Global

Quantitative Strategy
# Signal Processing

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# Strategy Crowding

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## An in-depth analysis of style crowding and investor herding

### The notion of crowding is inherently confusing

Crowding is a perplexing concept. Investors are constantly on the hunt for reliable crowding measures, but what does crowding really mean? Is it aggregate sentiment, market timing, or the inverse of trending? Or is crowding the tipping point when the strategy reverts? As a strategy becomes modestly crowded, it should outperform (to a point) as crowding takes hold. Alternately, can crowding measures simply be the inverse of a trending measure (which are widely known)? Undoubtedly, the concept of crowding can be baffling.

### We explore a diverse set of potential crowding measures

We explore a multitude of crowding measures including: valuation spreads, strategy expensiveness, market breadth, sentiment, shorting costs, institutional buying and selling, institutional ownership, stock pairwise correlation, tail dependence, concentration ratio, and funds flow, etc. Our research suggests that there is no silver bullet measure of crowding. There are series of useful measures that can hint as to which strategies are "crowded". The diversification ratio, for example, is a robust measure of investor crowding.

### How to read our crowding report

This report is an in-depth study of various "crowding" measures ranging from fairly simple metrics to more sophisticated ones. We have outlined the key findings within the first few pages. For those who want more details or clarity on our analysis, it may be useful to setup a meeting in person, over the phone, or attend one of our many webinars.

Source: gettyimages.com

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## Table Of Contents

# A letter to our readers

It is often said that quant strategies follow an evolutionary path: they are discovered, work well for a time, and then get crowded and arbitraged away. In this paper, we evaluate whether this is actually true by developing proxies for factor crowdedness. In theory, developing measures for strategy crowdedness should be fairly straightforward. In practice, however, it is rather difficult because we do not have a framework to compare the effectiveness of our crowding measures.

How does one measure crowding? How does one know if an indicator is a strong measure of investor crowding? Crowding is a concept that is often misunderstood. Investor crowding is often associated with poor future performance or a strong pullback in a strategy. While this may be true to some degree, our findings show that crowding can also be a healthy ingredient for stronger future performance. However, too much of one spice can potentially lead to distasteful returns. So where is the balance?

In this novel research, we explore the fine line between performance and crowding. We analyze a multitude of crowding measures from simple indicators, such as expensiveness and market breadth, to more cutting edge measures, such as short interest, stock pairwise correlations, and the co-movement effects in stocks' tail distributions. We also analyze more grassroots measures of investor herding using institutional holdings and ownership as well as funds flow data. Portfolio measures of crowding that we explore include the concentration and diversification ratio.

To test these measures, we introduce a fairly extensive analytical framework. We propose four methods to test for investor crowdedness: polynomial trend analysis, classification and regression trees or CART, multivariate regressions, and correlation analysis. Each algorithm has several benefits and drawbacks. However, the framework that we outline provides a sound structure for assessing strategy crowding.

As you will see, we believe that crowdedness is an important additional metric to consider when allocating to an investment strategy, selecting a factor (or factor weight) in an alpha model, or when deciding how to position a portfolio based on the current and future macroeconomic environment. We hope you enjoy the remainder of this report. Please contact us at dbeqs.americas@db.com for any questions.

Regards,

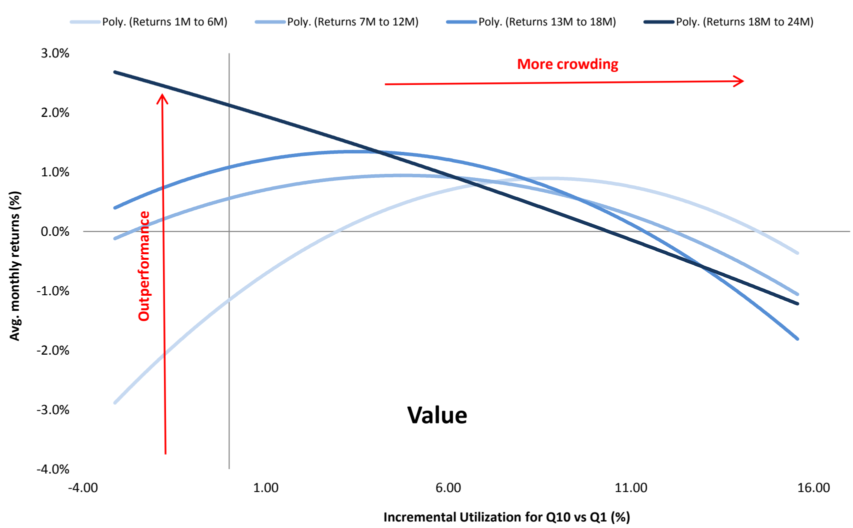
Yin, Javed, Gaurav, Sheng, and the quant team
**Deutsche Bank Quantitative Strategy**

# Five key findings

## 1. Crowding tends to be linked to future outperformance.

However, at extreme levels, crowded trades can lead to heighted risks of large drawdowns.

Figure 1: Crowding and the value portfolio



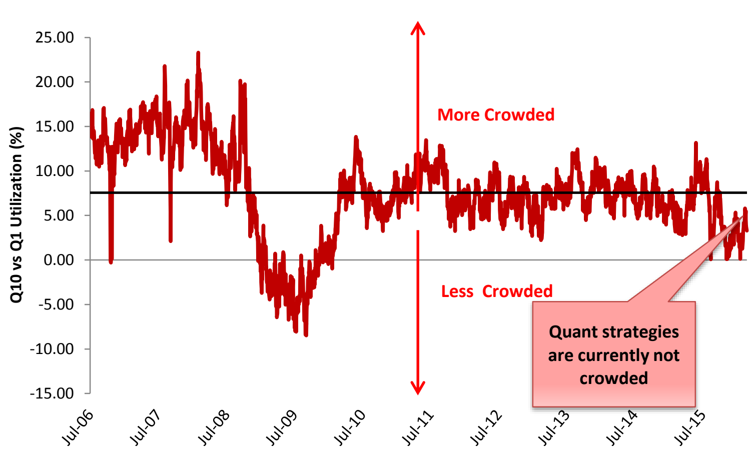

Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

*Figure 1 shows the forward returns of the value portfolio versus one measure of crowdedness. The value strategy tends to outperform as the strategy gets crowded. This outperformance tends to last for about 18 months. Thereafter, the value strategy tends to struggle rather significantly and with strong elasticity. Extreme levels of crowding (the very right side) are generally accompanied by future drawdowns and heighted risk.*

## 2. Generic quant strategies are currently not crowded.

Therefore, crowding is unlikely to be the reason for the challenging performance of most common factors in recent months.

Figure 2: Quant strategies and crowding



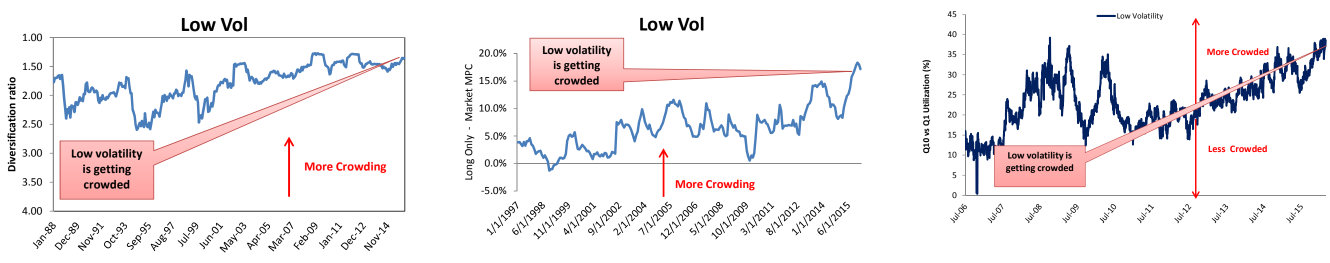

Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

*Figure 2 shows the crowdedness of a multi-factor model which is indicative of typical quantitative strategies. Currently, quant strategies do not appear to be crowded relative to historical levels*

## 3. However, low vol investing may be getting crowded

This is based on several measures we studied in this research.

Figure 3: Low volatility may be getting crowded based on the diversification ratio, pairwise correlations and utilization




*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Markit, Deutsche Bank*

## 4. Diversification Ratio is an effective crowding measure

In particular, it's a robust measure of crowdedness for low volatility and quality measures. Note that we explored over ten potential crowding measures.

*Figure 4 shows that the DR ratio is strongly negatively correlated to future annual returns for the low volatility and quality portfolios*

Figure 4: Correlation of DR and future annual returns

| | Div yield | Value | Momentum | Reversal | Growth | Quality | Low Vol | Sentiment |
|---|---|---|---|---|---|---|---|---|
| **DR Cap Weighted** | -4% | -20% | -19% | 35% | 11% | -49% | -64% | 35% |
| **DR Conviction Weighted** | 8% | -10% | -30% | 30% | -7% | -50% | -73% | 30% |

*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

## 5. See our crowding predictions over the next 12 months.

*Current prediction of future return is most consistent for value strategy with most proxies for crowdedness indicating an outperformance for the strategy over the next 12 months. On the other hand low vol remains the most crowded trade based on most proxies with a negative and volatile expectation on future returns*

Figure 5: Risk and return prediction (12 month ahead)

Return prediction (12 month ahead)

| Factors | Expensiveness | Market breadth | Short interest | Buying power | Concentration ratio | Diversification ratio | Overall |
|---|---|---|---|---|---|---|---|
| Div yield | Neutral | Negative | Neutral | Neutral | Neutral | Neutral | Neutral |
| Value | Positive | Neutral | Positive | Positive | Positive | Positive | Positive |
| Momentum | Positive | Positive | Negative | Positive | Negative | Positive | Neutral |
| Growth | Positive | Neutral | Neutral | Neutral | Neutral | Negative | Neutral |
| Quality | Neutral | Negative | Positive | Neutral | Neutral | Neutral | Neutral |
| Low Vol | Negative | Neutral | Neutral | Neutral | Neutral | Negative | Negative |
| Sentiment | Neutral | Negative | Neutral | Positive | Neutral | Neutral | Neutral |

Drawdown risk prediction (12 month ahead)

| Factors | Expensiveness | Market breadth | Short interest | Buying power | Concentration ratio | Diversification ratio | Overall |
|---|---|---|---|---|---|---|---|
| Div yield | Modest | Modest | Severe | Modest | Severe | Severe | Modest |
| Value | Severe | Modest | Modest | Severe | Severe | Severe | Severe |
| Momentum | Severe | Severe | Severe | Severe | Modest | Modest | Severe |
| Growth | Modest | Modest | Modest | Modest | Modest | Severe | Modest |
| Quality | Severe | Severe | Modest | Severe | Severe | Modest | Severe |
| Low Vol | Severe | Severe | Modest | Severe | Severe | Severe | Severe |
| Sentiment | Modest | Severe | Severe | Modest | Modest | Modest | Modest |

*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

# Classic measures

We begin by studying the conventional wisdom of strategy crowding. We explore whether strategy expensiveness (as measured by price to earnings multiples), historical performance, and sentiment conveyed by market breadth are possible crowding measures. Our analysis also provides some insight into the lead-lag effect of crowding and trending (i.e., does trending lead to crowding or vice versa).

## 1. Expensiveness

*One method to potentially gauge investor crowding or herding is by looking at the relative expensiveness of a particular market, sector, or strategy. If a strategy becomes overwhelmingly expensive, then this could be a potential crowding signal or turning point*

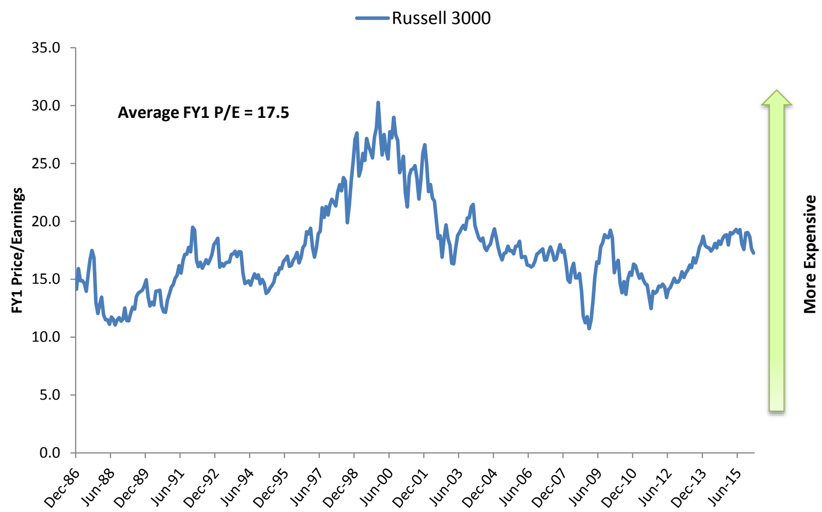
One method to potentially gauge investor crowding or herding is by looking at the relative expensiveness of a particular market, sector or strategy. If a strategy becomes overwhelmingly expensive, then this could be a potential crowding signal or indicate a potential turning point. To test this hypothesis, we simply compute the average price to earnings (P/E) for a particular market, sector, and strategy.

We can then analyze the correlation between the current P/E and future returns. If our indicator is negatively correlated to future performance, then this could suggest a valuation mean-reversal behavior. On the other hand, if it is positively correlated to future performance, then this would suggest a potential trending indicator. The strength of the correlation is also important. Note that correlation is only one approach we employ to understand the relationship between indicators and future returns.

We use the terms “mean-reversal” and “trending” loosely here. The term “mean-reversal” merely implies the likelihood of a future pullback, underperformance, or reversal in a strategy whereas “trending” implies potential future momentum or outperformance.

Figure 6 shows the Russell 3000 aggregate FY1 P/E ratio. The time-series commences from 1986. As P/E for the index increases, the broad equity market gets more expensive on a valuation basis. Note that the long-term average PE multiple during this entire period is 17.5x.

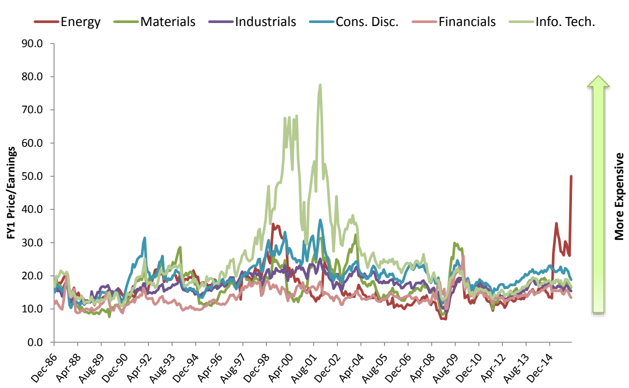
Figure 6: Russell 3000 aggregate FY1 price to earnings




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

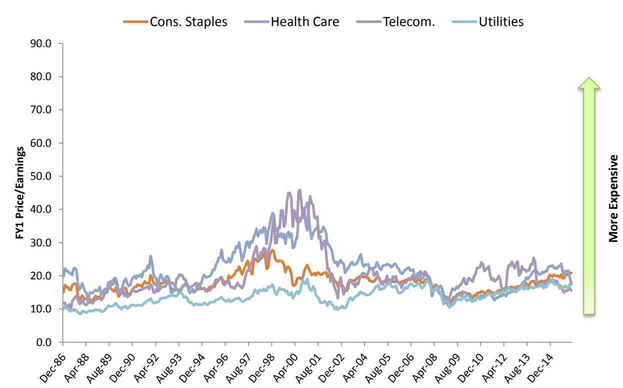
Figure 7 and Figure 8 show the PE at a sector level, delineated by cyclical versus defensive sectors. As expected the PE of cyclical sectors is more volatile than that of the defensive sectors.

Figure 7: FY1 PE for all cyclical sectors




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

Figure 8: FY1 PE for all defensive sectors



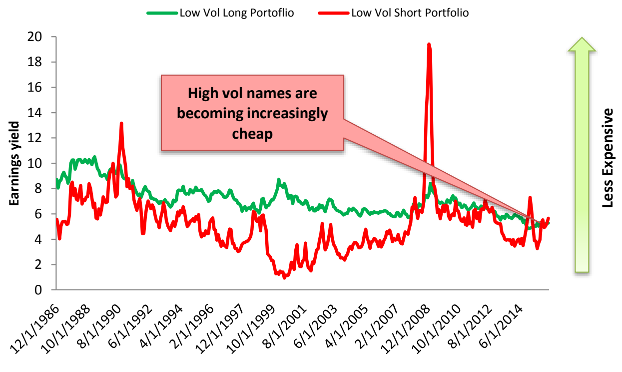

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

It is obvious from Figure 6 to Figure 8, that valuation multiples do not strictly follow a mean-reversal pattern, e. g., the market can stay expensive (or cheap) for a long time. Therefore, there could be some mild crowding as sectors get expensive, which is not necessarily negative. We will revisit this notion later in the report.

*It is important to highlight that expensiveness is not a contemporaneous measure; meaning that sectors become expensive overtime*

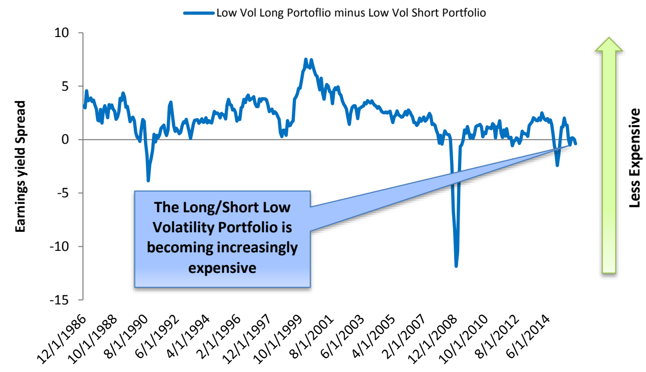
We also explore the expensiveness of a factor. Can expensiveness of a particular factor be a crowding indicator? To test this, we first compute the expensiveness of a broad set of quant factors. For example, take a long/short low volatility strategy. This is a portfolio that longs low volatility stocks and shorts high volatility stocks. We compute the average earnings yield (the inverse of P/E) for the long and short portfolios separately (see Figure 9). Then, we take the difference of the earnings yield for the long and short legs of the portfolio, which forms the valuation spread (see Figure 10).

Figure 9: Expensiveness of low volatility long and low volatility short




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

Figure 10: Expensiveness of long/short low volatility portfolio

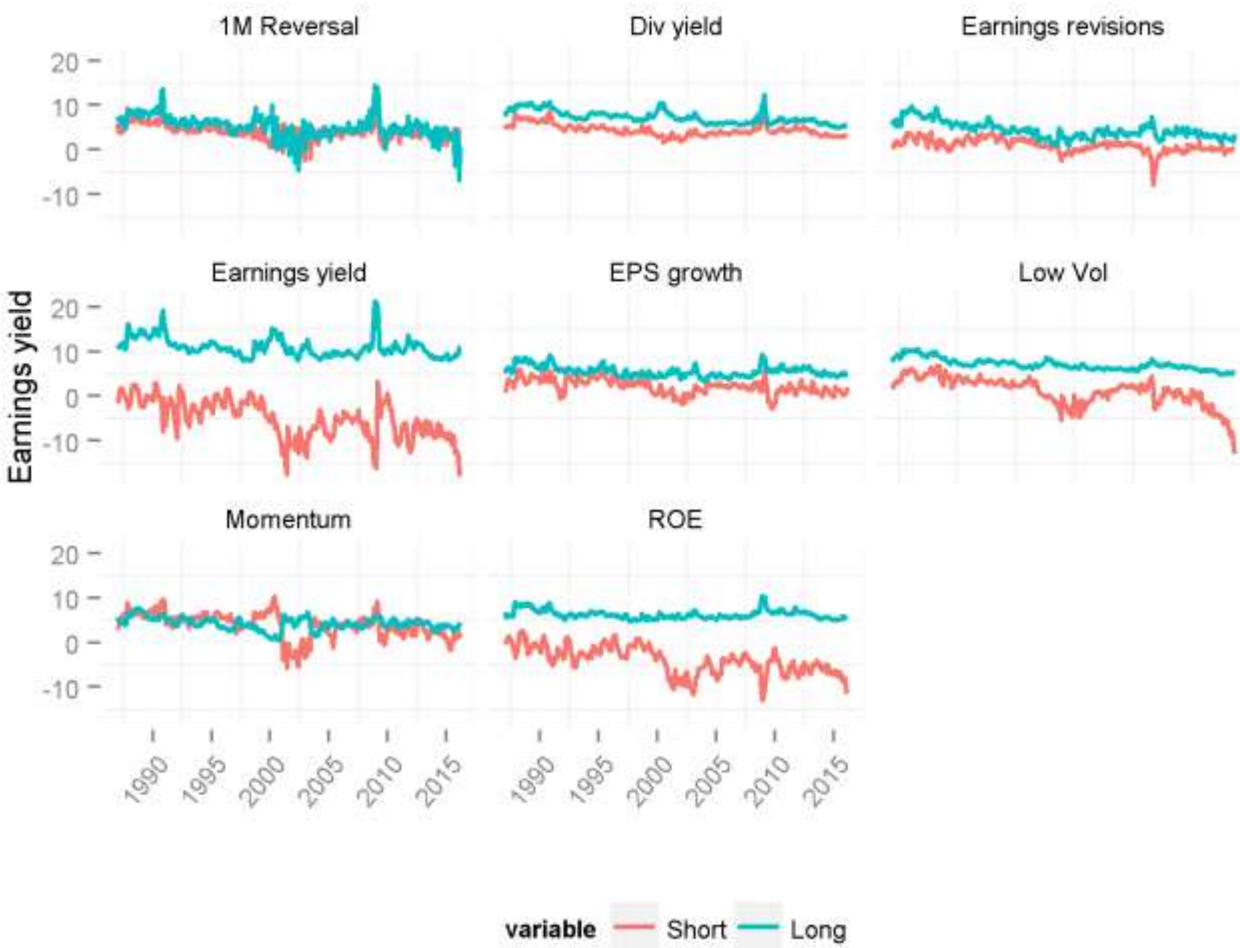



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

If the earnings yield spread increases, this means that low volatility stocks have become cheaper (i.e., the long portfolio is becoming cheaper), and high volatility stocks are becoming expensive (i.e., the short portfolio is becoming expensive). Therefore, the net effect is that the low volatility strategy is becoming cheaper. Currently, we find that low volatility long/short portfolio has become more expensive relative to historical norms. The main driver is that high volatility stocks (that makeup the short leg) are becoming cheaper. We build upon this notion and compute the expensiveness of various quantitative strategies including value, growth, momentum, reversal, and sentiment (see Figure 11 and Figure 12). All and all, the expensiveness of a market, sector, or strategy could be a potential crowding indicator.

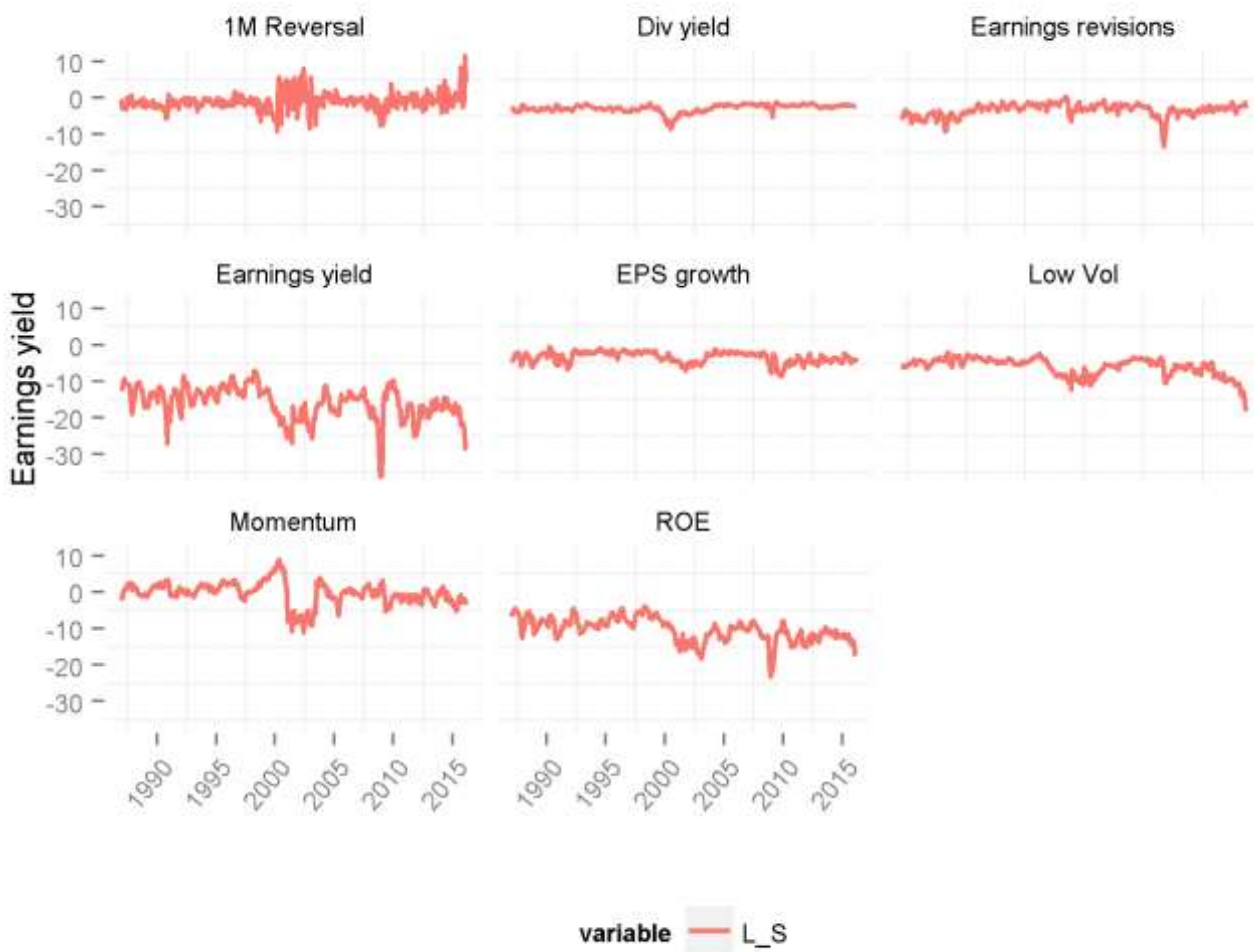
*Currently, we find that low volatility long/short portfolio is becoming expensive. The main driver is that high volatility stocks are becoming cheaper.*

Figure 11: Expensiveness of the separate long and short portfolios for various factors




*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

Figure 12: Expensiveness of common factors




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

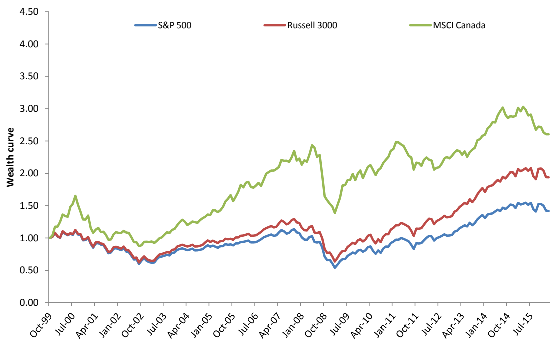
## 2. Historical performance

One often hears strategists announce that the performance of a particular market, strategy, or sector is overblown or has overshot. Watch out for a pullback or reversal. Indirectly, the idea is that the mere cumulative performance of a particular style or sector may be indicative of crowding. Can the historical performance of a factor, style or sector be a crowding indicator? Or, alternatively, is strong performance in a particular strategy indicative of future outperformance or trending (i.e., momentum or mean reversal)?

*One often hears strategists announce that the performance of a particular market, strategy, or sector is overblown or has overshot*

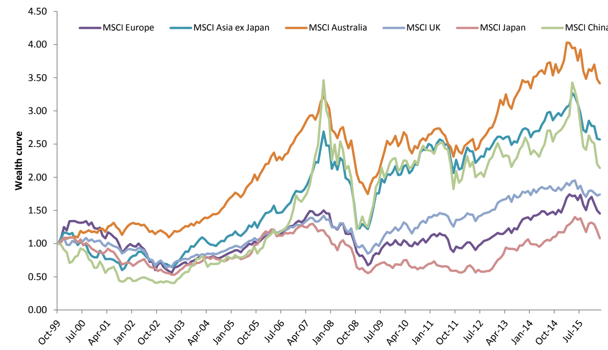
We start very simply, by observing the cumulative performance of various global indices. Figure 13 and Figure 14 show the wealth curve of North American and Global ex North American equity indices. At first glance, it seems that previous performance is more of a trending than crowding indicator. Simply analyzing the wealth curves show a steady trend in performance for most indices with only rare reversals or pull backs.

Figure 13: Wealth curve of North American stock market indices




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

Figure 14: Wealth curve of global ex-NA stock market indices




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

## 3. Market breadth

*We test whether the sentiment conveyed by market breadth indicators is a crowding or trending measure or neither?*

Market breadth is yet another indicator that is often widely discussed by investors. It is a sentiment indicator that may hint at the direction of the market. We test whether the sentiment conveyed by market breadth indicators is a crowding or trending measure?

Two widely used market breadth indicators are:[1]

1. Advance-Decline Ratio or AD ratio. The AD ratio is simply the number of stocks that went up minus # of stocks that were down over a given period. The metric is then divided by total number of stocks.

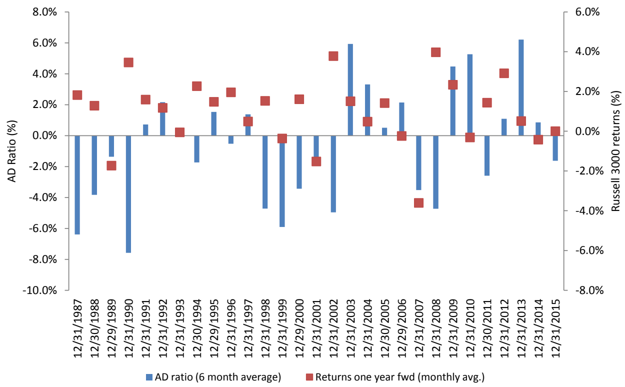
2. 52 Week High-Low Ratio or 52WHL ratio. The 52WHL ratio is the number of stocks near the 52 week high minus the number of stocks near the 52 week low.[2] The metric is divided by the total number of stocks.

To get a sense of these sentiment indicators, Figure 15 and Figure 16 show the AD and 52WHL ratio respectively, alongside the following 12-month Russell 3000 returns.

[1] See Rohal, et al [2016] for more details on market breadth indicators.

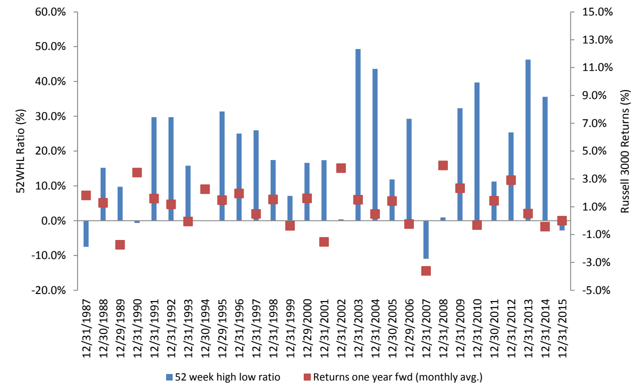
[2] Stocks near their 52-week high or low are those that are within 5% of their 52 week high or low.

Figure 15: AD ratio versus Russell 3000 forward returns




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

Figure 16: 52WHL versus Russell 3000 forward returns




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

We compute both sentiment metrics for the index, sectors, and style factors. To compute market breadth indicators for style factors, we simply compute each ratio separately for the long and short portfolios. Then, we subtract the market breadth indicator of the short portfolio from that of the long portfolio.

For example, for the long/short Low Volatility portfolio, we compute Low Vol AD Long minus Low Vol AD short. This way if the long portfolio indicates positive sentiment, while the short portfolio indicates negative sentiment, the long/short portfolio should show strong positive sentiment. We note that negative sentiment stocks are being shorted.

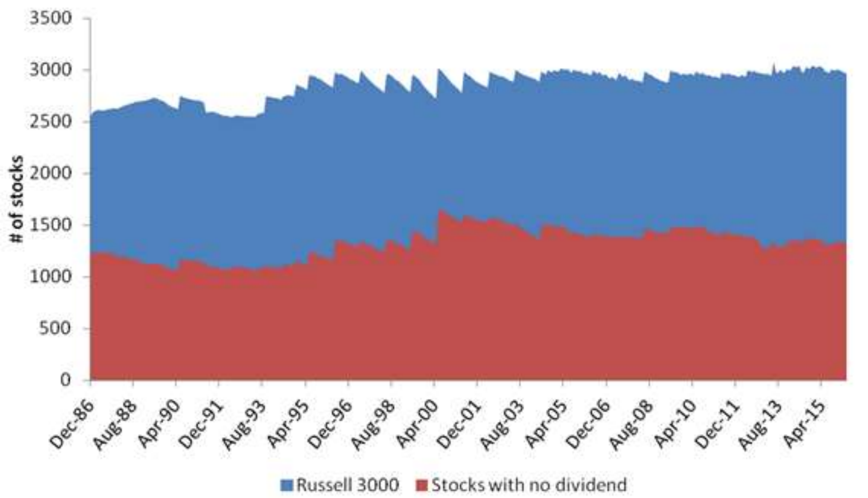
## Testing for crowdedness of the dividend/income strategy

*To test the efficacy of our crowding indicators, we analyze the relationship between our crowding indicators and future returns. If our indicator is negatively correlated to future performance, then this would suggest that it is a possible herding measure.*

To test the efficacy of all the aforementioned crowding indicators, we begin by simply analyzing the relationship between our crowding indicators and future returns for a particular strategy. We analyze the relationship between the dividend yield portfolio and market breadth. We chose to analyze the dividend yield portfolio because it is considered a defensive strategy, especially when risk aversion is high. As such, it may be more susceptible to a crowded trade now.

In the US market, many companies do not pay regular dividends (see Figure 17). Therefore, we form our dividend portfolio by buying the top 10% of companies with the highest dividend yield and shorting all companies that do not pay dividends.

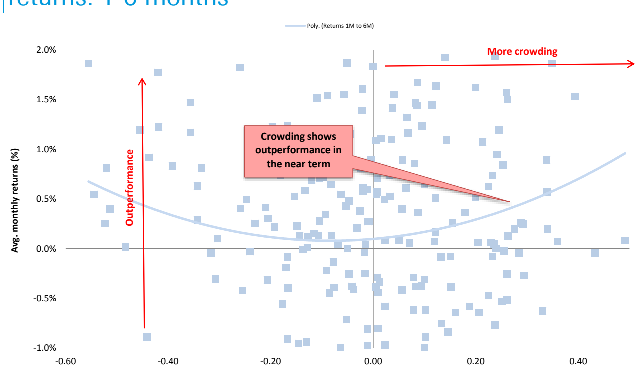
Figure 17: Coverage of companies not paying dividends in the Russell 3000




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

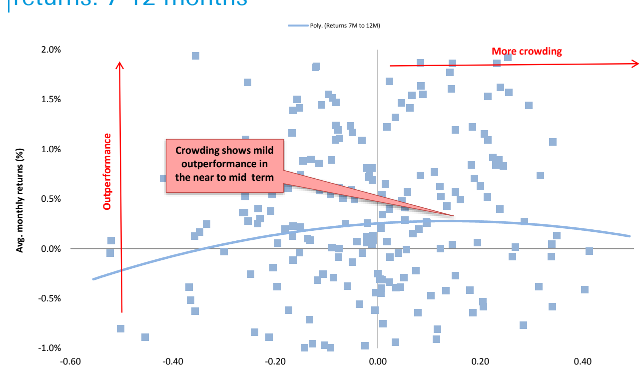
Figure 18 is a scatter plot between 52WHL of the dividend yield portfolio and the future one-to-six month average returns for the dividend portfolio.[3] To better understand the relationship between crowding and future returns, we overlay a polynomial fit on the scatter plot. Interestingly, we see a positive relationship between crowding and future one-to-six month return of the dividend portfolio. This reiterates our hypothesis that crowding can actually lead to stronger future performance.

Figure 18: 52WHL and the dividend portfolio future returns: 1-6 months




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

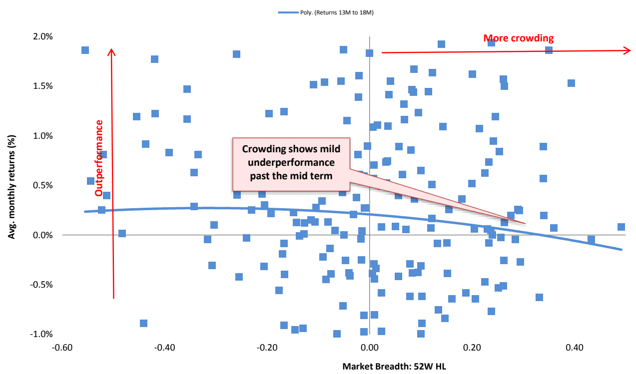
Figure 19: 52WHL and the dividend portfolio future returns: 7-12 months




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

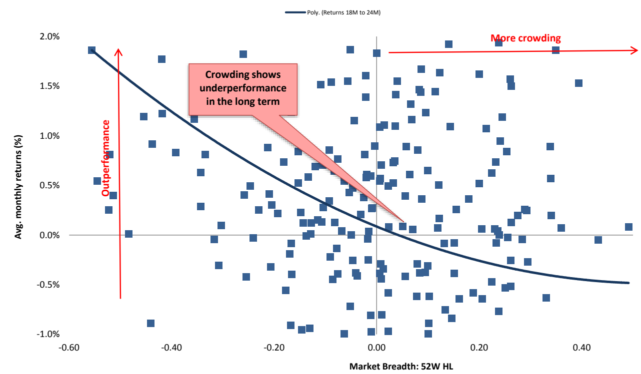
[3] The future returns are the average of the monthly returns using a range of one to six months.

Figure 20: 52WHL and the dividend portfolio future returns: 13 to 18 months




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

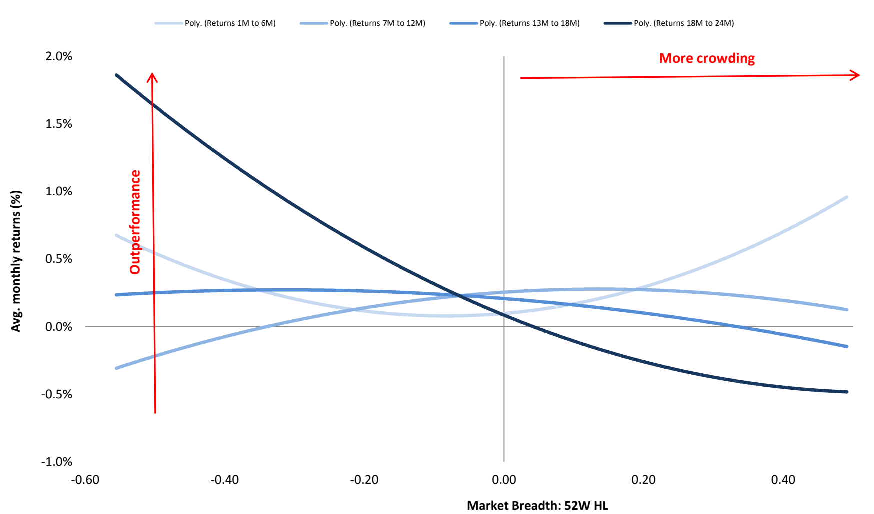
Figure 21: 52WHL and the dividend portfolio future returns: 19 to 24 months




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

However, as we compare our crowding measure to returns further into the future, the positive association between crowding and future returns eases. For example, the relationship between market breadth and future 13-18 month returns (see Figure 20) and 19-24 month returns (see Figure 21) is clearly negative.

Figure 22: 52WHL and the dividend portfolio and all period future returns




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

*In the long term, minor changes in crowding show underperformance. In fact, the elasticity of crowding is fairly strong. This means that small changes in expensiveness are associated with more significant levels of underperformance*

Combining all the charts from the various future return horizons (see Figure 22) yields some interesting findings:

- In the near to medium term, crowding in fact leads to stronger performance for the dividend yield portfolio.
- In the long term, the elasticity of crowding is fairly strong. This means that small changes in crowding are associated with more significant changes in performance.
- Crowding at extreme levels (the very right side of the chart) is associated with future drawdowns, irrespective of the periodicity of future returns.

By no means are these findings definitive, but they do provide a framework for analyzing and assessing potential crowding measures.

## Testing crowdedness for classic measures

*To get a better sense of how well all the aforementioned measures gauge investor crowding, we develop a crowding performance matrix*

To get a better sense of how well all the classic measures gauge investor crowding, we develop a crowding performance matrix. Essentially we want to test the relationship of our potential crowding measures with future performance. To do this we simply analyze the correlation between our crowding measures and future returns.

We run the crowding performance matrix for some common factors (see Figure 23). Generally speaking, crowding is positively correlated to near-term performance, but negatively associated with long-term returns.

Overall, the results for our classic measures are mixed yet promising. Albeit, the strength of the correlation measures are not that strong. Next, we reach into our quant toolbox and investigate more sophisticated measures of crowding.

Figure 23: Classic measures, crowding performance matrix for factors

| Factors | P/E | | | | Performance | | | | AD ratio | | | | 52 week HL | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| Dividend yield | -43% | -34% | -27% | -14% | -13% | -16% | -7% | -14% | -1% | 0% | -6% | -18% | 2% | 5% | -4% | -24% |
| Earnings yield | -4% | -1% | 3% | 3% | 13% | -8% | -15% | -29% | 19% | -3% | -12% | -37% | 5% | -11% | -8% | -21% |
| Momentum | 4% | 18% | 25% | 30% | 17% | 9% | 0% | 11% | 33% | 7% | 4% | -9% | 26% | 8% | 4% | -7% |
| 1M Reversal | 2% | 1% | -12% | -4% | -13% | -10% | -4% | 7% | -23% | -28% | -23% | -25% | 5% | 1% | 5% | -4% |
| Growth | 17% | -1% | 3% | 4% | 16% | 5% | 5% | 1% | 30% | 4% | -2% | -12% | 23% | 7% | 9% | -9% |
| Quality | 19% | 14% | 12% | 16% | 0% | -17% | -13% | -24% | 26% | -7% | -5% | -21% | 14% | -8% | -6% | -14% |
| Low Volailtiy | -20% | -15% | -14% | 2% | -2% | -15% | -21% | -28% | 22% | 8% | -7% | -28% | 15% | 6% | -4% | -17% |
| Sentiment | 4% | -7% | -16% | -18% | 15% | 12% | 23% | 27% | 24% | 3% | 1% | 9% | 29% | 16% | 18% | 5% |
| Avg. Monthly Returns | 1 to 6 | 7 to 12 | 13 to 18 | 19 to 24 | 1 to 6 | 7 to 12 | 13 to 18 | 19 to 24 | 1 to 6 | 7 to 12 | 13 to 18 | 19 to 24 | 1 to 6 | 7 to 12 | 13 to 18 | 19 to 24 |

*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

# Novel crowding measures

## 4. Short interest

In our previous research, we have suggested other crowding measures (see Cahan, Luo, Alvarez, Jussa [2012a]). In this section, we update and extend this research.

Our methodology is based closely on the one proposed in Hanson and Sunderam [2011]. Suppose we have a proxy for investor appetite for a particular subset of stocks – like the short interest used in Hanson and Sunderam. Then at each point in time $t$, we regress that proxy cross-sectionally onto dummy variables that denote whether a stock falls into each quantile of a set of $j$ quant factors (e.g., value, momentum, and so on). We also include dummy variables for size and volatility as controls. More specifically, we have:

*The advantage of their approach is that it is cross-sectional and therefore is less backwards looking. It does not rely on trailing regressions to compute style sensitivities*

$$\mathrm{C}_{\mathrm{i,t}} = c + \sum_{j=1}^{J} \sum_{q=2}^{Q} \beta_{i,t,j,q} D_{i,t,j,q} + \sum_{q=2}^{Q} \beta_{i,t,size,q} D_{i,t,size,q} + \sum_{q=2}^{Q} \beta_{i,t,\sigma,q} D_{i,t,\sigma,q} + \varepsilon_{i,t}$$

where $C_{i,t}$ is the crowdedness score (e. g., short interest) for stock $i$ at time $t$ for a crowdedness proxy variable, $D_{i,t,j,q}$ is a dummy variable that indicates if stock $i$ is in the $q$-th quantile of factor $j$ at time $t$, and $D_{i,t,size,q}$ and $D_{i,t,\sigma,q}$ are dummy variables denoting if stock $i$ is in the $q$-th quantile of size and volatility at time $t$. In our analysis we set $Q$ =10, i.e. deciles, and omit the lowest decile from the dummy variables. We order our variables such that the least attractive decile is denoted $q$ =10. Hence by tracking the coefficient $\beta_{i,t,j,10}$ over time, we can measure the amount by which stocks that are unattractive, as measured by factor $j$, have a different score on the proxy variable compared to attractive stocks, after controlling for size, volatility, and potentially other quant factors.

For example, consider the value factor. If expensive (i.e. unattractive) stocks are more heavily shorted than cheap (i.e. attractive) stocks at a given point in time, then this might indicate that institutional investors (who are more likely to short) are heavily invested in value.

### Problems with using traditional short interest data

When looking for ways to measure factor crowding, the securities lending market seems a natural place to start. The idea is simple: if investors are, in aggregate, heavily shorting stocks that look unattractive on a particular factor, then that would suggest that more capital is chasing that particular strategy.

However, there are some limitations. First, we traditionally source short interest data from Compustat, which is available at a monthly frequency and is snapped on the 15th of each month. This means there can be up to a two week lag between when the data was captured and when it is available to the market.

Second, when we use short interest (i.e., the percent of total shares that are currently sold short) as the measure of shorting demand, we ignore the supply side. The problem with short interest is that it does not capture the supply side of the securities lending equation. For example, if two stocks both have 2%

short interest (based on total numbers of shares outstanding), but one stock has a lendable supply of 4% and the other has a supply of 10%, then clearly the first stock is much more heavily shorted relative to its lendable supply, even though both stocks would have the same ranking on the traditional short interest metric.

### Advantages of the Markit securities finance (MSF) dataset

To address these drawbacks, we leverage a unique database of securities lending activity from Markit (formerly called DataExplorers). We discussed this data set in considerable details, in our previous research, (see Cahan, et al [2012]). There are several advantages to using the MSF dataset. First, the MSF database is updated daily and is available on a T+2 basis. This negates the lag problem that comes with other datasets,

Second, the MSF database captures both the supply and demand sides of the securities lending market. In particular, a metric called Utilization is useful. It measures the shorting activity in a stock as a percentage of the pool of lendable supply in that stock, rather than as a percentage of the total shares on issue. This gives a more accurate depiction of the true level of shorting in a stock.

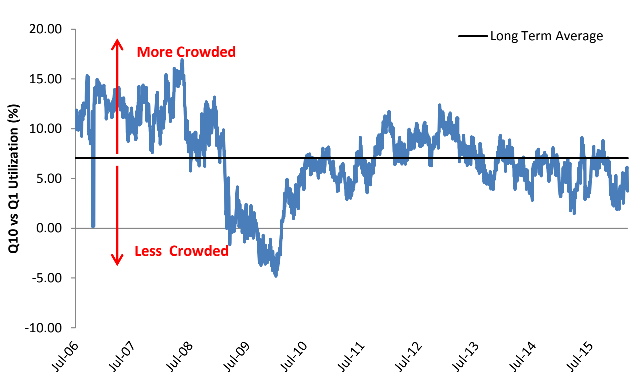
### Factor crowding using utilization

*Using the daily Utilization metric from Markit, we conduct the cross-sectional regression of the above equation on a daily basis from 2006 (when the DataExplorer database starts) to present*

Using the daily Utilization metric computed from the MSF database, we conduct the above cross-sectional regression on a daily basis from 2006 (when the MSF database starts). Figure 24 shows the coefficients for decile 10 stocks for the Value factor. Again, this chart is, loosely speaking, measuring the difference in Utilization for Q10 stocks (i.e. unattractive) stocks versus Q1 (i.e., attractive) stocks.

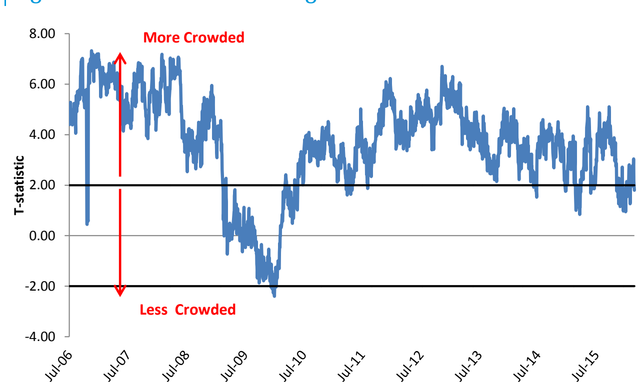
For example, the long-term average of the Value factor is around 7%. This indicates that over the long-run, expensive stocks tend to have Utilization that is 7% higher than cheap stocks, after controlling for differences in size and volatility. Obviously, expensive stocks tend to be more heavily shorted than cheap stocks. Furthermore, as shown in Figure 25, these differences tend to be statistically significant most of the time (roughly a t-statistic greater than 2.00 or less than -2.00).

Figure 24: Incremental Utilization for Q10 vs. Q1 – value




Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

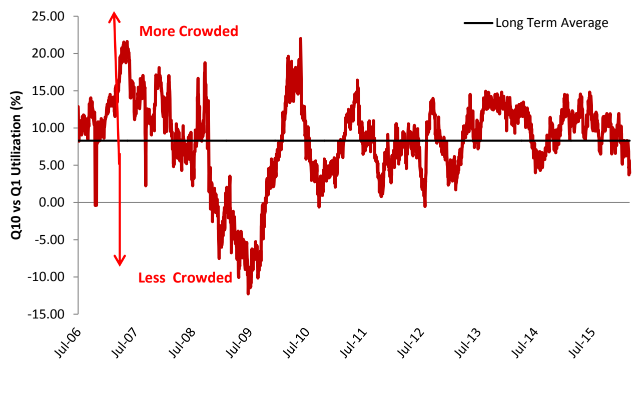
Figure 25: T-statistic for regression coefficients – value




Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

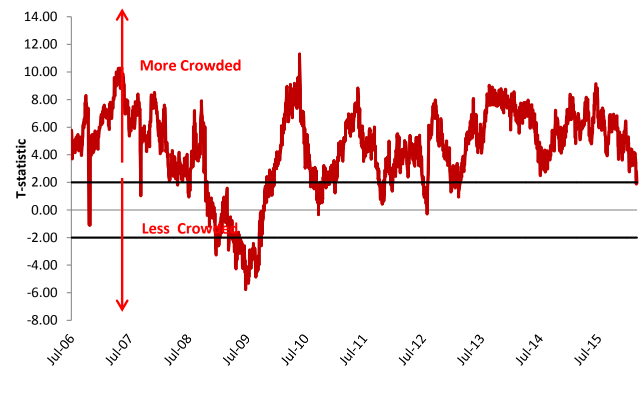
The same applies to Momentum – on average, past losers have higher Utilization than past-winners (see Figure 26 and Figure 27). Neither momentum or value appears to be currently crowded.

Figure 26: Incremental Utilization for Q10 vs. Q1 – momentum




Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 27: T-statistic for regression coefficients – momentum



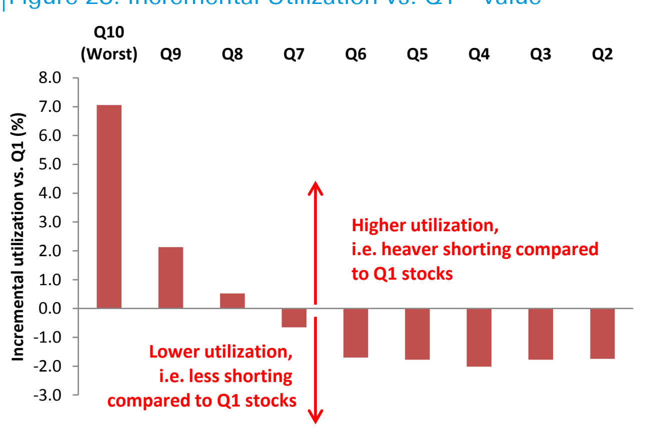

Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

## Robustness checks

So far we have been looking at the difference in Utilization between the best and worse stocks on a particular factor. However, if the intensity of shorting activity is a proxy for crowdedness, then we should observe a monotonic relationship between factor scores and Utilization.

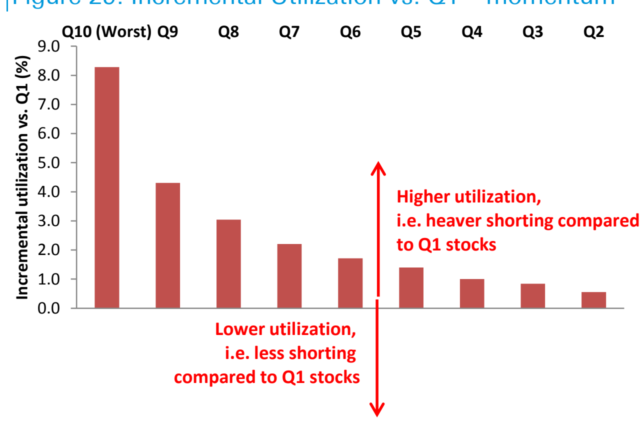
This is indeed the case. Figure 28 and Figure 29 show the difference in Utilization between decile one (most attractive) stocks and the other deciles, for Value and Momentum, respectively and measured over the whole history from 2006. In both cases, the results are quite monotonic; shorting is heaviest for expensive stocks and past-loser stocks, and then declines gradually as one moves towards more attractive stocks.

Figure 28: Incremental Utilization vs. Q1 – value




Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

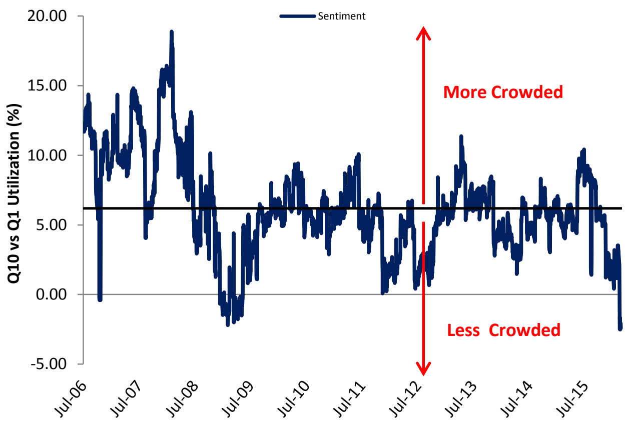
Figure 29: Incremental Utilization vs. Q1 – momentum




Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

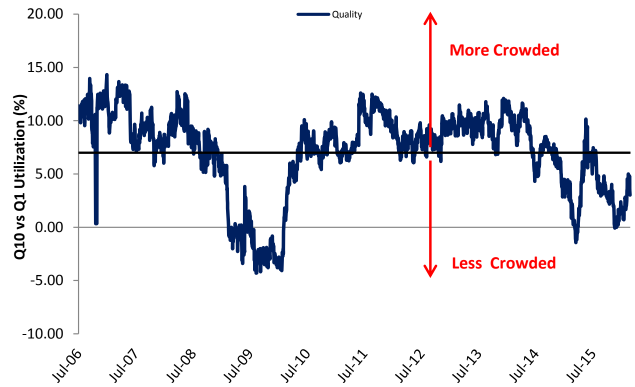
Analyzing the other quant factors in isolation, Figure 30 to Figure 33 show the coefficients for common quant factors including: sentiment, quality, growth, and reversal. Currently, other than reversal and low vol, most of these factors do not appear to be crowded, based on the utilization concept.

Figure 30: Incremental Utilization for Q10 vs. Q1 – sentiment



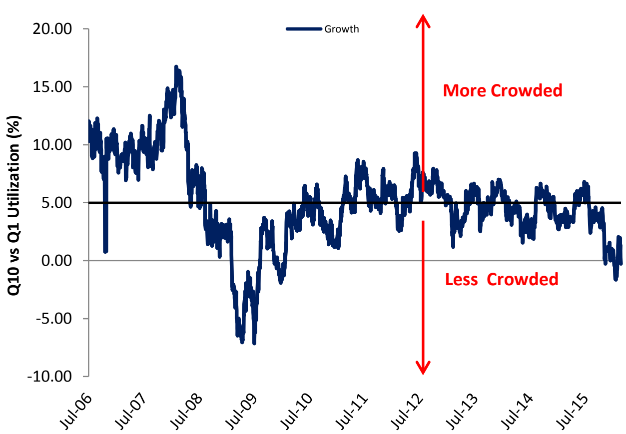

Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 31: Incremental Utilization for Q10 vs. Q1 – quality



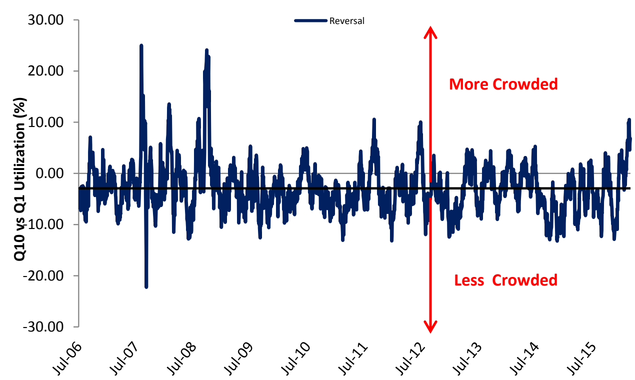

Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 32: Incremental Utilization for Q10 vs. Q1 – growth



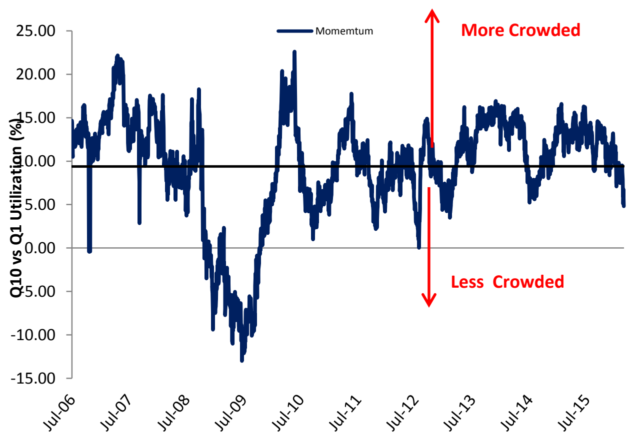

Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 33: Incremental Utilization for Q10 vs. Q1 – reversal



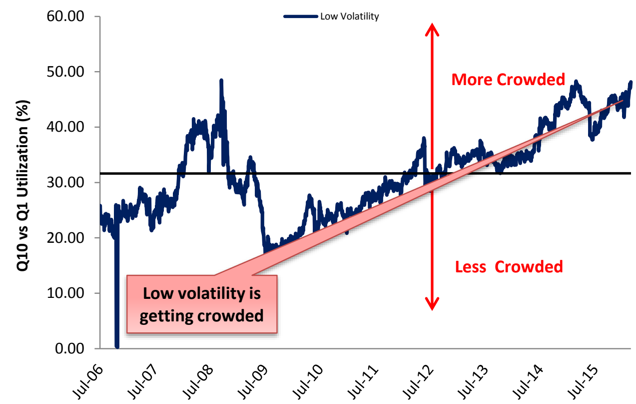

Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 34: Incremental Utilization for Q10 vs. Q1 – momentum




Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 35: Incremental Utilization for Q10 vs. Q1 – low volatility




Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

We highlight low volatility separately because it is a special case. Volatility is a dummy variable in our regression.[4] We did not add it in as additional quant factor. Low volatility appears to be expensive. However, we must also keep in mind that on average, high volatility stocks are expensive to short. As such, low volatility should be scrutinized against its own history. Based on this crowding measure, low volatility appears to be as crowded as it was during the financial crisis when investors simultaneously plunged into defensive, low volatility stocks. We will discuss more appropriate measures of crowding for low volatility strategies in the next few sections.

## Are quant strategies crowded on average?

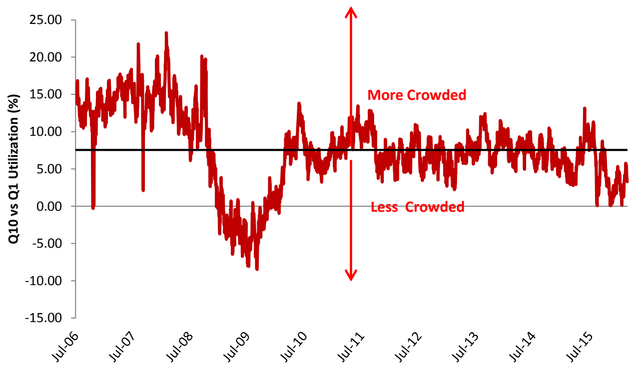
*Putting everything together, we can measure the crowdedness of quant strategies overall by constructing a simple multifactor model with six common quant factors*

So far, we have concentrated on quant factors in isolation. Putting everything together, we can measure the crowdedness of quant strategies overall by analyzing a simple multifactor model with six standard quant factors. These factors are: value, growth, momentum, sentiment, quality, and reversal. Note we excluded low volatility because it is a control variable in the regression. We z-score each factor and form an equally-weighted alpha signal. Then we rerun our regression analysis, using one multifactor alpha signal instead of individual factors.

Figure 36 shows the incremental Utilization for unattractive stocks (Q10) compared to attractive stocks (Q1), and Figure 37 shows the corresponding t-statistic. If we believe our six-factor model is somewhat representative of a typical quant strategy, then these charts should give us a good feel for how crowded the overall quant space is, at least in a relative sense (i.e. compared to history). The results do tend to support the commonly held thesis that quant crowding was high in the pre-crisis period, fell sharply through the worst of the financial crisis, and has now started to increase again albeit at lower levels than before. However, currently we observe no significant crowding within the quant space, based on our incremental utilization coefficient.

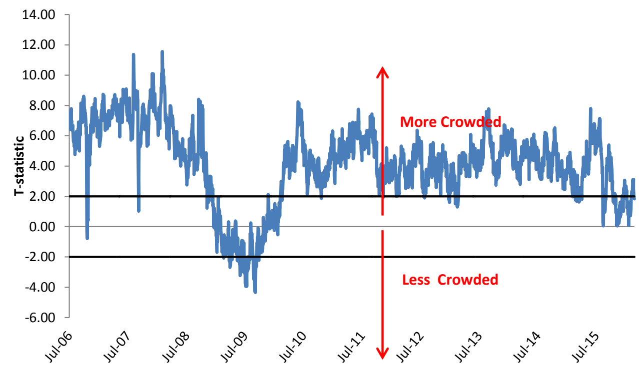
[4] We inverted the coefficient to make it comparable to the other quant factors

Figure 36: Incremental Utilization for Q10 vs. Q1 – multifactor




*Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

Figure 37: T-statistic for regression coefficients – multifactor




*Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

As a result of this evidence, we would suggest that concerns about crowding in the overall quant space are less than what they might have been pre financial crisis. At the individual factor level, there are some indications for concern. For example, the low volatility factor in particular is showing a level of crowdedness that is on par with pre financial crisis levels. In conclusion, we believe that the use of real-time securities lending data coupled with various crowding metrics are an effective way to monitor these trends.

## Crowding and performance – classification analysis

There are several analytical methods that we can employ to grasp the relationship between crowding and future performance. One method is to use a classification and regression tree or CART model.[5] The input to this model (or the independent variable) is our crowding indicator based on utilization.[6] The output to the model (or the dependant variable) is future returns.

Figure 38 shows the results of the CART model on the value portfolio using our utilization measure as a crowding indicator. Note that we used 12-month future returns for the model. The results show that low levels of crowding are associated with higher 12-month future returns, in contrast to more crowded periods. Interestingly, higher levels of crowding are also associated with positive 12-month returns but with lower average returns. The p-value is also insignificant.

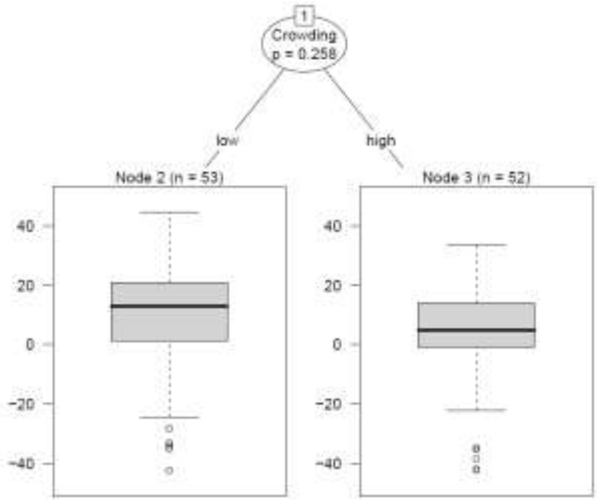
If we re-run our CART model using 13 month to 24-month future returns, we get even more interesting results, (see Figure 39) shows that low levels of crowding are still associated with modest positive returns. However, higher levels of crowding are associated with significantly negative and more volatile returns (with wider range of return distribution).

---

[5] We have used the CART model in many of our previous research, e. g. Luo, et al [2010], Wang, et al [2014].

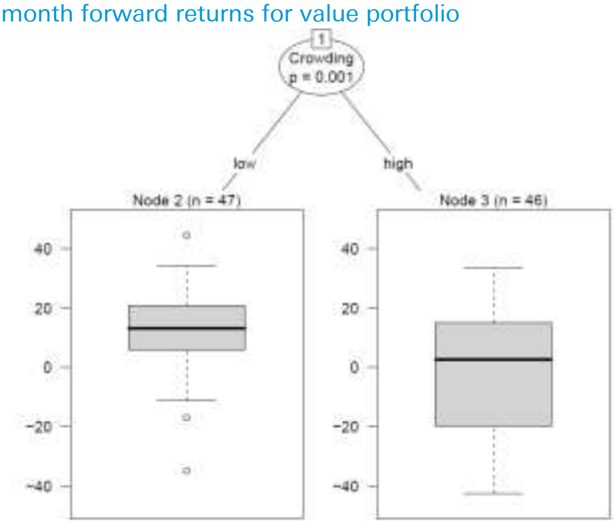
[6] To make the analysis more intuitive, we separate the crowding input into two measures, high crowding and low crowding. High crowding are values above the median and low crowding are values below the median. Note that the median is calculated over the entire history.

Figure 38: CART: incremental utilization and 12-month forward returns for value portfolio




Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 39: CART: incremental utilization and 13-24-month forward returns for value portfolio




Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

The results from our CART analysis are fairly interesting and intuitive. To test the robustness of the results, we can employ a simple multivariate regression framework to test for crowding and future performance.

## Crowding and performance – Multivariate regression analysis

We regress future factor returns against four explanatory variables: crowding, crowding squared (to capture extreme levels of crowding), change in crowding (to capture sudden shifts in crowding), crowding saturation (to capture level of crowding with respect to recent high). The regression takes the following form:

$$r_{t+n} = \beta_0 + \beta_1 crowding_t + \beta_2 (crowding)_t{}^2 + \beta_3 \Delta crowding_t + \beta_4 crowding\ saturation_t + \varepsilon_t$$

Where crowding saturation is defined as:

$$crowding\ saturation_t = Max\left(crowding_{t,} crowding_{t-1,} \ldots crowding_{t-36}\right) - \ crowding_t$$

We run two regressions using 12- and 24-month future returns. Our crowding measure is incremental utilization. Figure 40 below shows the results of the regression on the value portfolio. All the coefficients are statistically significant. The crowding and crowding squared measure both have negative coefficients, indicating that negative future returns can be explained by crowding and extreme levels of crowding.

Figure 40: Multivariate regression using incremental utilization and forward returns for value portfolio

| | 12 Month Forward Returns | | 24 Month Forward Returns | |
|---|---|---|---|---|
| | Beta | T-Stat | Beta | T-Stat |
| Crowding | (4.77) | (3.76) | (13.42) | (8.95) |
| Crowding squared | (2.98) | (2.02) | (5.99) | (3.61) |
| Crowding change | 1.62 | 3.14 | 3.76 | 6.94 |
| Crowding saturation | (3.40) | (3.05) | (7.27) | (5.7) |

Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

We ran the multivariate regressions for all the common factors. Figure 41 shows the average coefficients and test statistics. Again, for 24-month future returns, all the coefficients are statistically significant. The crowding and crowding squared measure both have negative coefficients.

Figure 41: Average coefficients for multivariate regression using incremental utilization

| | 12-Month Forward Returns | | 24-Month Forward Returns | |
|---|---|---|---|---|
| | Average Beta | Average T-stat | Average Beta | Average T-stat |
| Crowding | (3.71) | (3.04) | (8.77) | (5.40) |
| Crowding squared | 1.06 | 0.12 | (4.33) | (2.32) |
| Crowding change | 1.59 | 3.41 | 2.67 | 4.83 |
| Crowding saturation | (3.39) | (3.78) | (5.71) | (3.90) |

*Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

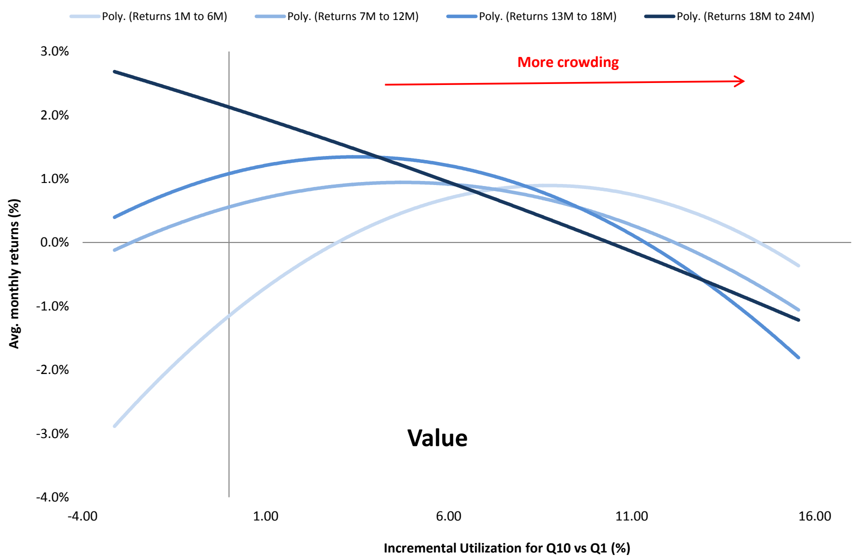
## Crowding and performance – Scatter plot analysis

Next we investigate the relationship between these factor crowding measures and future performance using scatter plot analysis. Figure 42 is a scatter plot between incremental utilization for the value factor and future monthly returns to the value portfolio (1 to 6 months, 7 to 12 months, 13 to 18 months, and 18 to 24 months). To gain more clarity on the relationship between incremental utilization and forward returns, we fit a polynomial function through each series of future returns. Analyzing the chart yields some insightful findings:

*In the near to medium term, mild crowding in fact adds to the performance of the value strategy. We see a positive relationship between incremental utilization and future performance*

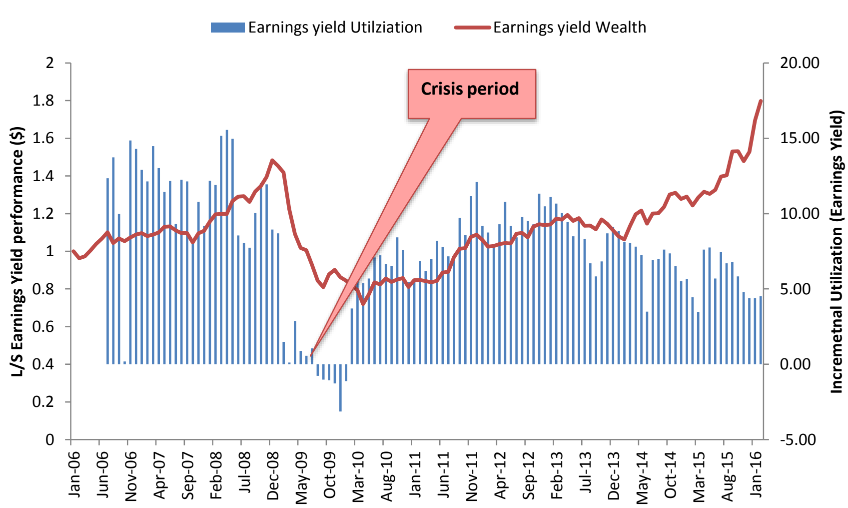
- In the near to medium term, mild crowding in fact adds to the performance of the value strategy. We see a positive relationship between incremental utilization and future performance.
- In the long term, minor changes in crowding show underperformance. In fact, the elasticity of crowding is fairly strong. This means that small changes in incremental utilization are associated within significant levels of underperformance.
- Crowding at extreme levels (the very right side of the chart) is associated with future underperformance irrespective of the periodicity of future returns. At extreme levels of crowding, we see underperformance in the near and long term.
- Extreme levels of crowding (or negative utilization) are typically associated with crisis periods. In a typical market regime, value investors would typically prefer to buy cheap stocks and short or underweight expensive stocks. During the onset of the financial crisis, investors likely bought safe haven, expensive stocks and shorted cheap stocks. This would cause a reduction in incremental utilization or it could even turn negative (see Figure 43).

Figure 42: Incremental utilization and future performance for value




Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

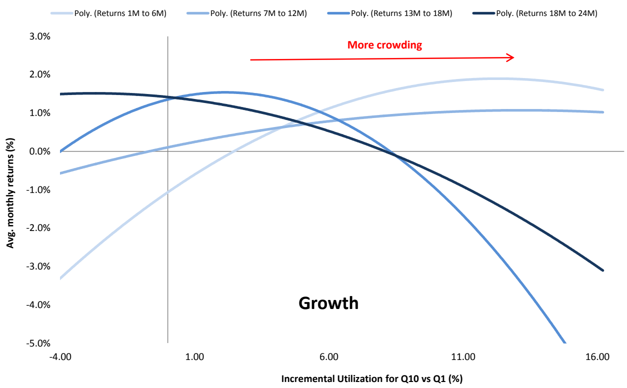
Figure 43: Time series of incremental utilization for value portfolio




Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

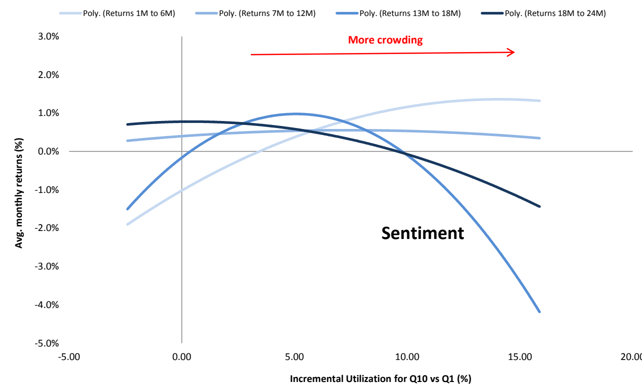
We ran a similar analysis for other standard quant portfolios (see Figure 44 to Figure 47). Most factors showed a similar polynomial pattern.

Figure 44: Utilization and performance – growth



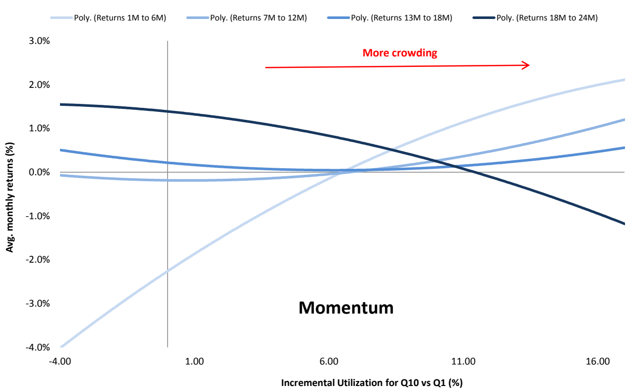

Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 45: Utilization and performance – sentiment



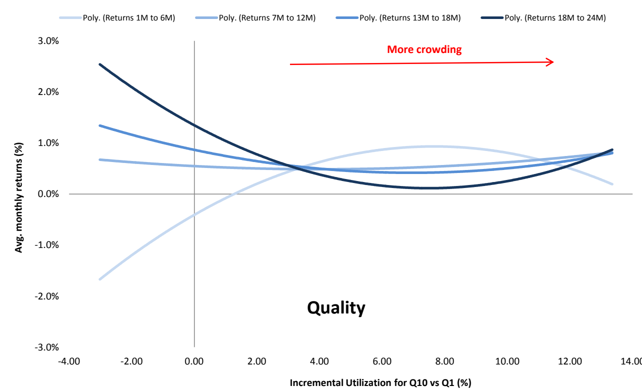

Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 46: Utilization and performance – momentum




Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

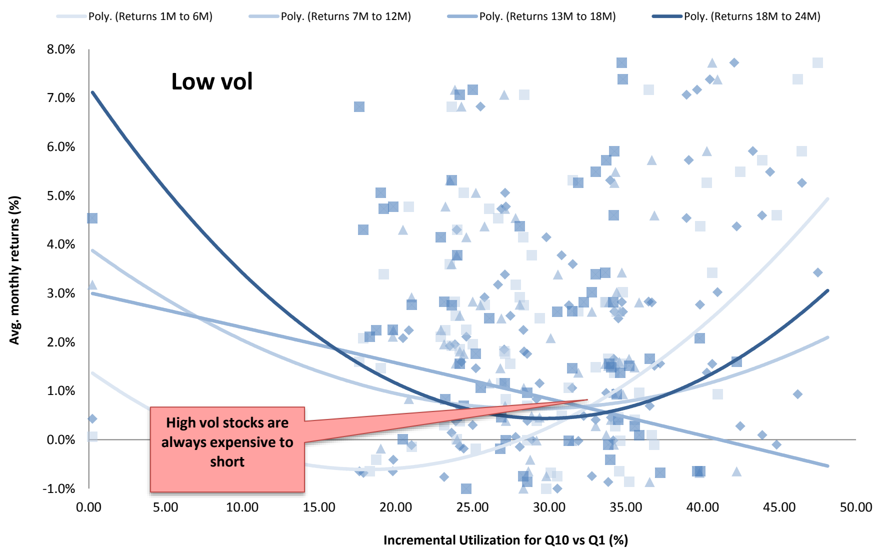
Figure 47: Utilization and performance – quality




Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

The one exception is low volatility (see Figure 48), the dummy variable in the regression. Highly volatile stocks tend to more heavily shorted than low volatility stocks. Additionally, high volatility stocks are also more expensive to short than low volatility stocks. The cluster of incremental utilization for low volatility is higher than any other factor.

Figure 48: Incremental utilization and future performance for low volatility



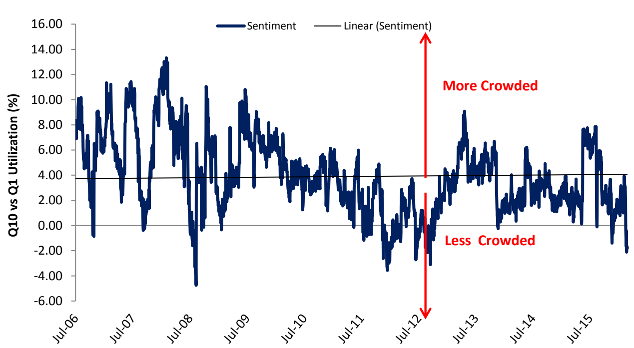

*Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

*One of the drawbacks of using a single multifactor z-score within the regression is that there is no control for other quant factors*

## What's crowded after controlling for all quant factors?

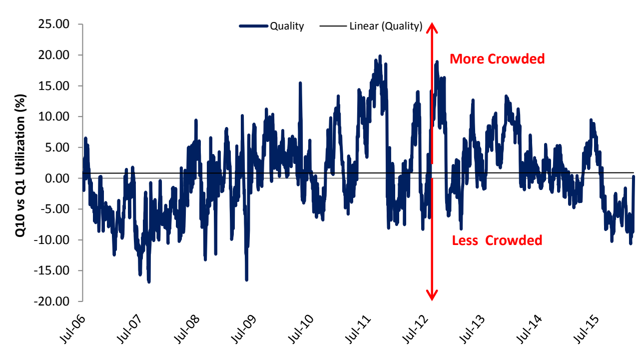
One of the drawbacks of using a single multifactor z-score within the regression is that there is no control for other quant factors. Therefore, we repeat our regressions with the factors as individual independent variables (plus Size and Volatility as controls). Figure 49 to Figure 54 show the coefficients of the regression. As we are using a cross-sectional regression framework, we need to keep in mind that there may be some correlation between the independent variables for which we have not accounted. However, the coefficients should give us a sense of which factors are crowded after controlling for other strategies. Other than low vol and short-term reversal factors, the other common systematic strategies do not appear to be crowded.

Figure 49: Incremental Utilization for Q10 vs. Q1 – sentiment



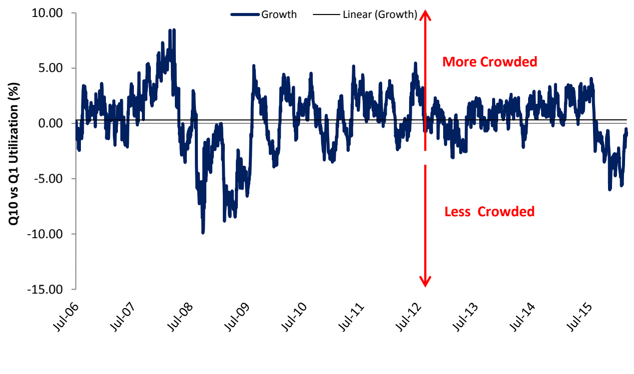

*Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

Figure 50: Incremental Utilization for Q10 vs. Q1 – quality



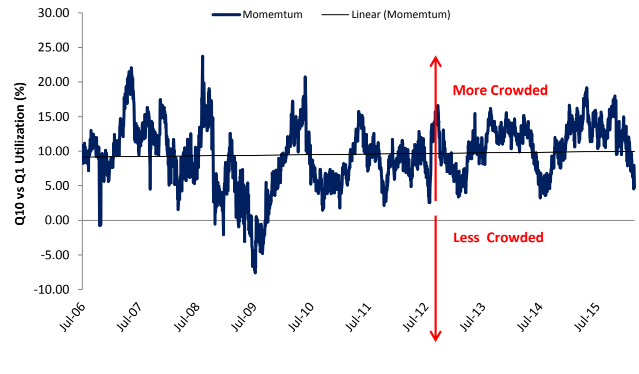

*Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

Figure 51: Incremental Utilization for Q10 vs. Q1 – growth



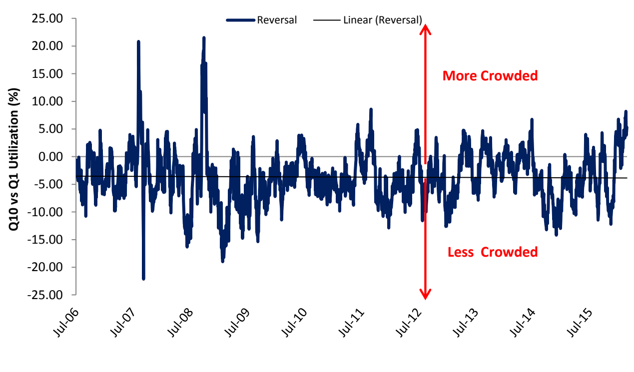

*Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

Figure 52: Incremental Utilization for Q10 vs. Q1 – momentum



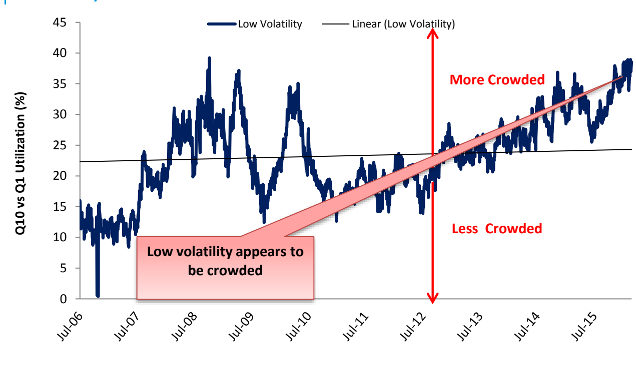

*Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

Figure 53: Incremental Utilization for Q10 vs. Q1 – reversal




*Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

Figure 54: Incremental Utilization for Q10 vs. Q1 – low volatility




*Source: Bloomberg Finance LP, Compustat, Markit, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

## 5. Mean pairwise correlation

*If the MPC for a particular strategy, market, or sector is much higher than the market as a whole, then that could indicate that investors are trading these stocks as a group instead of individually*

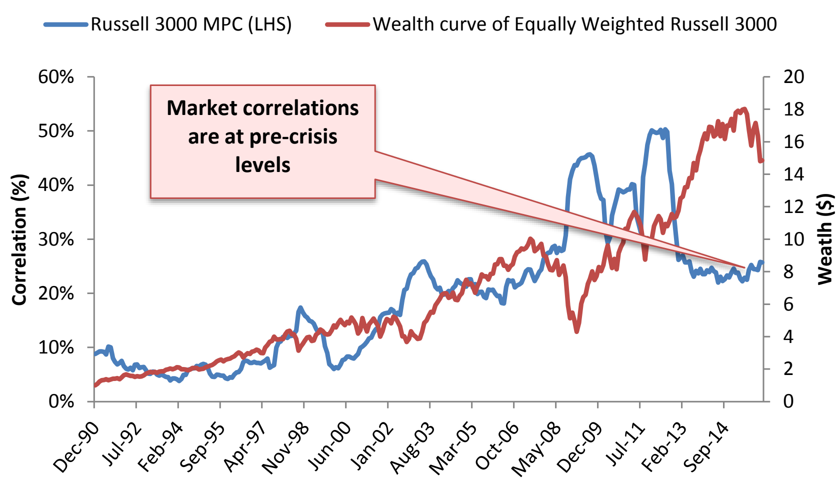
Yet another potential crowding measure could be the pairwise correlation among stocks. In one of our previous research, we quantified crowdedness in low risk strategies using pairwise correlation and tail dependence (see Cahan, Alvarez, Luo, et al [2012b]). Recall that stock pairwise correlation is calculated by taking every possible pair of stocks and computing the correlation of their returns. Taking the mean value across all the pairs results in the mean pairwise correlation or MPC. Intuitively, this captures the tendency of stocks to move together or herd. If the MPC for a particular strategy, market, or sector is much higher than the market as a whole, then that could indicate that investors are trading these stocks as a group instead of individually. Additionally, if pairwise correlation had increased over time, that could indicate rising crowdedness in a strategy.

To start, we plot the market MPC alongside the Russell 3000 index (see Figure 55). We note a significant uptick in MPC during the financial crisis as well as the European debt crisis. Currently, correlation levels have dropped to pre-crisis levels. Broadly speaking, Figure 55 shows that market stress episodes tend to be accompanied by sharp increases in MPC. This is consistent with the notion that during times of distress, investors sell first and ask questions later. This results in stocks being traded more as a basket rather than based on their individual characteristics.

*Currently, correlation levels have dropped to pre-crisis levels. Broadly speaking, the chart shows that market selloff episodes are accompanied by sharp increases in MPC*

Additionally, market-wide MPC was fairly low in the early 1990s when factor performance was strong. In recent years, MPC has been elevated, likely because of the proliferation of systematic and passive strategies while factor performance has been challenging.

Figure 55: MPC of Russell 3000




*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

To compute MPC for our factor portfolios, we compute the MPC of the long leg of the factor portfolio and subtract the MPC of the market.[7] As such, if the MPC of a factor portfolio is much higher than the market, this could be an indication of investor crowding. A value greater than zero would indicate that the factor portfolio is more correlated than the market.

To begin, we analyze the time-series MPC of the value portfolio (see Figure 56). We find that the value strategy peaked in mid-2007, which coincides with the 2007-quant crisis. This coincides with conventional wisdom that investors were chasing inexpensive, risky stocks during the bull market. However, during the onset of the financial crisis; investors steered clear of these risky stocks and hence the crowdedness of value drops significantly. This scenario aligns well with our utilization measure of crowding (see Figure 57). It showed that during the financial crisis, inexpensive stocks became cheaper to short than expensive stocks. This is because during the financial crisis investors preferred more stable, companies which tend to be more expensive. Currently,

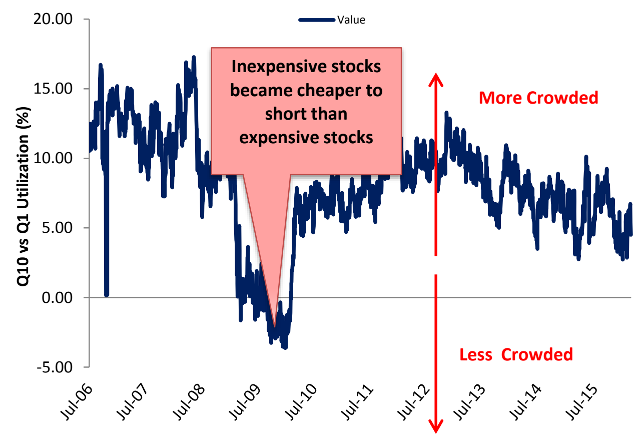
[7] The MPC is based on equally weighted factor portfolios.

the MPC measure seems to suggest that value factor is somewhat crowded and approaching the 2007 levels.

Figure 56: MPC of long value minus market


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

Figure 57: Incremental utilization for value




Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Markit, Thomson Reuters, Deutsche Bank

Analyzing the relative MPC of the quality portfolio during the financial crisis yields similar intuitive results (see Figure 58). In the bull market, leading up to the financial crisis, the quality portfolio became less crowded as inventors chased risky, low quality stocks. However, during the onset of the financial crisis, investors flocked to quality stocks. As such, quality became more crowded. Again, this aligns well with our intuition in the events surrounding the financial crisis.

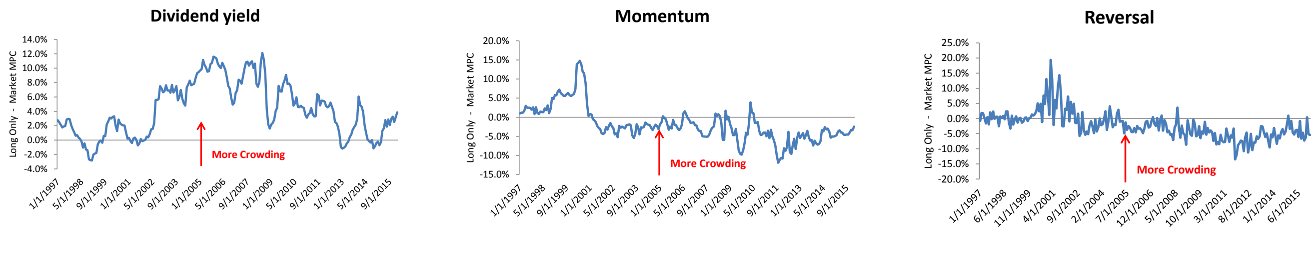
*In the bull market, leading up to the financial crisis, the quality portfolio became less crowded as inventors chased risky, low quality stocks.*

Figure 58: MPC of long quality minus market


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

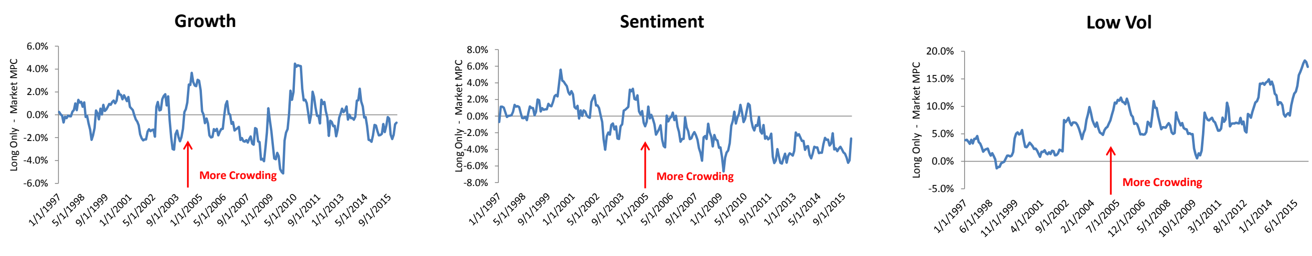
Since our MPC measure of crowdedness makes intuitive sense, we run it for all other standard quantitative portfolios (see Figure 59 and Figure 60). Interestingly, based on MPC, most factors do not show excessive levels of crowding relative to history. The one exception is the low volatility portfolio which shows a continued trend of crowdedness.

Figure 59: MPC of factor portfolios: dividend yield, momentum, and reversal




*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

Figure 60: MPC of factor portfolios: growth, sentiment, and low volatility




*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

## Performance of MPC

We further study the relationship between MPC and future returns (see Figure 61)[8]. The results are fairly mixed.

Figure 61: MPC and future factor returns

| Factors | MPC long only rel. to R3K | | | |
|---|---|---|---|---|
| Dividend yield | -7% | 2% | -8% | -1% |
| Earnings yield | -28% | -21% | -13% | -11% |
| Momentum | 12% | 17% | 5% | 14% |
| 1M Reversal | 2% | 7% | 8% | 27% |
| EPS growth | 25% | 21% | 6% | 8% |
| ROE | -13% | -13% | -2% | 14% |
| Low Vol | 2% | 10% | 4% | -7% |
| Earnings revisions | 9% | 16% | 22% | 14% |
| **Avg. Monthly Returns** | **1 to 6** | **7 to 12** | **13 to 18** | **19 to 24** |

*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

In fact, running the multivariate regression analysis (see Figure 88) shows that most coefficients are statistically insignificant.

[8] Future returns are based on the long only leg of the equally weighted factor portfolio excess to the Russell 3000 equally weighted index.

Figure 62: Average coefficients for multivariate regression using MPC

| | 12 Month Forward Returns | | 24 Month Forward Returns | |
|---|---|---|---|---|
| | Average Beta | Average T-stat | Average Beta | Average T-stat |
| Crowding | (0.34) | (0.18) | (0.38) | 0.08 |
| Crowding squared | (0.01) | (1.60) | 0.00 | (0.77) |
| Crowding change | (0.79) | (1.99) | (0.94) | (1.88) |
| Crowding saturation | (0.79) | (1.37) | (0.94) | (1.09) |

*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

### Mean downside pairwise correlation (MDPC)

We also test a similar measure to MPC called mean downside pairwise correlation or MDPC. The only difference between the two measures is that MDPC computes the stocks pairwise correlations only when the market was down. We found that MPC and MDPC are strongly correlated (i.e., greater than 90%) and as such the results did not differ significantly.

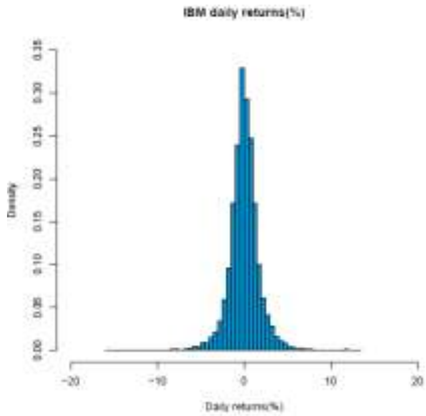
## 6. Minimum tail dependence

A few years ago, we published and analyzed tail dependence as a measure for crowding (see Cahan, R., Alvarez, M., Luo, Y. et al. [2012a] and Luo et al [2014]). In this section, we update and enhance upon our previous research. We proposed a metric based on the likelihood that two stocks have large negative returns at the same time. After all, this is the co-movement that we really care about. Stocks can move for all kinds of reasons – supply/demand imbalances, news flow, etc. – which can disguise the true linkage between stock returns. However, in times of stress, the real relationships between stocks are laid bare, as we have seen all too often in recent years. A convenient way to capture this idea is a Copula. Without getting too bogged down in the technical details (interested readers can refer to Nelsen [1999] for example), a Copula is a function that describes the dependency structure between two random variables. One of the key features of a Copula is that the Copula is independent of the marginal distribution of each of the random variables.

*We found that MPC and MDPC were strongly correlated (i.e. greater than 90%) and as such the results did not differ significantly*

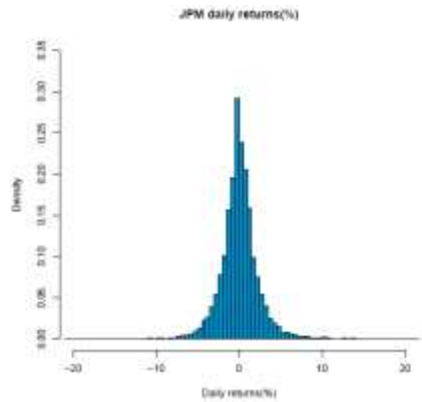
The Copula describes how likely it is that stock i has a return of $r_i$ at the same time as stock j has a return of $r_j$. In particular, we care mainly about how likely it is that stock i has a big negative return at the same time as stock j also has a big negative return. We can best visualize this idea with some pictures. Consider the marginal or independent distribution of three stocks: JP Morgan, IBM, and Citigroup (see Figure 63 to Figure 64).

Figure 63: IBM distribution



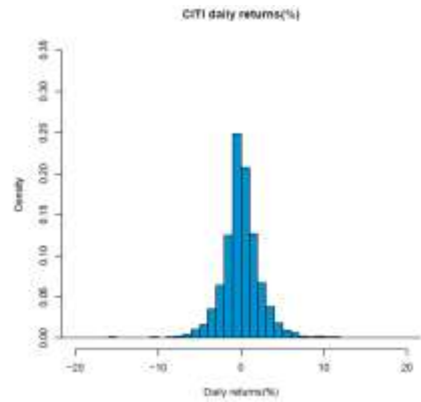

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 64: JPM distribution




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

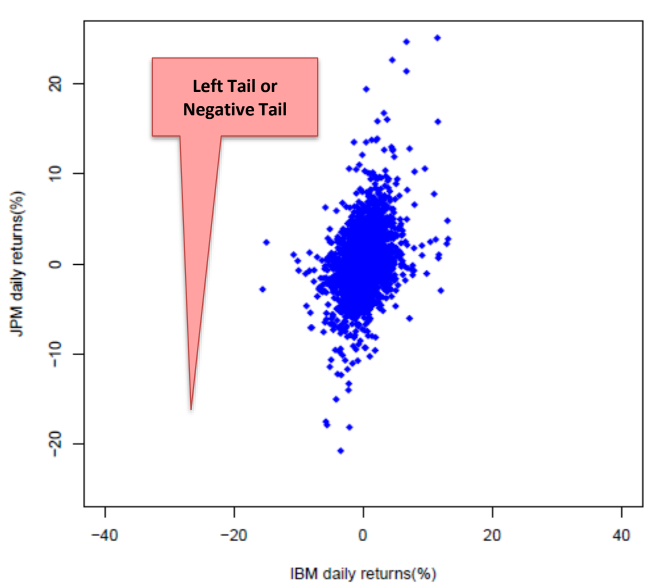
Figure 65: CITIGROUP distribution




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

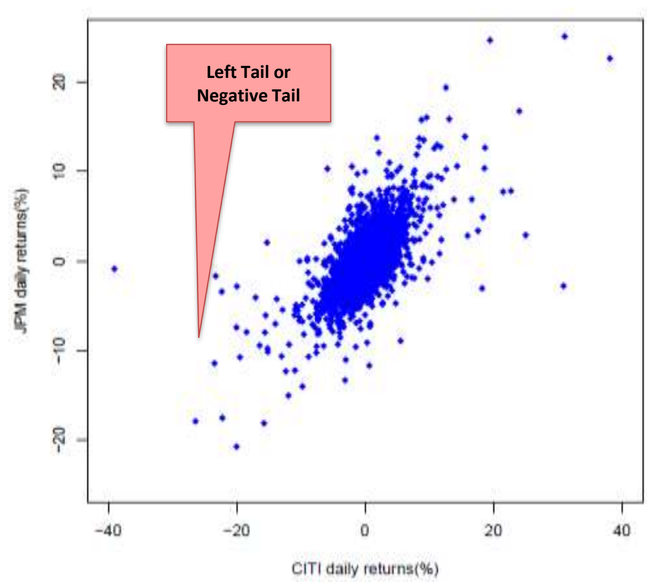
Since, JPM and CITIGROUP are within the same industry group, we would expect them to be more correlated than JPM and IBM or CITIGROUP and IBM. The correlation coefficient measures the overall strength of the relationship between the two stocks. However, the correlation coefficient gives little information about how stocks co-move across the tails of the distribution. For example, JPM and IBM have an overall return correlation of 39% whereas JPM and CITIGROUP have an overall correlation of 66%. However, this says little about the correlation within the tails. Figure 66 and Figure 67 hint that JPM and IBM are less correlated in the left tail (far left of the chart) than JPM and CITIGROUP. For JPM and CITIGROUP, it suggests that a large negative return for one stock will likely be accompanied by a large negative return of the other stock (i.e. JPM and CITIGROUP are more strongly correlated in the left tail than JPM and IBM).

Figure 66: JPM and IBM




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

Figure 67: CITIGROUP and JPM



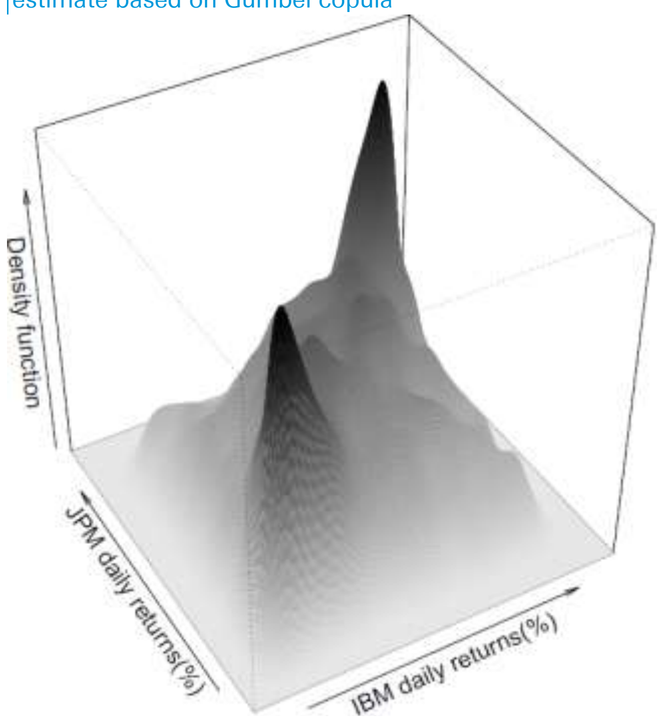

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

This is where Copulae come into the picture. A Copula can provide a more complete codependence structure across the bivariate distributions. It can provide control and correlation structure over what parts of the distributions the variables are most strongly (or weakly) associated.

*A copula can provide a correlation structure across the distributions. It can provide control and structure over what parts of the distributions the variables are most strongly (or weakly) associated*

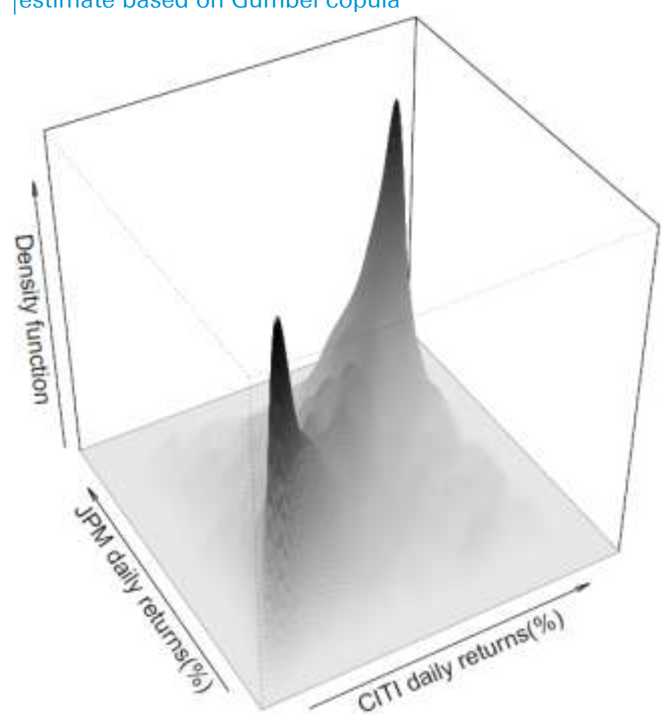
Consider two copulae, fit at a given point in time to two pairs of stocks: JPM-IBM (see Figure 68) and JPM-CITIGROUP (see Figure 69).The "surface" in these charts is the probability density functions, i.e., it tells us how likely we are to see a given pair of returns occurring together (note that the returns are normalized between 0 and 1, such that simultaneous large negative returns are in the back corner of each chart for easier visualization). The large spikes in the end of the charts show that in both cases, there is a much higher probability of having large negative returns than large positive returns, or any other possible combination of returns.

Figure 68: JP Morgan–IBM Tail Dependence, point estimate based on Gumbel copula




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

Figure 69: JP Morgan–Citigroup Tail Dependence, point estimate based on Gumbel copula



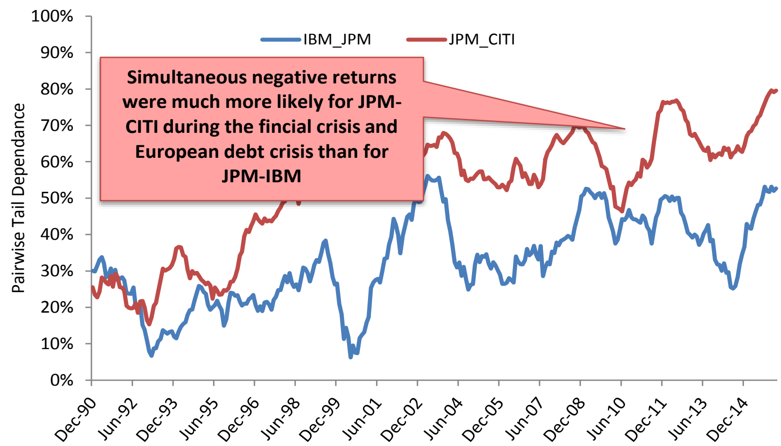

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

More formally, we can measure a quantity called the asymptotic tail dependence which describes how variables co-move in the tails of the distributions. In rough terms, it measures how likely it is that we see large negative returns to both stocks at the same time, i.e. how "high" is the spike in the back corner of the charts. In this particular case, it is clear that there is a higher probability of JPM and CITIGROUP having concurrent negative returns, compared to JPM and IBM. This is probably not a surprise.

*More formally, we can measure a quantity called the asymptotic tail dependence which describes how variables co-move in the tails of the distributions. In rough terms, it measures how likely it is that we see large negative returns to both stocks at the same time*

Suppose we extend the example and consider how the tail dependence of our two pairs of stocks changes through time (see Figure 70). Once again, the results are intuitive. Through the financial crisis, the tail dependence of JPM-CITIGROUP increased dramatically, much more so than JPM-IBM.

Figure 70: Time-series of JPM–CITIGROUP and JPM–IBM Tail Dependence




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

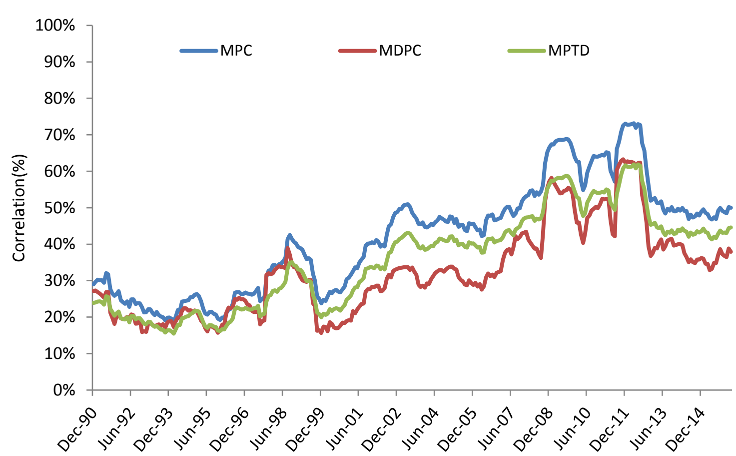
## Tail dependence as a herding measure

Next, we generalize this concept to the whole universe. At the end of each month, we obtain daily returns for the past year for each stock in the Russell 1000 at that point in time. Then, for each pair of stocks, we compute the negative tail dependence by using maximum likelihood to fit a Gumbel copula to the daily returns.[9]As one might imagine, this methodology is quite processor and data intensive.

*To make a long story short and avoid unnecessary analysis, our results find that MPTD is highly correlated to MPC and MDPC*

To make a long story short and, our results find that MPTD is highly correlated to MPC and MDPC (see Figure 71). In fact, MPTD is even more correlated to MDPC. This is somewhat expected and intuitive. Recall that MPC proved to be a descent crowding measure for quant factors.

Figure 71: Russell 3000 stock wise correlation using MPC, MDPC, and MPTD




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

[9] There are a wide range of different copulas that have been tested on stock return data. We pick the Gumbel copula for a few reasons. First, it is asymmetric and allows greater tail dependence in the tail (note that for this reason we multiply all our returns by -1 before fitting the copula). Second, it is widely used in the academic literature on modeling the dependency structure of stock returns (see for example Ruenzia and Weigert [2012], also reviewed in our March 2012 edition of Academic Insights).

# Grassroots crowding measures

In this section, we examine more direct measures of crowding based on investor holding and interest (i.e., buying power). These are metrics that we would expect to be more reliable measures of crowding because they use information that is directly related to how investor share positions.

## Holdings based measures

On face value, using the holdings data reported directly by money managers (via 13F and other regulatory filings) seems to be the most obvious way to measure crowdedness. If most managers hold deep value stocks then we might infer that value strategies are crowded. Unfortunately, the problem with ownership data is the lag between when a fund actually holds a position and when it has to report that position (roughly two months later).This means that any information gleaned from ownership data will be somewhat backwards looking. Nonetheless, it is worth investigating.

*We use the Thomson Reuters ownership database as our source for fund holdings. Note that 13F disclosures are typically filed quarterly by intuitions*

We use the Thomson Reuters ownership database as our source for fund holdings.[10] The Thomson Reuter's institutional dataset collects holding data from global institutions, mutual funds, and individual investors. Short and cash positions are not disclosed in the Thomson Reuters database. Data is available on a quarterly basis since 13F disclosures are typically filed quarterly by intuitions. Using this data, we compute the percentage of ownership for each stock on each quarter end, using the most recently reported regulatory filings. The percentage of ownership is essentially shares held by a class of institutions divided by total shares outstanding. We term this as ownership intensity factor.

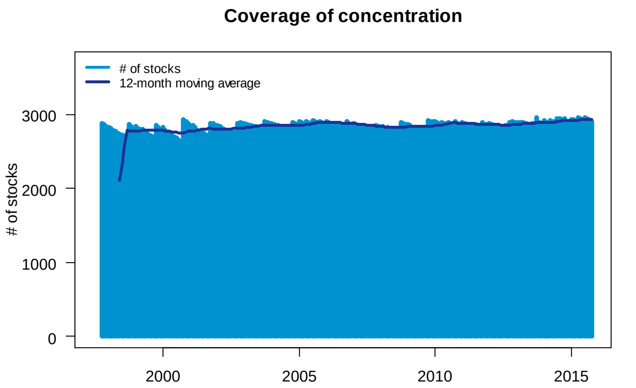
## 7. Ownership intensity

We test whether ownership intensity is indicative of crowding. Figure 72 shows the times series coverage of the ownership intensity factor within the Russell 3000 universe. The coverage is fairly strong. Undoubtedly, every stock should have an owner and our dataset has an expansive breadth of owners. We also analyze the distribution of the change in intensity (see Figure 73).

Interestingly, the figure shows that the average change in ownership for companies is approximately 0.5%. The mean and median are both positive which suggests that on average, owners increase their positions in companies. It may also reflect the onset of institutional money into equities and out of other asset classes.

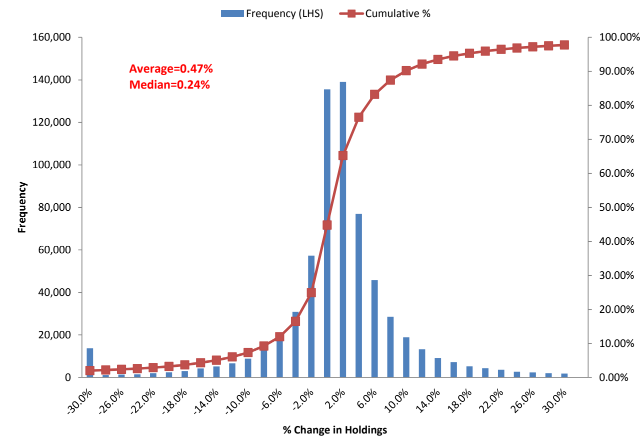
[10] We have published multiple research papers using this database, see Jussa et al [2014], Wang et al [2014], and Wang et al [2106].

Figure 72: Coverage of ownership intensity




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

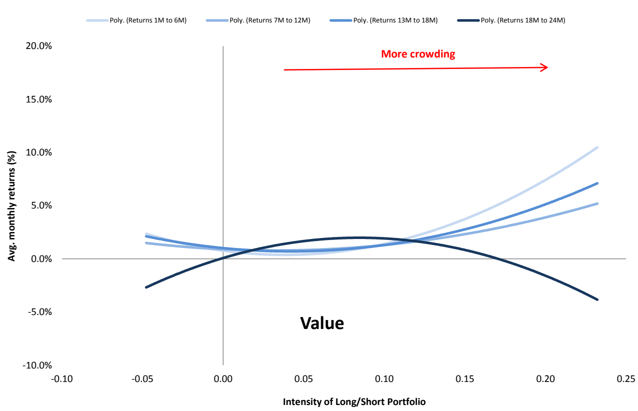
Figure 73: Time series percentiles of ownership intensity




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

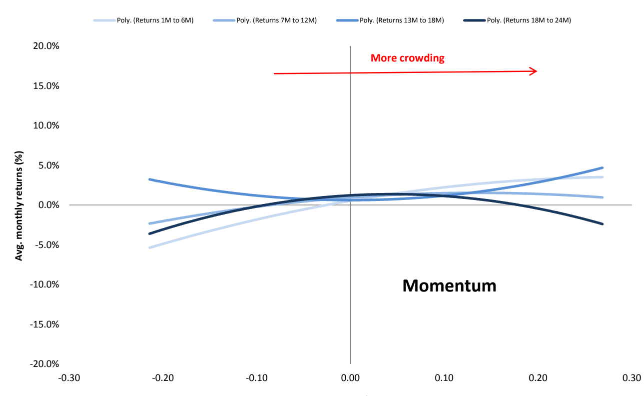
We compute the intensity of the factor portfolio by subtracting the short leg intensity from the long leg intensity. Ownership intensity provides a useful and intuitive measure of crowding (see Figure 74 to Figure 79). Essentially the correlation between factor intensity and future factor returns becomes consistently negative near the two year mark. This is especially the case for value, growth, momentum and low volatility. Ownership intensity could be a strong long-term predictor of crowding. Additionally, the results show a near-term outperformance when the strategies begin to become crowded.

Figure 74: Intensity and performance – value



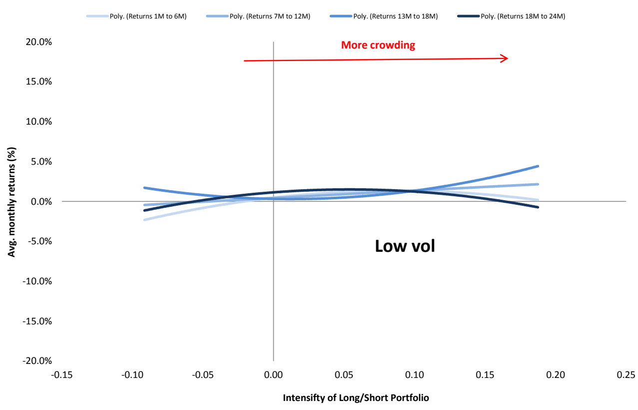

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 75: Intensity and performance – momentum



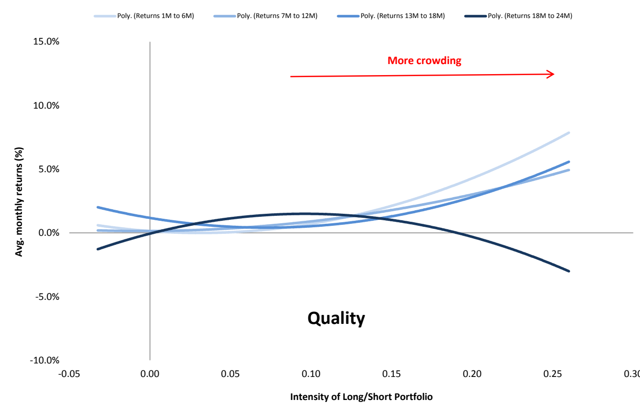

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 76: Intensity and performance – low volatility



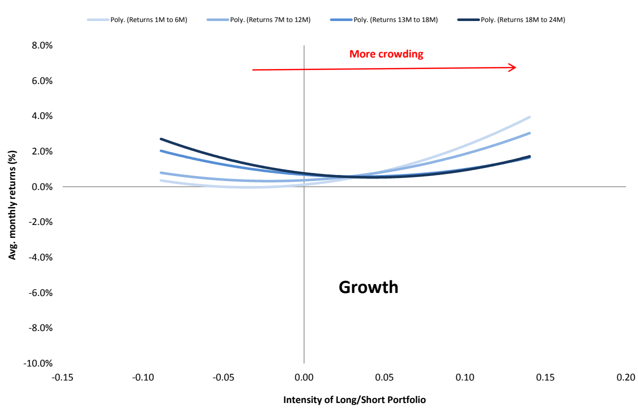

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 77: Intensity and performance – quality



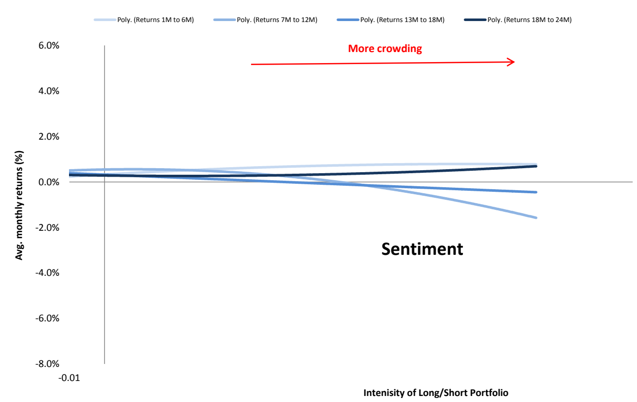

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 78: Intensity and performance – growth




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

Figure 79: Intensity and performance – sentiment




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

Next, we take this opportunity to revisit our short interest regression model and replace it with ownership intensity measure.

## Owner intensity – regression model

Another means of integrating ownership intensity into our crowding analysis is to bridge in our short interest dataset. Recall that our crowding indicator based on utilization used the following regression:

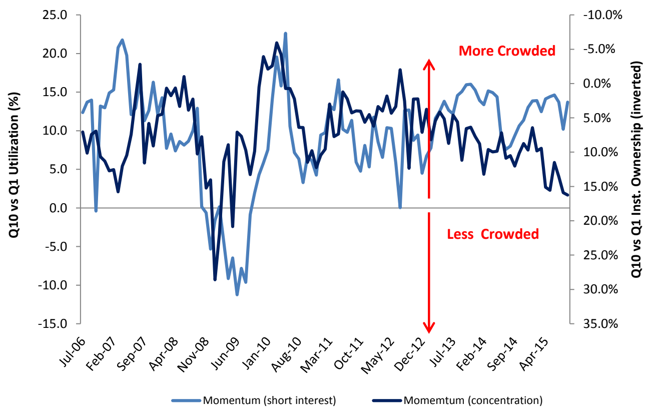
$$\mathrm{C}_{i,t} = c + \sum_{j=1}^{J} \sum_{q=2}^{Q} \beta_{i,t,j,q} D_{i,t,j,q} + \sum_{q=2}^{Q} \beta_{i,t,size,q} D_{i,t,size,q} + \sum_{q=2}^{Q} \beta_{i,t,\sigma,q} D_{i,t,\sigma,q} + \varepsilon_{i,t}$$

We redefine our crowding measure by simply using the ownership intensity metric as our dependant variable, $C_{i,t}$ (instead of utilization). In Figure 80 and Figure 81, we compare the results for Value and Momentum to those obtained using Utilization. It turns out the charts match to a certain degree but also show significant difference at times. The results for Value using the Utilization-based metric show that crowdedness is rising, while the Institutional Ownership-based metric show it is declining.

*We redefine our crowding measure by simply using the ownership intensity metric as our dependant variable*

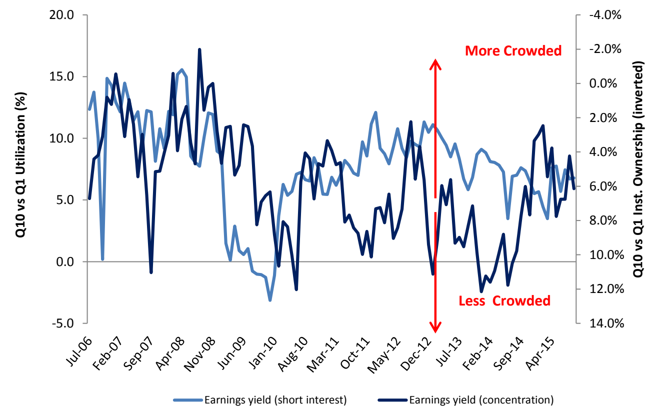
Given the lag in the institutional holdings data, would we prefer Utilization as our primary means of determining factor crowdedness? Not necessarily. The close match between the charts does give us some comfort that we are on the right track.

Figure 80: Incremental Utilization versus incremental Institutional Ownership for Q10 value stocks




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

Figure 81: Incremental Utilization versus incremental Institutional Ownership for Q10 Momentum stocks




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

Next, we analyze another potential crowding measure based on institutional ownership.

## 8. Buying power

In Sias [2002], herding is measured using the holdings dataset consisted of observing buying patterns of investors or owners. An owner is defined as a buyer if the ownership of the stock increases. More specifically, if the position held by the owner increases as a fraction of the shares outstanding, then the owner is a buyer. For example, if an owner held 0.01% shares of IBM and the following quarter it held 0.02% shares of IBM, then it would be classified as a buyer.[11] For each stock $s$ at each quarter end $q$ the herding or buying power measure is simply:

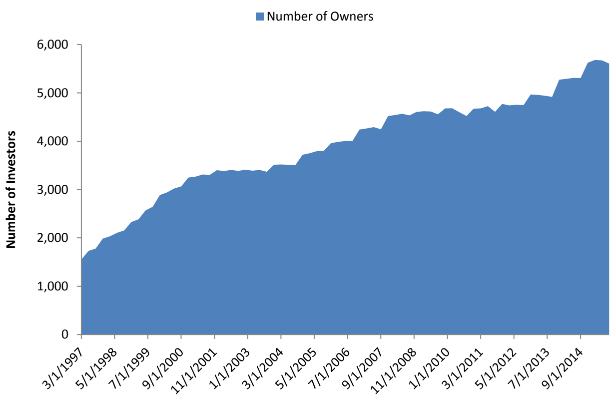
$$\text{buying\_power}_{s,q} = \frac{\#\text{ of Owners Buying}_{s,q}}{\#\text{ of Owners Buying}_{s,q} + \#\text{ of Owners Selling}_{s,q}}$$

Since the data is measured quarterly, owners that buy and sell the same number of shares within the same quarter will not be counted as a trade. By aggregating the buying power at a sector, market, and strategy level, we can test whether this measure is indicative of crowding. To get a better sense of the dataset, Figure 82 plots the number of owners over time. The current number of owners exceeds 5,000 investors. Figure 83 shows the average number of stocks held by owners. Investors on average hold approximately 75 stocks.

*Sias' approach to measure herding using the holdings dataset was by observing buying patterns of investors*

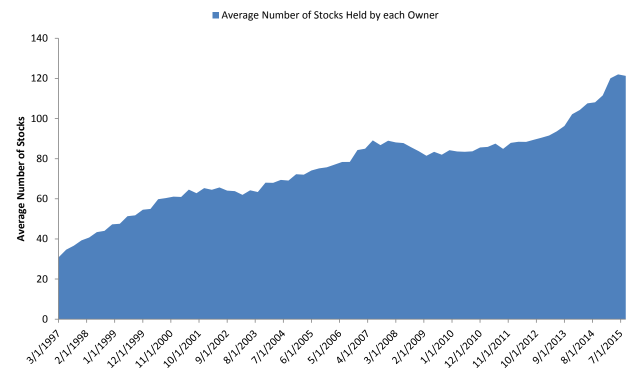
[11] Note that 0.01% and 0.02% represent shares held over shares outstanding for that particular institution at quarter end.

Figure 82: Time series of the number of owners




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

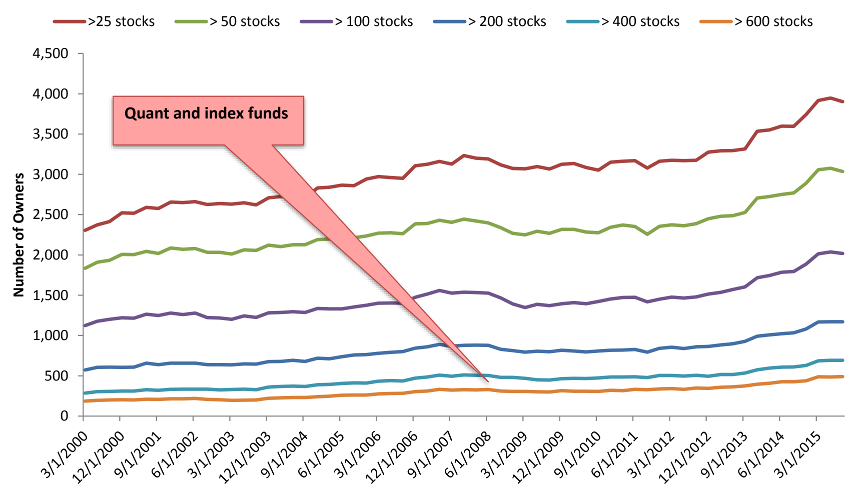
Figure 83: Average number of securities held by owners




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

Lastly, Figure 84 shows the number of owners alongside stocks held. The chart shows that there are fewer owners who own a large numbers stocks, as expected. Owners tending to hold a significantly large number of stocks tend to be quant and index funds.

Figure 84: Number of owners and stocks held




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

We compute the buying power of the portfolio by subtracting the buying power of the long leg minus the buying power of the short leg. We can then analyze the correlation between the buying power and future returns. If our indicator is negatively correlated to future performance, then this would suggest a mean-reversal behavior. On the other hand, if it is positively correlated to future performance, then this would suggest a potential trending indicator. The strength of the correlation is also important.

Buying power based crowding measures are strongly and consistently negatively correlated to future returns for all quantitative factors (see Figure 85).

Figure 85: Comparing buying power and intensity for quant factors

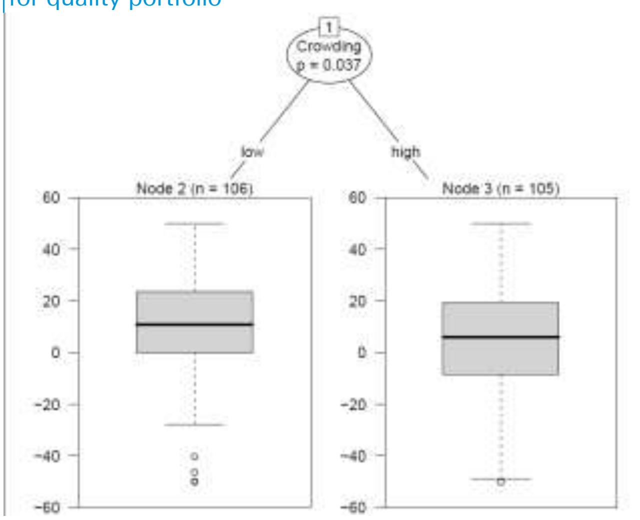
| Factors | Intensity | | | | Buying power | | | |
|---|---|---|---|---|---|---|---|---|
| Dividend yield | 11% | 20% | 26% | 18% | -5% | -14% | -2% | -21% |
| Earnings yield | 26% | 12% | 16% | 3% | -14% | -17% | -18% | -16% |
| Momentum | 34% | 13% | 8% | 3% | 7% | 7% | -4% | 13% |
| 1M Reversal | 4% | -23% | -5% | 6% | 36% | 0% | -20% | 7% |
| EPS growth | 33% | 25% | 1% | -3% | -8% | -16% | -17% | 1% |
| ROE | 34% | 24% | 15% | -4% | -20% | -21% | -12% | -5% |
| Low Vol | 7% | 11% | 13% | 0% | -11% | -20% | -11% | -12% |
| Earnings revisions | 13% | -4% | -13% | -1% | -21% | 1% | -13% | 4% |
| Avg. Monthly Returns | 1 to 6 | 7 to 12 | 13 to 18 | 19 to 24 | 1 to 6 | 7 to 12 | 13 to 18 | 19 to 24 |

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

*The ownership intensity factor merely shows the level of institutional ownership for each sector or strategy. It is lagged by one quarter. On the other hand, the buying power factor shows the interest from buyers in a stock quarter over quarter*

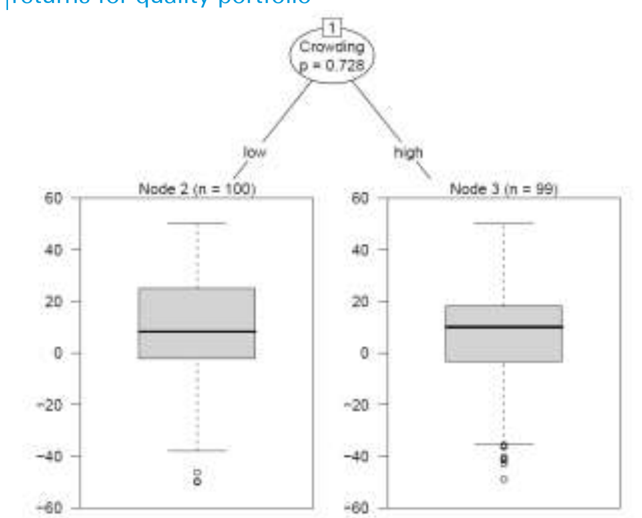
This can be seen more clearly when running the CART model on the quality portfolio using buying power as the crowding measure (see Figure 86 and Figure 87). At high levels of crowding, 12-month forward returns tend to be slightly lower and more negatively skewed than 13 to 24-month forward returns.

Figure 86: Buying power and 12-month forward returns for quality portfolio




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

Figure 87: Buying power and 13 to 24-month forward returns for quality portfolio




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

We also run a multivariate regression analysis on future 12- and 24 month returns using buying power (see Figure 88). The results show that the longer horizon of 24 month future returns does not improve the significance level. The results can potentially be explained by the fact that the ownership data is delayed and lagged. This may explain why the results show more severe impact on the near term rather than the long term returns.

Figure 88: Average coefficients for multivariate regression using buying power

| | 12-Month Forward Returns | | 24-Month Forward Returns | |
|---|---|---|---|---|
| | Average Beta | Average T-stat | Average Beta | Average T-stat |
| Crowding | (2.23) | (3.09) | (4.62) | (4.01) |
| Crowding squared | 0.01 | 0.55 | 0.03 | 1.96 |
| Crowding change | 0.96 | 1.88 | 1.08 | 1.31 |
| Crowding saturation | (0.54) | (1.20) | (2.18) | (2.90) |

*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

It is also important to highlight that the ownership intensity and buying power are similar yet different factors. The ownership intensity factor shows the level of institutional ownership for each sector or strategy. It is lagged by one quarter. On the other hand, the buying power factor shows the interest from buyers in a stock quarter over quarter. Its gives an indication of pure investor demand for a particular sector or strategy.

# The ultimate crowding measures

In this section, we examine two portfolio level of crowding measures: the concentration and diversification ratios. We have studied them as crowding measures in Luo, et al [2014] and Wang, et al [2016].

## 9. Concentration ratio

In classic economics, the concentration ratio is a measure of the output produced by each firm in an industry. CR4 measure the market share of the four largest firms in an industry. Similarly, CR8 measures the market share of the eight largest firms in an industry. The concentration ratio is a measure of market control within an industry. It essentially measures the degree to which an industry is oligopolistic (i.e., dominated by a few companies).

The traditional measure of competitiveness and concentration is the Herfindahl index:

$$Herfindahl\_Index = \sum \mathrm{market\_shares_n}^2$$

A similar measure of company domination can be calculated at the portfolio level. The measure is called the concentration ratio or CR[12].

$$CR = \frac{\sum_{i=1}^{N} w_i^2 \sigma_i^2}{\left(\sum_{i=1}^{N} w_i \sigma_i\right)^2}$$

*In general, if a portfolio has heavy positioning in volatile names, the CR would reflect that this portfolio is concentrated*

It is a measure of portfolio concentration that takes the volatility of the stocks into account. A higher CR is indicative of more concentrated positioning. For example, take the hedge fund aggregate portfolio (HFA) based on institutional ownership data. This simply aggregates the positions of most hedge funds. It shows which companies most hedge funds are heavily invested in. If the HFA portfolio has significant positions in a few highly volatile companies, then the CR would show that this portfolio is fairly "concentrated".

In general, if a portfolio has heavy positioning in volatile names, then the CR would reflect that this portfolio is concentrated. In effect, the CR measures not only the concentration of weights, but also the concentration of risks as assets are weighted proportionally by their volatilities. [13]

### The concentration ratio and portfolio crowding

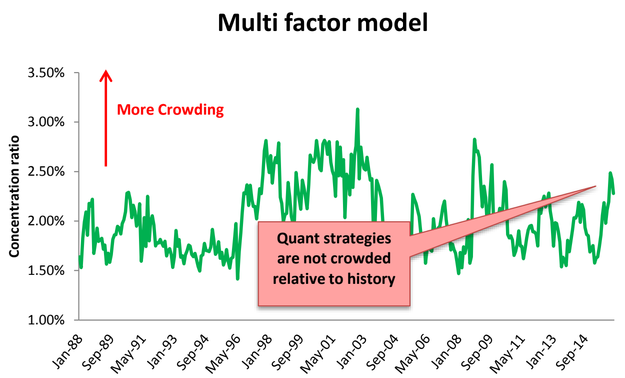
The CR ratio is typically used to measure crowdedness in aggregate portfolios. For example, the CR can be used to measure the crowdedness of the HFA portfolio described earlier. However, quants typically invest in a larger number of securities than typical hedge funds. To test whether quantitative strategies are crowded, we construct the quantitative representative portfolio or QRP.

[12] As shown in Choueifaty and Coignard [2008] and Luo, et al [2014]

[13] See Choueifaty and Coignard [2008] for more details.

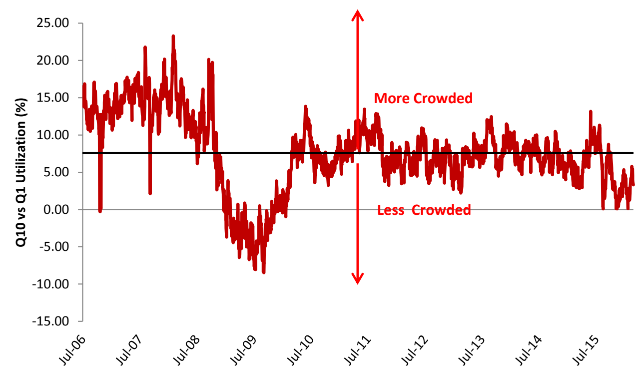
To do this we simply build a portfolio based on standard factors that quants typically use, such as value, growth, momentum, sentiment, low volatility, and quality. We sector neutralize each factor because quants typically avoid making sector calls. Combining all these factors together forms our multifactor, long only portfolio. We take the top 300 best stocks based on this multifactor model and market cap weight them within the portfolio. We select a fixed number of stocks (i.e., 300) because the CR ratio is fairly sensitive to the number of securities. All else being equal, a larger breadth of securities will decrease the CR ratio. Figure 89 shows the CR ratio for our QRP.

Figure 89: CR for QRP (all history)




*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

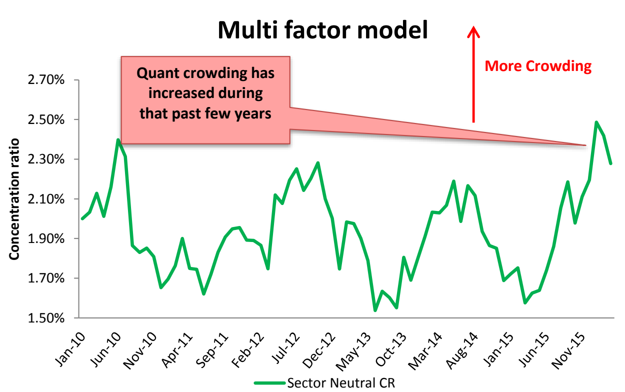
Figure 90: Incremental utilization for multifactor model




*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Markit, Deutsche Bank*

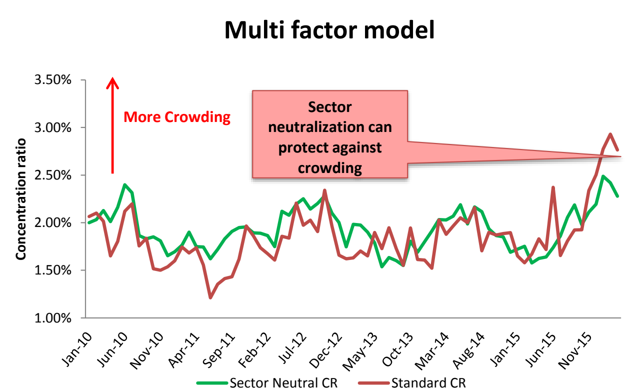
The results show that quant strategies are not overly crowded relative to history, but more so than using our incremental utilization measure, (see Figure 90). Figure 91 shows an uptick of crowding in recent years. Quant crowding is at a five-year high as measured by CR. We also find that quant strategies that are not currently sector neutralized show even stronger signs of crowding (see Figure 92). This would imply that currently, quant strategies are sensitive to sector effects. Sector neutralization tends to lower the volatility of a portfolio.

Figure 91: CR for QRP (recent history)




*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

Figure 92: Non-sector neutral CR



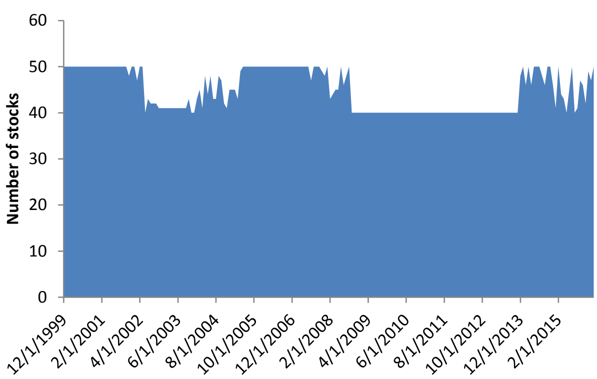

*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

We also find that the correlation between CR and forward annual QRP excess returns is -20%. However, the overall crowdedness of QRP tells us little about the underlying factors behind the model.

One of the most widely discussed and employed underlying drivers of quant portfolios is low volatility. We can also use CR to measure the crowdedness of low volatility or minimum variance portfolio. We construct our minimum variance portfolio using stocks in the S&P 500 universe.[14] We assign a 5% maximum asset weight constraint and limit our portfolio with around 40 and 50 stocks.

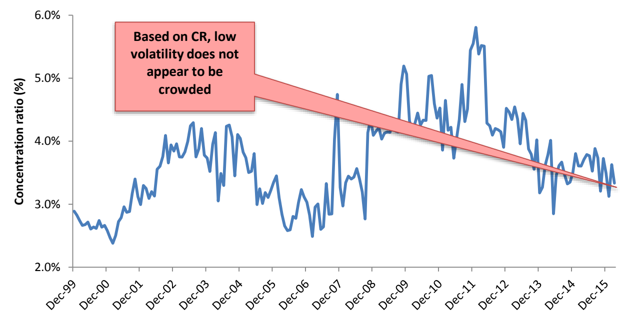
Figure 93 shows the number of stocks in the minimum variance portfolio. Figure 94 shows the time series CR for the minimum variance portfolio.[15] CR shows that low volatility strategies are currently not crowded. This seems to contradict with the other crowding measure we have analyzed thus far.

Figure 93: Coverage of minimum variance portfolio




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

Figure 94: CR for minimum variance portfolio




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

## Real life portfolio simulations

As a robustness check, we create another multi-factor model using a blend of quant factors. We employ a mean variance optimization using the Axioma medium-term fundamental risk model to create a long-only active portfolio with the Russell 1000 as benchmark. We also set a 5% maximum asset weight constraint. Additionally, we ensure that the portfolio holds between 90 and 100 stocks. This portfolio serves as a proxy for a typical quantitative manager.

Next, we compute the CR of this portfolio. We compute the market relative CR by subtracting the Russell 1000 CR. [16] Figure 95 shows the relative CR from 1994 onwards. The results indicate no significant crowding relative to history. We also backtested a sector-neutral quant portfolio. This also showed no significant levels of quant crowding relative to history (see Figure 96).[17]

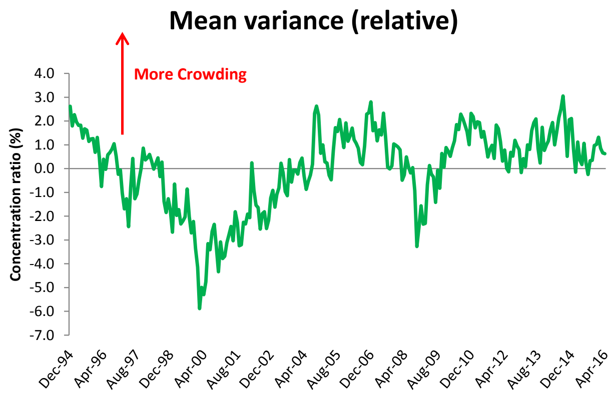
[14] We use the Axioma risk model to optimize the minimum variance portfolio.

[15] The volatility is calculated based on daily returns over the past three years.

[16] We use the Axioma risk model for the calculation of the concentration ratio. We also Z-score the CR prior to computing the relative CR.

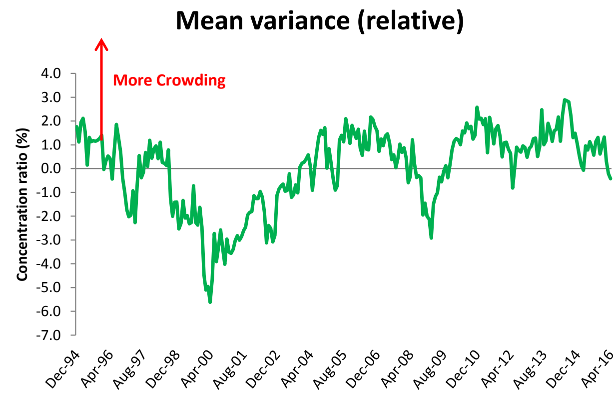
[17] We sector neutralized the alpha signal instead of using a constraint in the Axioma optimizer.

Figure 95: CR for optimized portfolio – Russell 1000




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

Figure 96: CR for optimized portfolio – sector neutral – Russell 1000




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

We also find that the correlation between relative CR (as well as sector-neutral relative CR) and forward annual excess returns is -40% and - 39% respectively. This would suggest that relative CR is a reasonable measure of crowding.

However, the CR does not consider the correlation among stocks in the portfolio. We address this next by introducing the diversification ratio.

## 10. Diversification ratio

The diversification ratio (DR) is similar to CR, but it takes into account the correlation among the stocks in the portfolio (see Luo, Wang, Cahan, et al [2013]). It is defined as the weighted average volatility divided by the total portfolio volatility (which accounts for correlation). [18]

$$DR = \frac{\sum_{i=1}^{N} w_i \sigma_i}{\sigma_{\mathrm{p}}}$$

$$\sigma_{\mathrm{p}} = \sqrt{\sum_{i=1}^{N} w_i^2 \sigma_i^2 + \sum_{i} \sum_{i \neq j}^{N} w_i w_j \sigma_i \sigma_j \rho_{ij}}$$

*The diversification ratio (DR) is similar to CR, but it takes into account the correlation of the stocks in the portfolio*

In general, if a portfolio has heavy positioning in volatile names that are highly correlated, the DR would reflect that this portfolio is concentrated. Reverting back to our HFA example, if the HFA portfolio has significant positions in a few highly volatile companies, then the DR would show that this portfolio is undiversified or concentrated. If those names are also highly correlated, then the DR would show significant concentration. The DR can also be written as a function of CR. Therefore, the higher the pairwise correlation, the lower the DR.

$$\mathrm{DR} = \frac{1}{\sqrt{\rho_{\mathrm{average}}\ (1 - \mathrm{CR}) + \mathrm{CR}}}$$

[18] See Choueifaty and Coignard [2008] for more details.

## The diversification ratio and factor crowding

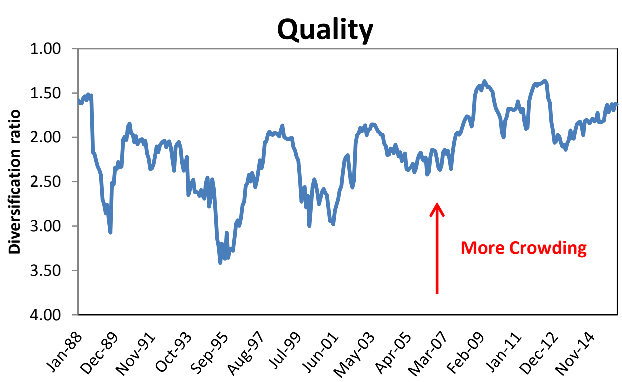
We test how well DR can measure factor crowdedness using a similar methodology outlined for CR.[19] We construct long only factor portfolio reflective of the strategies that quants and other investors typically invest in. These portfolios are: value, growth, momentum, sentiment, quality, reversal, and low volatility. To construct these portfolios, we take the top 50 names ranked by each factor. The universe is the Russell 3000. Note that the portfolios are not sector neutralized.

Furthermore, we market cap weight as well as conviction weight (i.e., factor-score weight). We also apply a 5% maximum weight constraint. Figure 97 and Figure 98 show the time series DR for the momentum and low volatility portfolio, respectively. We have inverted the y-axis, therefore a higher reading is indicative of less diversification, more concentration, and hence more crowding. We immediately notice that the DR has a trending component. On average, it has increased over time.

*Based on DR, quality and low volatility are showing signs of crowdedness, relative to their own history*

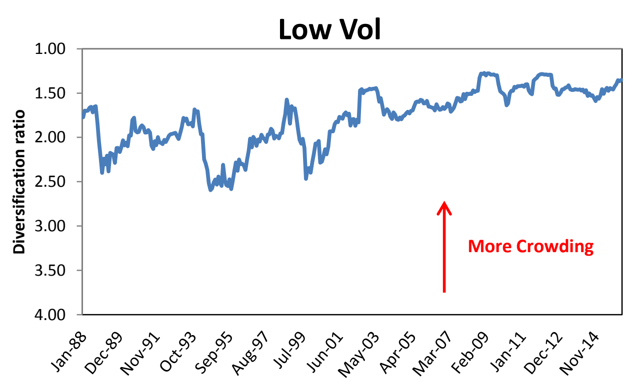
This likely reflects the fact that more systematic and passive strategies have entered the marketplace post the 1990s. And investors are chasing similar strategies causing an increase in correlation. Based on DR, quality and low volatility are showing signs of crowdedness, relative to their own history.

Figure 97: DR for quality cap-weighted portfolio




*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

Figure 98: DR for low volatility cap-weighted portfolio

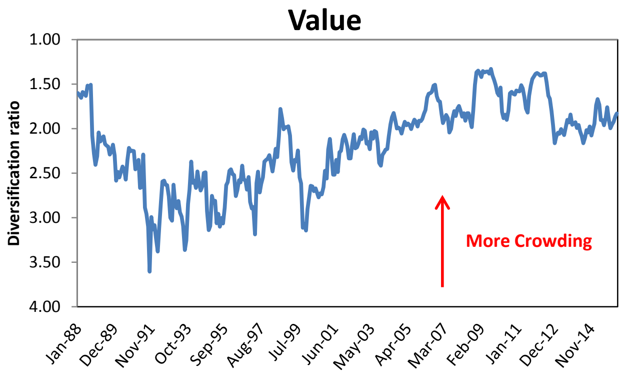



*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

We also analyze the time series DR for the other factor portfolios (see Figure 99 to Figure 102). Again the DR ratio is showing an increasing trend overtime.

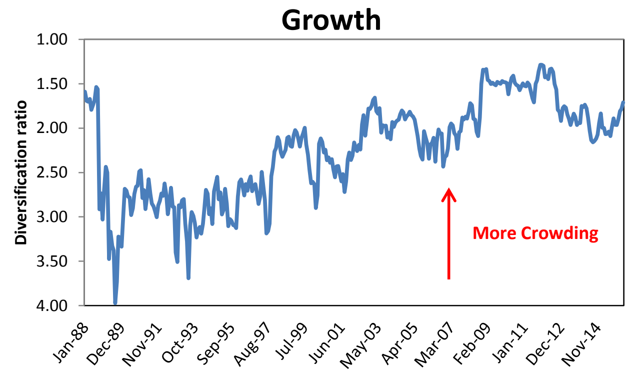
[19] The calculation of DR requires the covariance matrix. We compute the sample covariance matrix for the DR calculation using one year of daily returns.

Figure 99: DR for value cap-weighted portfolio



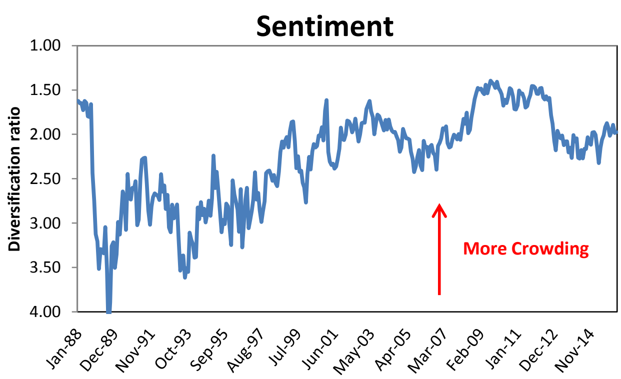

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 100: DR for growth cap-weighted portfolio



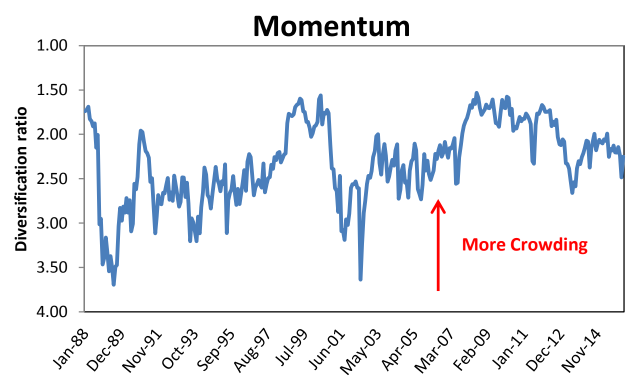

Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

Figure 101: DR for sentiment cap-weighted portfolio




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

Figure 102: DR for momentum cap-weighted portfolio




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

Again, we need to test how the DR is related to future performance. We compute the correlation between DR and future 12-month cumulative returns (see Figure 103).

As shown in Figure 103, the correlation between DR, for the cap-weighted quality and low volatility portfolio and one-year future returns are sizeable – 49% and -64%, respectively. Overall, there is no significant difference between the cap-weighted and conviction-weighted portfolios.

Figure 103:DR and crowdedness

| | Div yield | Value | Momentum | Reversal | Growth | Quality | Low Vol | Sentiment |
|---|---|---|---|---|---|---|---|---|
| **DR Cap Weighted** | -4% | -20% | -19% | 35% | 11% | -49% | -64% | 35% |
| **DR Conviction Weighted** | 8% | -10% | -30% | 30% | -7% | -50% | -73% | 30% |

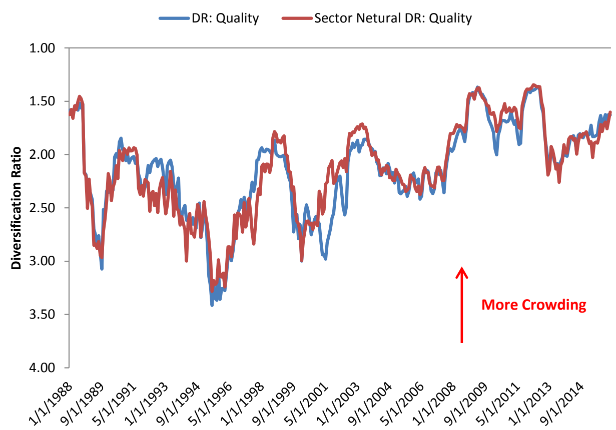
Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank

# Robustness checks for the diversification ratio

## Sector effects

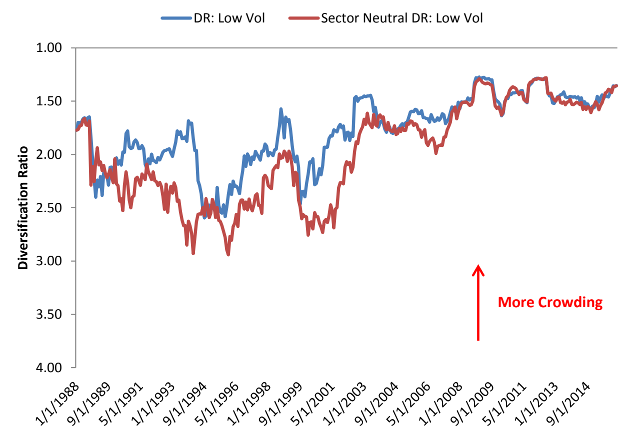
Factor portfolios can take on significant sector exposure. Therefore the strong results behind the DR crowding metric may be driven by sector effect. As such, we sector adjust our factor portfolio and repeat our analysis.[20] Figure 104 and Figure 105 compare the time series DR and sector adjusted DR for the quality and low volatility portfolios. We see no significant difference between the original DR and sector adjusted DR.

Figure 104: Sector adjusted DR for quality cap-weighted portfolio




*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

Figure 105: Sector adjusted DR for low volatility cap-weighted portfolio




*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

In terms of the influence of sectors, using adjusted DR as a crowding measure, we see no significant differences when compared to the original DR measure (see Figure 106).[21] This implies that the strong performance of DR as a crowding measure is not driven primarily by sectors.

Figure 106:DR sector adjusted and crowdedness

| | Div yield | Value | Momentum | Reversal | Growth | Quality | Low Vol | Sentiment |
|---|---|---|---|---|---|---|---|---|
| **DR Cap Weighted** | -4% | -20% | -19% | 35% | 11% | -49% | -64% | 35% |
| **DR Cap Weighted (sector neutral)** | -12% | 1% | -14% | 24% | 5% | -39% | -66% | 33% |

*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

## Trend effects

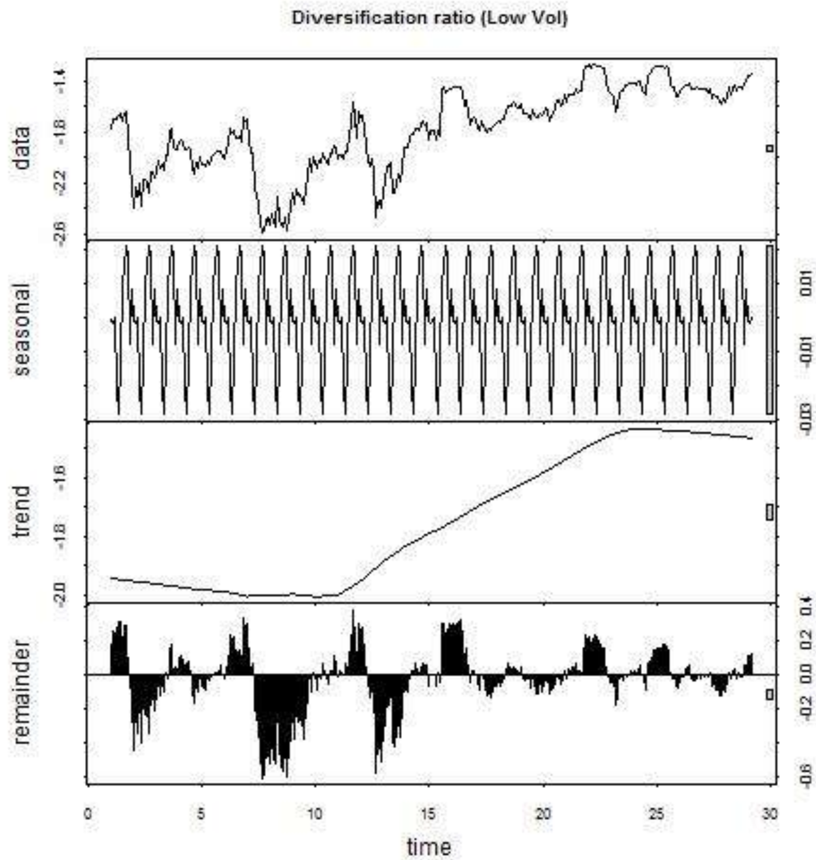
Next, we perform one more robustness check. We recall that the DR had a significant trend component while returns normally do not. In this last section, we de-trend our DR measure to test if it still holds up as an adequate crowding measure. Figure 107 shows the original DR ratio, the seasonal component, the trend component, and the residual DR (RDR).[22] The seasonal component is fairly small. However, the trend component is significant. The RDR is what really interests us.

[20] We sector adjust our factor portfolios by z-score the factors cross-sectionally across the GICS level 1 sectors rather than cross-sectionally across the entire Russell 3000 universe.

[21] The correlation is computed from the year 2000 onwards.

[22] We use the STL package in R to de-trend the DR ratio.

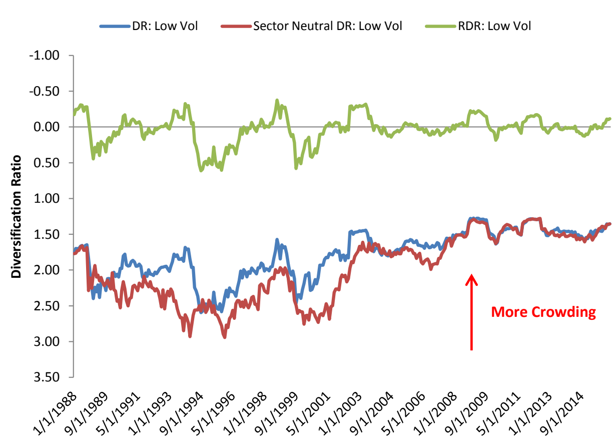
Figure 107:De-trending DR




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

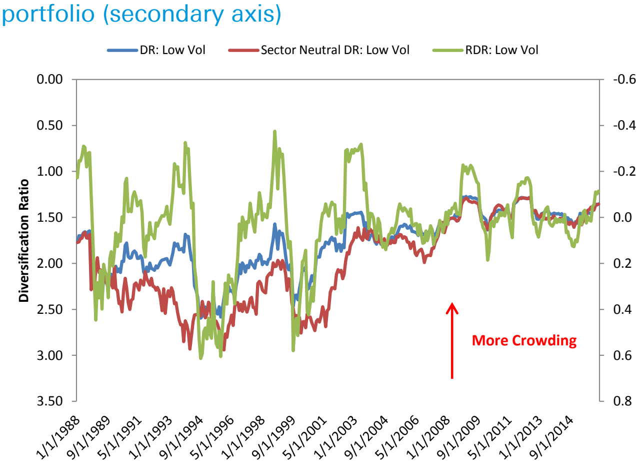
Figure 108 compares the original DR, sector DR, and the RDR. Note that the RDR does show mild signs of crowding (i.e., its currently above zero). This can be seen more easily by putting the RDR onto the secondary axis (see Figure 109).

Figure 108: Residual DR for low volatility cap-weighted portfolio




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

Figure 109: Residual DR for low volatility cap-weighted portfolio (secondary axis)




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

In terms of the strength of RDR as a crowding measure, we see no significant differences compared to the original and sector adjusted DR's (see Figure 110). Again, our results reiterate that DR is a robust and effective measure of investor crowding, especially for low volatility.

Figure 110: DR remainder and crowdedness

| | Div yield | Value | Momentum | Reversal | Growth | Quality | Low Vol | Sentiment |
|---|---|---|---|---|---|---|---|---|
| DR Cap Weighted | -4% | -20% | -19% | 35% | 11% | -49% | -64% | 35% |
| DR Cap Weighted (sector neutral) | -12% | 1% | -14% | 24% | 5% | -39% | -66% | 33% |
| DR Cap Weighted (residual) | 11% | 5% | -15% | 33% | 21% | -22% | -51% | 34% |

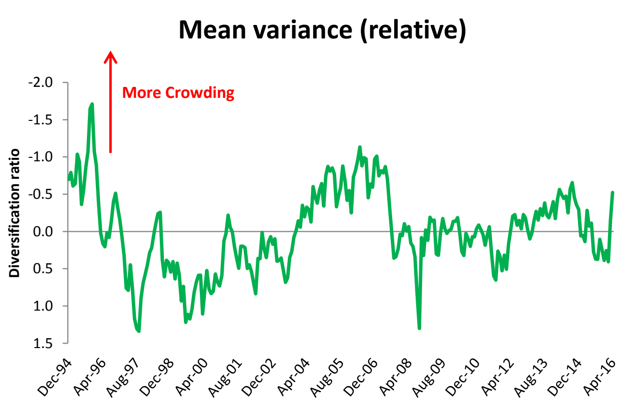
*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

## Real life portfolio simulations

Lastly, we use the same multi-factor model (a blend of quant factors) to create a long-only optimized portfolio. We employ a mean variance optimization using the Axioma medium-term fundamental risk model. We also set a 5% maximum asset weight constraint. Additionally, we ensure that the portfolio holds between 90-100 stocks.

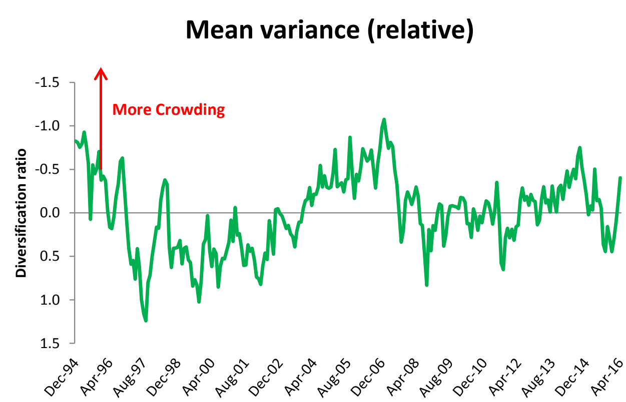
Next, we compute the DR of this portfolio and further subtract the market DR (based on the Russell 1000 index). To compute the market relative DR, we divide by the Russell 1000 DR. [23] Figure 95 shows the relative DR from 1994 onwards. The results indicate no significant quant crowding relative to history. We also backtested a sector-neutral quant portfolio. This also shows only modest levels of quant crowding relative to history (see Figure 96).[24]

Figure 111: DR for mean variance portfolio – Russell 1000




*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

Figure 112: DR for mean variance portfolio – sector neutral – Russell 1000




*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, Deutsche Bank*

We want to highlight that the correlation between relative DR (as well as sector neutral relative DR) and forward annual excess returns is -15% and -9%, respectively.

[23] We use the Axioma risk model for the calculation of the concentration ratio. We also Z-score the CR prior to computing the relative CR.

[24] We sector neutralized the alpha signal instead of using a constraint in the Axioma optimizer.

# What about funds flow?

Lastly, we examine the practicality of using funds flow data as a measure of crowding. The results suggest that funds flow is an interesting dataset; but, it is more effective as a conditional variable to gauge the initial stages of crowding. Funds flow is useful at assessing inflection points in the market. Irrespective, we highlight the funds flow dataset in this research and welcome the opportunity to do further research on it.

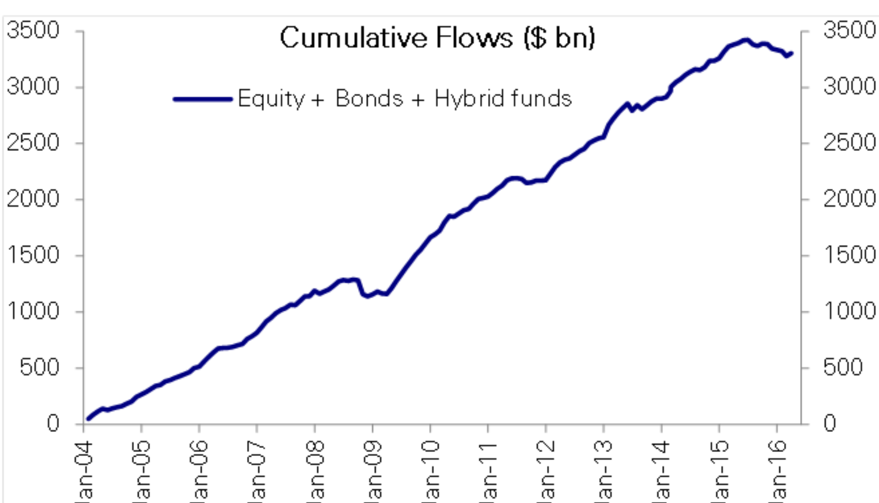
### A brief introduction of funds flow

Fund flows track net new end-investor money flowing into or out of mutual funds and ETFs. Our data set (from data providers EPFR Global and ICI) tracks funds with total assets under management of almost $22 trillion globally covering products across a wide range of asset classes, regions, countries, sectors, styles and sizes. Fund flows provide an important measure of investor demand and when combined with supply indicators explain movements in prices well. For example, simple measures of US equity demand based on fund flows and supply (issuance and buybacks) when combined have a 75% correlation with quarterly S&P 500 price changes over the last 20 years. To get a better sense of the dataset, we briefly analyze some recent themes based on the funds flow dataset.

### Key recent trends and rotations

The data shows a large remarkably steady pool of combined inflows into equity, bond and asset allocation (hybrid) funds running around $325bn a year for the last ten years (see Figure 113). What is the source of these steady flows? We view the steady flows as a normal allocation from new savings. If some proportion of income is saved, some proportion of this "new money" will be allocated to bonds and equities and the rest to cash. Savings and its allocation to bonds and equities explain why the norm in financial markets is of inflows. Their steadiness is an empirical regularity and likely reflects the steadiness of global savings.

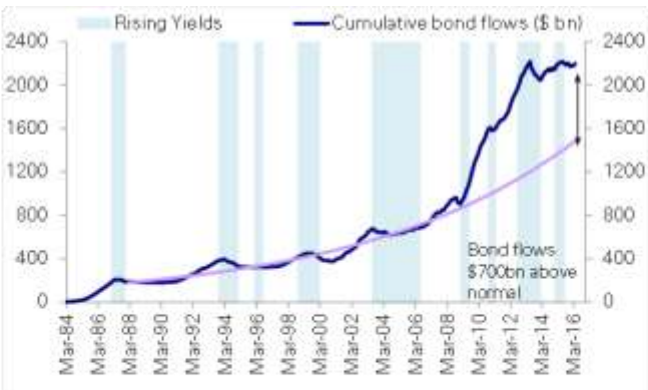
Figure 113: Pool of combined inflows into equity, bond, and hybrid funds




*Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, EPFR Global, ICI, Deutsche Bank*

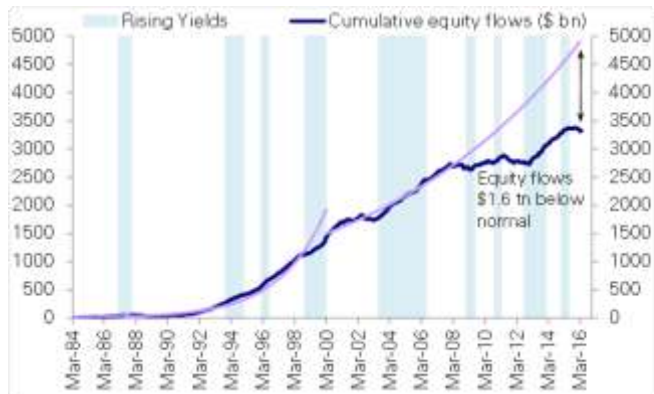
Breaking it down, the data shows a large over-allocation to fixed income above the normal trend whereas allocation to equities has been below the trend (see Figure 114 and Figure 115). Rotation from equities to bonds is common around recessions historically, but in the present cycle, it has continued well beyond the typical period. This has been driven by the absence so far of sustained rate normalization which is the normal cyclical asset reallocation mechanism between bonds and equities. An extended period of rate normalization may see a re-allocation back to equities. The potential scope is massive as cumulative flows to bonds relative to the historical trend are extremely high (+$770 billion above trend) while to equities are very low (-$1.4 trillions).

Figure 114: Allocation to bonds is above trend




Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, EPFR Global, ICI, Deutsche Bank

Figure 115: Allocations to equities is below trend

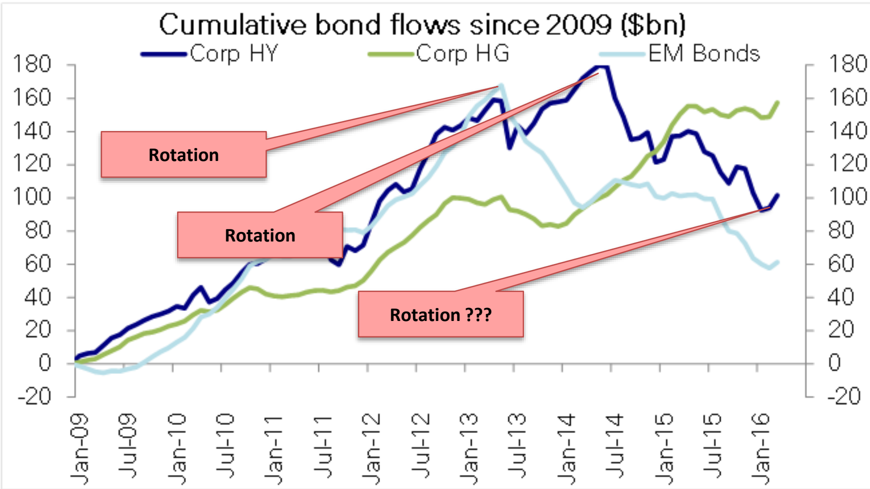



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, EPFR Global, ICI, Deutsche Bank

### Funds flow, crowding, and rotations

The funds flow dataset provides a rich source of investor insight. In particular, funds flow is useful at capturing persistent and consistent trends as well as rotations within asset classes. For example, in 2013 we saw a strong rotation out of emerging market bonds and into high-yield corporate bonds (see Figure 116). Thereafter high-yield bonds have seen a large outflow rotation since June 2014 of last year when oil prices began to fall. Currently it appears that high-yield and high-grade corporate bonds, as well as emerging market bonds, could be in a “rotationary” state. However, this difficult to accurately gauge or predict.

Figure 116: Bond rotation episodes

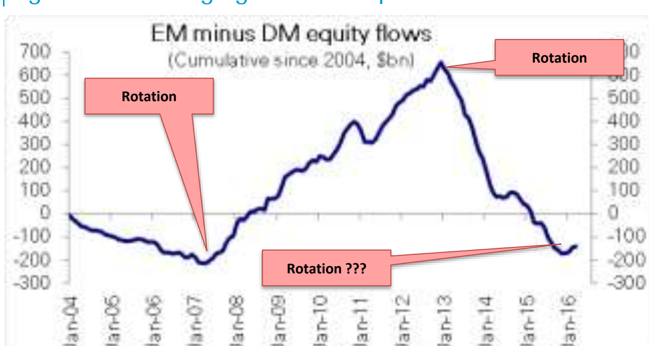



Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, EPFR Global, ICI, Deutsche Bank

*Whilst funds flow is an important and insightful metrics, incorporating the dataset into crowding may be challenging. Trending episodes are typically long, consistent and persistent. As such, rotations are difficult to gauge and predict*

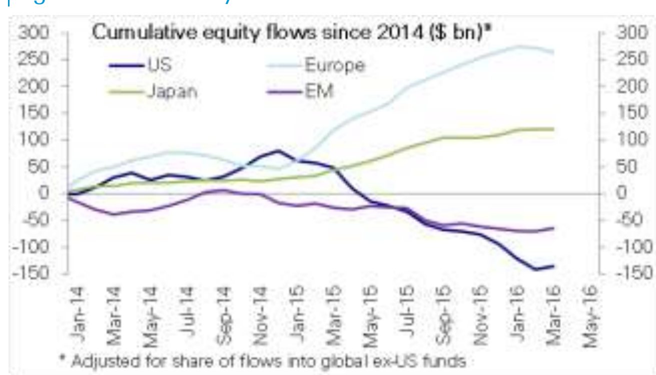
When analyzing funds flow for equities, we observe more rotations. Emerging markets (EM) relative growth peaked in 2010, EM equities began to see outflows with a modest lag beginning in early 2011 (see Figure 117). After a brief respite in 2012, outflows resumed in early 2013 and initially benefited all of developed market (DM) equities, but went primarily to Europe and Japan since early 2015 (see Figure 118). Currently, we could be at another inflection point as relative outflows out of EM and into DM has turned. However, this is difficult to predict even at the country level.

Figure 117: Emerging and developed market rotations




Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, EPFR Global, ICI, Deutsche Bank

Figure 118: Country rotations




Source: Bloomberg Finance LP, Compustat, IBES, Russell, S&P, Thomson Reuters, EPFR Global, ICI, Deutsche Bank

Whilst funds flow is an important and insightful metric, incorporating the dataset into crowding may be challenging. Trending episodes are typically long, consistent, and persistent. As such, rotations are difficult to gauge and predict. Funds flow may be useful as a conditional variable to gauge the initial stages of crowding. Irrespective, we highlight the funds flow dataset in this research and welcome the opportunity to do further research on these useful and insightful measures. Please keep an eye out for further research in this space.

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