5.93	5.21	(10.99)	9.70	(2.42)	(19.64)
76 Moving average crossover, 15W-36W	11.10	5.59	(6.44)	13.93	14.66	(20.26)	13.77	18.96	3.28	(28.78)	0.32
77 Log float-adj capitalization	18.01	20.51	6.19	15.84	22.94	45.42	31.59	(1.50)	16.78	21.61	4.87
78 # of month in the database	11.46	14.13	1.49	11.39	1.43	5.83	23.82	(5.65)	9.13	5.76	14.81
79 DB composite options factor	(0.30)	10.74	0.11	4.62	(10.34)	6.84	6.23	1.29	6.89	(32.78)	4.63

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

Appendix 1

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