LOST IN THE CROWD?

Identifying and Measuring Crowded Strategies and Trades

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June 2015
EXECUTIVE SUMMARY

The “quant meltdown” of August 2007 and the subsequent unfolding of the global financial crisis highlighted the risks of crowded investment strategies. The rapid growth of “smart beta” indexes and their use in ETFs has added to the need for scrutiny. Accounting for crowding risk is necessary for any investment strategy because it may explain a substantial portion of strategy risk and performance during certain periods, especially during times of excessive market volatility.¹

In this paper, we propose a set of four key metrics — our “MSCI Crowding Scorecard” — for monitoring and detecting the crowding risk of any investment strategy. This work builds on our innovative analysis of historical behaviors of investment strategies and MSCI’s next generation equity risk models which incorporate Systematic Equity Strategies (SES):

MSCI Crowding Scorecard

1. Mutual Fund Trading Activity
2. Hedge Fund Trading Activity
3. Pair-wise Correlations (“co-momentum”)
4. Valuation Dispersion

The first two measures help capture crowding in the trading activity of various market participants, such as Value and Growth managers, and pinpoint the overlap in trading activity of otherwise heterogeneous investors. The last two measures capture the pricing and valuation impacts of such trading activity. Both sets of measures are essential in developing a Crowding Scorecard.

Finally, using the Crowding Scorecard, we find there were reasons to be moderately concerned about crowding in the U.S. Momentum factor as of the end of 2014.

The MSCI Crowding Scorecard can also be applied to single stocks, indexes and active strategies, making it an important tool for investment and risk managers following both quantitative and fundamental strategies — including recently popular factor index approaches. Using this approach can help managers understand the risks of overlap in trading strategies that may not be apparent by focusing on one of these metrics alone.

Our next areas of research are to extend the analysis to a global universe and to build stock-specific crowding scores.

¹ We first discussed the importance of Systematic Equity Strategy (SES) factors in capturing crowding risk in Bayraktar, Mehmet K., Stan Radchenko, Kurt Winkelmann and Peter J. Zangari. (2013). Employing Systematic Equity Strategies: Distinguishing Important Sources of Risk from Common Sources of Return. MSCI Research. (Access restricted to clients.)
INTRODUCTION

Since the “quant meltdown” of August 2007 and the subsequent unfolding of the global financial crisis, interest in measuring and monitoring crowding of systematic investment strategies has grown substantially. The rapid growth of smart beta indexes and their use in ETFs has only added to the degree of scrutiny.

A prevailing consensus for the cause of the quant meltdown is that similarities in quantitative equity managers’ holdings and trading styles together with their collective need for liquidity during the crisis led to sharply negative returns for many popular quantitative strategies. These outlier returns confounded the average correlations between strategies that had been historically observed and upon which many quant models’ construction was predicated.2

Perhaps an even more striking example of a crowded trade took place during the global financial crisis. This time, the wider investment community “ran for the exits,” pushing the stock prices of financial firms towards zero. The bounce-back of these securities during March 2009 was so significant that it resulted in one of the worst-ever historical performances of the Momentum factor and Momentum-based investment strategies.

By analyzing the historical behaviors of investment strategies, in particular around these events, as well as drawing on existing academic and empirical research, we have developed a set of four crowding metrics, which together we call our “MSCI Crowding Scorecard”:

1. Mutual Fund Trading Activity (using mutual fund holdings and trades)
2. Hedge Fund Trading Activity (based on short-interest)
3. Pair-wise Correlations (“co-momentum”)
4. Valuation Dispersion (using price-to-book spreads)

MSCI’s Crowding Scorecard, which can also be applied to single stocks, indexes and active strategies, is an innovative tool for investment and risk managers following both quantitative and fundamental strategies — including recently popular factor index approaches.

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2 There is considerable debate as to the exact trigger. For example, Khandani and Lo (2007, 2008) analyzed hedge-fund data alongside high frequency simulations to suggest that the rapid liquidation of a few (even one) large quantitative equity market-neutral funds was enough to set events in motion. Others, such as Emrich and Crow (2007, 2008), have suggested that the enormous growth in assets under management allied to then prevailing levels of leverage in essentially copycat quant strategies made for a fragile “quant bubble.” They found that portfolio managers had not noticed that they had changed from being price-takers into price-makers.
The MSCI Crowding Scorecard can help managers understand the risks of overlap in trading strategies that may not be apparent by focusing on one of these metrics alone.
WHAT ARE CROWDED TRADES AND POSITIONS?

Crowded trades refer to trading activity involving a significant number of market participants with large pools of capital who trade in and out of stock positions in order to pursue the same, or very similar, investment strategies. A crowded position happens when there is a significant overlap of portfolio positions and allocations as a result of crowded trades which, in total, add up to a significant share of a stock’s free-float market capitalization.³

Crowded trades generally result (at least in the short- to medium-term) in improved market efficiency. As a result, the forward-looking (expected) risk-adjusted return of a strategy declines as it becomes more crowded. Crowding thus reduces the future effectiveness of a given investment strategy in predicting stock returns. Depending on the extent of frictions, such as shorting constraints and transactions costs, this overlap of positions among managers may result in extreme levels of risk when those investors experience negative shocks in other parts of their portfolios, forcing them to liquidate their positions (selling what they can, rather than what they would necessarily like to). These “fire sales” may then cause losses for other investors following the same strategy and result in further liquidations, driving stock prices into a downward spiral. The “quant meltdown” is now a classic example of a crowded trade that resulted in significant performance drawdowns.

Crowding risk also affects a wide range of so-called “unanchored” strategies, such as Momentum or Quality, that do not rely on a consistent or independent estimate of fundamental value (Hong & Stein (1999), Stein (2009)). Investors tend to employ reasonable capacity assumptions in pursuing their own strategy, but they may underestimate the aggregate amount of capital following similar strategies. In this case, stock prices may over- or under-shoot their fundamental value and experience a sharp correction in subsequent periods as prices adjust to reflect fundamentals.

Given the potential risks associated with trading such strategies, it is important for managers to identify and measure them. To help portfolio and risk managers manage these risks, we have strengthened our models by including Systematic Equity Strategy (SES) factors in all our new generation MSCI equity models. We view SES factors as proxies of popular, potentially crowded systematic investment strategies.⁴ Next, we develop a set of metrics for the

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³ Thesmar (2011) and Greenwood and Thesmar (2011) define a crowded trading strategy as one where a significant amount of assets are tied to the same signal whereas a crowded asset is a stock which is co-owned to a great extent by traders or portfolio managers using the same signal.

monitoring and diagnosis of crowding in factors, MSCI’s Crowding Scorecard, which can also apply to factor indexes, portfolios, alpha signals, trades and even stocks.

EXISTING APPROACHES TO MEASURE CROWDING

When developing MSCI’s Crowding Scorecard, we divided crowding metrics into two broad categories: returns-based and holdings-based. Although the mix of assets (and how the assets are managed) of a particular strategy may determine which approach is most appropriate, we believe both have advantages and disadvantages. We recommend investors use them together.

Returns-based analysis can provide timely and high frequency measures of investor trading activity, and hence crowding. Returns-based metrics capture activity that is impacted by the market’s overall liquidity indirectly and not necessarily by crowding and trading in a particular strategy. In contrast, holdings-based analysis includes the use of institutional holdings, flows data and short-interest data, providing a direct measure of institutional trades and potentially insights into style tilts of investor purchases and sales. However, this granularity comes at a cost: holdings data have lower publishing frequency compared to returns data and may be released with a substantial lag. Appendix 1 provides a comprehensive summary of the metrics used in the relevant literature.

RETURNS-BASED CROWDING METRICS

Returns-based crowding metrics may be further divided into metrics that use individual stock returns data and those that use aggregate fund level returns data.

Strategy crowding is a concentration by investors in stocks with similar properties, leading to increased correlations. In particular, Lou and Polk (2013) looked at stock-specific return partial-correlations, so-called “co-momentum,” among various sets of stocks (top or bottom decile, for example) based on rankings of SES-type stock characteristics. Similarly, Cahan et al. (2012b) proposed using median pairwise stock correlation and median pairwise tail dependence to evaluate a variety of minimum variance strategies.

Fund-based return metrics follow a similar approach using fund data. For example, Gustafson and Halper (2010, 2011) used two returns-based measures: median pairwise monthly excess fund return correlations and signs of a near-zero median return for the fund peer group allied to low dispersion of returns across the peer group. Pojarliev and Levich (2013) used fund returns to estimate fund sensitivity to systematic factors in currency

5 SEC regulation allows mutual funds to provide holdings data with a lag up to 45 days.
6 Net of the Fama-French size, value and market factors.
Markets and measured crowding via the percentage difference between the number of funds with significant positive and negative exposures.

**HOLDINGS-BASED CROWDING METRICS**

Holdings-based crowding metrics are based on institutional holdings and flows data, short interest data and valuation-based metrics as measures and symptoms of the crowding of managers into particular strategies. The underlying idea is that stocks with significant tilts, either long or short, and especially with a high correlation of changes in these active weights, might be crowded and thus vulnerable to excess volatility or sharp reversals.

Gustafson and Halper (2010, 2011) calculated average pair-wise correlations for total and active weights and also looked at average factor exposures to check for signs of heterogeneity among portfolio managers.

Thesmar (2011) used mutual fund flows data to develop a “fragility” measure that aims to capture the similarity in fund flows and concentration of portfolios’ holdings. The measure is based upon the covariance matrix of flow-driven trades, weighted by ownership, and is high when stock ownership is concentrated and owners face volatile and correlated flow patterns.

Cahan et al (2012a) and Hanson and Sunderam (2014) used short interest data to detect factors that institutional investors are tilting on. These papers examine differences in short interest level between sets of stocks grouped based on their factor exposures, adjusted for common risk factors. Intuitively, there should be a high degree of difference in the level of short interest between stocks that score poorly and those that score highly based on an SES factor because investors are expected to short poorly ranked stocks and go long highly ranked stocks.

Different markets may benefit from their own specialized crowding measures, especially in respect of holdings-based metrics. For example, Murakami et al (2014) examined the influence of crowding on factor performance using a measure emphasizing the influence of non-resident investors. In recent academic work, Yost-Bremm (2014) looked at the impact of crowding for factor indexes related to the Fama-French factors at rebalances while Dangl and Kaschot (2013) focused on signs of over-crowding and over-valuation in minimum variance investing.

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8 Hanson and Sunderam (2014) use the level of short interest while Cahan et al. (2012a) look at capacity utilization.
THE MSCI CROWDING SCORECARD

In this section, we build on the existing literature regarding crowding risk and introduce four metrics that collectively aim to capture crowding risk:

- Mutual Fund Trading Activity (using mutual fund holdings and trades)
- Hedge Fund Trading Activity (based on short-interest)
- Pair-wise Correlations (“co-momentum”)
- Valuation Dispersion (using price-to-book spreads)

MUTUAL FUND TRADING ACTIVITY

Our first measure of crowding captures the factor exposures of the aggregate trading portfolio of U.S. mutual funds using MSCI’s Peer Analytics dataset. The details of the metric construction are presented in Appendix 2. Our premise is that crowding in a factor can be observed via the aggregate holdings and trading of mutual fund managers.

We illustrate the approach using the Momentum Factor in Exhibit 1, which shows the estimated exposure of the aggregate trading portfolio to the Momentum factor over the period 2004-2014. We also show the cumulative performance of the factor. The exhibit indicates that:

- Mutual funds were net buyers of Momentum over 2004-2007. The behavior then changed in 2008 when they became net sellers until the beginning of 2011.
- The level of negative exposure to Momentum of mutual funds’ trades was largest during the Momentum crash of March-April 2009.
- Net purchases of Momentum returned near their pre-crisis levels in 2011 and 2013.
Exhibit 1: U.S. Mutual Fund Trading Activity for the Momentum Factor

INVESTOR HETEROGENEITY AND CROWDED TRADES

One of the most common ways to discriminate between Mutual Fund Managers is to separate them into “Value” and “Growth” managers. In Exhibit 2, we show the percentile ranking of managers’ exposures to the factors in MSCI’s US Equity model based on their self-classification. We see that this qualitative separation is actually reflected in a difference of factor exposures. If we focus on the highest and lowest exposures (those either above the 70th or below the 30th percentile), we find the intuitive result that Growth managers are on average over-exposed to the Growth, Profitability and Sentiment factors and underexposed to the Value, Earnings Yield, Leverage and Dividend Yield factors. In contrast, Value managers are over-exposed to the Value, Earnings Yield and Leverage factors and under-exposed to Profitability, Growth and Residual Volatility.

To capture self-classification, we screened the fund name for specific keywords: Growth, Value, Income, Dividend, Quality, Volatility, Momentum, Focus, Index, Large, Mid, Small and Micro.
Exhibit 2: U.S. Active Mutual Fund Manager Classification and Actual Factor Exposures

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</table>

Source: Barra US Total Market Model, Barra Peer Analytics

Exhibit 2 shows that Value and Growth managers have on average shown distinct factor exposures. But to what extent do differences in holdings translate into different trading patterns? Exhibit 3 shows the breakdown of trading activity of Value vs. Growth managers and measures their exposure to Momentum.

From the chart, it is clear that on average Growth managers tended to be buyers of Momentum and Value managers tended to be sellers. It is also clear that Growth managers turned sellers of Momentum towards the end of 2008, well before the crash in the factor returns in March 2009. Interestingly, there was a great degree of overlap in the trading of Momentum of both Value and Growth managers during the periods leading up to and after this crash.

While Exhibit 3 shows a circumstantial link between the aggregate trading activity of Value and Growth Mutual Fund Managers in the Momentum factor and sharp reversals in the factor itself, it tells only a part of the story. After all, markets have to clear and there is always a buyer for someone who is selling, so there might be other agents who are taking...
the other side of these trades and diluting any potential crowding effect. To examine this phenomenon, we develop metrics to capture the trading activity of hedge fund managers.

Exhibit 3: Trading Activity of U.S. Mutual Funds in Momentum Factor

![Chart showing trading activity of U.S. Mutual Funds in Momentum Factor]

*Source: Barra US Total Market Model, Barra Peer Analytics*

**HEDGE FUND TRADING ACTIVITY**

One major difference between the trading style of mutual funds and hedge funds is that hedge funds frequently use shorting and leverage. We use short interest data for hedge funds and capture crowding in an investment strategy by looking at short activity among securities that are not favored by the strategy. The crowding measure is then constructed as the difference in the level of short interest for bottom- and top-ranked names based on the strategy. The higher the spread, the higher is the level of crowding among hedge funds. The details of the crowding metric construction are presented in Appendix 2.

Exhibit 4 presents the level of short interest for the bottom quintile of the Momentum factor (“Negative Momentum”), the top quintile (“Positive Momentum”) and the spread between the two. We observe:

- The negative Momentum names have a significantly higher level of short interest than the market while positive Momentum names see shorting in line with or below that of the market. This may reflect the popularity of the Momentum factor among hedge funds, played primarily on the short side.
- The popularity of Momentum among hedge funds declined over the 2008-2010 period as reflected in the falling level of short interest among negative Momentum names. However, the popularity of the factor recovered from 2011 to 2014.

**Exhibit 4: Short Interest for Positive and Negative Momentum Factor Quintiles**

<table>
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<th>Short Interest (in %)</th>
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<tr>
<td>Negative Momentum</td>
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<tr>
<td>Positive Momentum</td>
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<tr>
<td>Net</td>
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</table>

Source: Barra US Total Market Model, Barra Peer Analytics

**PAIR-WISE CORRELATIONS**

Mutual Fund Trading Activity and Short Interest focus on measuring the commonality of trading activity of two rather distinct sets of market participants, to detect potentially crowded trades. Commonality in trading does not by itself necessarily point to crowding. After all, trades in aggregate cancel out – there is always a buyer for every seller. It is the price impact of trades that matters.

To assess this impact we add to our existing metrics the average pair-wise excess return correlations between stocks.\(^{11}\) Large pools of capital flowing into an investment strategy are expected to result in purchases of those securities that score most highly according to that

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\(^{11}\) This notion is similar to the idea of co-momentum from Lou and Polk (2013).
strategy. Conversely, outflows of capital are expected to result in sales of those same securities along with net purchases of securities that have a low score according to the strategy. In both cases, stock-level pair-wise correlations within the highest and lowest quartiles are expected to increase.

We measure stock-level correlations by first stripping out the systematic component of stocks returns (i.e., using stock-specific returns from the long-term US Total Market Model), and then calculating rolling pair-wise correlations of those securities that fall in either the top or the bottom quintile of factor scores.

The pair-wise correlations for the Accruals component of the Earnings Quality factor in the Barra US Total Market Model are shown in Exhibit 5. The chart illustrates a strong seasonal pattern in correlations during earnings announcement periods. Balance sheet and income statement information is updated quarterly, so there is increased trading based on this information. The average pair-wise correlations of both the top and bottom quintiles of this factor have generally been above the middle quintile, illustrating the popularity of this factor; the higher pair-wise correlation in the top quintile and the general trend upward in this measure show the greater and increasing popularity of playing this factor on the long side (i.e. buying higher Earnings Quality names).
In the previous section, we argued that when factor crowding is an issue, groups of securities based on their over- or under-exposure to that factor might exhibit similar return patterns. Another symptom of crowding, especially for unanchored investment strategies, might be the movement of securities' valuations further from fundamentals. One way to measure the effect of crowding is therefore to examine the valuation spreads of securities in top vs. bottom deciles of an investment strategy. To calculate a valuation spread, for example, we compute the difference in average book-to-price (B/P) ratio of top and bottom decile stocks. This is the fourth metric in our Crowding Scorecard.

We show the cumulative returns of Leverage and the B/P valuation spread observed over the 1989-2014 period in Exhibit 6. The significant drawdown of the Leverage factor started at the beginning of 2007 and has bounced back since the 2008 crisis. We think of the great financial crisis as a market-wide re-pricing of leverage risk; the cumulative performance of the Leverage factor is consistent with this. When we examine the Valuation Spread of high-vs. low-leverage companies, we see that this spread hit all-time high levels during the crisis. Highly levered companies became much cheaper than their lower-levered counterparts, as investors shunned Leverage.
Exhibit 6: Valuation Spread of Leverage Factor

Period: January 29, 1988 to January 30, 2014; Source: Barra US Total Market Model
PUTTING IT ALL TOGETHER

We combine the four metrics into the MSCI Crowding Scorecard. It provides a multi-faceted view of key market participants’ aggregate loading in an investment strategy, offering a gauge as to whether crowding has developed. The Crowding Scorecard for the U.S. Momentum factor over the last decade can be seen in Exhibit 7. We observe:

- Mutual fund selling of Momentum in September 2014 has stopped.
- At the same time, shorting activity has recently been trending upwards.
- Average stock pair-wise correlation in the top and bottom deciles has increased to levels exceeded only in the 2009 “Momentum Crash” and the “Tech Bubble.”
- Valuation spreads of high vs. low Momentum stocks widening and below median.

Overall, we believe there are reasons to be moderately concerned about crowding in the Momentum factor, based on these four indicators. (In Appendix 3, we present the MSCI Crowding Scorecard for additional investment strategies.)

Exhibit 7: MSCI Crowding Scorecard for the Momentum Factor
CONCLUSION

Interest in crowding has grown substantially over the past decade. The “quant meltdown” of August 2007 and the subsequent unfolding of the global financial crisis generated significant interest in the design of metrics to capture the “crowdedness” of an investment strategy. The rapid growth of factor indexes (also referred to as “smart beta” strategies) and their use in ETFs has increased the need for managers and investors alike to understand the impact of crowding.

Given the potential risks associated with such trading strategies, it is important for managers to identify and measure their crowding risk. In this paper, we developed a set of metrics for the monitoring and diagnosis of crowding in factors, our MSCI Crowding Scorecard. We showcased the MSCI Crowding Scorecard for Momentum investment strategy and presented results for a range of key alpha and risk factors in MSCI’s US Total Market Model to assess their recent state of crowding.

The MSCI Crowding Scorecard, which can also be applied to single stocks, indexes and active strategies, is an important tool for investment and risk managers, following both quantitative and fundamental strategies — including recently popular factor index approaches. Using this Scorecard can help managers understand the risks of overlap in trading strategies which may not be apparent by focusing on a single metric alone.

In short, MSCI’s Crowding Scorecard can help managers and investors from getting lost in the crowd.
REFERENCES


Gustafson, Keith and Patricia Halper. (2011). “Are Quants All Fishing in the Same Small Pond with the Same Tackle Box?” Annual Northfield Conference presentation.


## APPENDIX 1: A SURVEY OF CROWDING METRICS

<table>
<thead>
<tr>
<th>Name</th>
<th>Description</th>
<th>Example Reference</th>
<th>Type</th>
</tr>
</thead>
<tbody>
<tr>
<td>Predicted transaction costs</td>
<td>The crowdedness of a trade basket is measured by ex-ante estimates of trade impact costs</td>
<td>Cheung &amp; Mishra (2010)</td>
<td>Holdings</td>
</tr>
<tr>
<td>Diffusion index of funds with high and low exposures to a given factor/strategy</td>
<td>The % difference between no. of funds with a significant (threshold) pos. exposure and with a significant (threshold) neg. exposure</td>
<td>Pojarliev &amp; Levich (2009)</td>
<td>Holdings</td>
</tr>
<tr>
<td>Correlation of peer group active returns</td>
<td>Median pair-wise excess return correlations of peer fund returns</td>
<td>Gustafson &amp; Halper (2010)</td>
<td>Returns</td>
</tr>
<tr>
<td>Correlation of peer group portfolio weights</td>
<td>Average pair-wise correlation of total and active portfolio weights within peer group of funds</td>
<td>Gustafson &amp; Halper (2010)</td>
<td>Holdings</td>
</tr>
<tr>
<td>Peer group factor loading dispersion</td>
<td>Average portfolio exposure to risk or alpha factors and dispersion</td>
<td>Gustafson &amp; Halper (2010)</td>
<td>Returns</td>
</tr>
<tr>
<td>Peer group return median and dispersion</td>
<td>Coincidence of near zero median excess returns with low dispersion</td>
<td>Gustafson &amp; Halper (2010)</td>
<td>Returns</td>
</tr>
<tr>
<td>Fragility and co-fragility</td>
<td>The (co-)variance between fund weights in a stock, weighted by AUM, and calculated with the covariance matrix of fund flows</td>
<td>Thesmar (2011), Greenwood &amp; Thesmar (2011)</td>
<td>Holdings</td>
</tr>
<tr>
<td>Percentage of shares outstanding held by active country funds</td>
<td>Calculated at the stock or factor level, the percentage of shares outstanding held by active country (Japan) funds</td>
<td>Murakami (2014)</td>
<td>Holdings</td>
</tr>
<tr>
<td>Cross-sectional decile-spread crowding beta</td>
<td>Beta of high factor decile indicator from a cross-sectional regression of the chosen crowding metric on the factors adjusted for size and volatility</td>
<td>Hanson &amp; Sunderam (2014), Cahan et al (2012a)</td>
<td>Holdings</td>
</tr>
<tr>
<td>Median pair-wise correlation for stocks in a strategy (vs market or sector indexes)</td>
<td>Correlation calculated for each pair of stocks in turn in strategy portfolio</td>
<td>Cahan et al (2012b)</td>
<td>Returns</td>
</tr>
<tr>
<td>Median pair-wise tail dependence (vs market or sector indexes)</td>
<td>Tail dependence of each stock pair in strategy using Gumbel copula for downside co-movement</td>
<td>Cahan et al (2012b)</td>
<td>Returns</td>
</tr>
<tr>
<td>Co-momentum</td>
<td>Abnormal return correlation among stocks in the top factor deciles</td>
<td>Lou &amp; Polk (2013)</td>
<td>Returns</td>
</tr>
</tbody>
</table>
APPENDIX 2: MSCI CROWDING METRICS – DETAILED METHODOLOGY

A. THE SHORT-INTEREST CROWDING METRIC

We follow the cross-sectional approach proposed by Hanson and Sunderam (2014) and regress stock i’s level of short interest capacity utilization rate on a set of size, value, and momentum quintile dummies as well as quintile dummies of the factor of interest. In particular, we run the following cross-sectional regression at each period t:

\[ SR_t = \theta_t + k_t^{\text{Factor}} + k_t^{\text{VAL}} + k_t^{\text{MOM}} + k_t^{\text{SIZE}} + \epsilon_t \]

where \( SR_t \) is Sungard Astec Securities Lending Data on short interest capacity utilization rate at period t, \( k_t^{\text{Factor}} \) measures the difference in the level of short interest across quintiles of the factor of interest that are not explained by popular Value, Size and Momentum factors.

In the regression, we omit quintile 3 for the factor of interest so that the parameter set \( k \) measures the difference in the level of short interest relative to the omitted quintile. For example, \( k_t^{\text{MOM(1)}} \) indicates the increase in capacity utilization for negative momentum names relative to the omitted quintile 3. To improve the accuracy of the estimated coefficients and pick up medium-term trends in factor crowding, the coefficients are estimated using a panel of daily returns. The estimation window is 63 business days. To reduce the impact of liquidity issues and trading costs, we reduce the estimation universe to the top 1,500 names by market capitalization.

The crowding measure is constructed as the difference in \( k_t^{\text{Factor(1)}} \) and \( k_t^{\text{Factor(5)}} \) coefficients. The higher the spread in these coefficients, the higher the crowding we perceive in the factor among hedge funds.

B. THE TRADING ACTIVITY CROWDING METRIC

The trading activity crowding metric utilizes data on mutual fund holdings obtained from the Barra Peer Analytics dataset. We look at US Equity mutual funds for the period 2004-2014. The metric is computed in several steps:

Step 1. For each position \( i \) in the mutual fund \( k \), estimate monthly trading activity as the difference between the market value of positions at period (t) and the return-adjusted value of the position at period (t-1):

\[ Trade_{i,k,t} = MVAL_{i,k,t} - (1 + r_{i,t})MVAL_{i,k,t-1} \]

where \( r_{i,t} \) is monthly return of stock \( i \). The trading activity is computed for the funds that have been in the sample for at least two periods so that the aggregate trades are not
impacted by the introduction of new funds in coverage. Many funds do not report their holdings monthly. For these mutual funds, we pro-rate the estimated trades linearly over the entire period between rebalancing dates.

Step 2. Compute aggregate dollar value of trading activity across all mutual funds:

$$Trade_{i,t} = \sum_{k=1}^{K} Trade_{i,k,t}, \ i = 1,2, ..., N$$

Step 3. Compute normalized trading portfolio weights:

$$w_{i,t} = \frac{Trade_{i,t}}{\sum_{i=1}^{N} Trade_{i,t}^+}$$

where $Trade_{i,t}^+ = Trade_{i,t}$ if $Trade_{i,t} > 0$ and 0 otherwise. The resulting trading portfolio is not dollar-neutral unless the aggregate flows to mutual funds are zero and the aggregate purchases and sales net each other off.

Step 4. Compute factor exposures of the trading portfolio. We use factor exposures of the trading portfolio as a measure of crowding. Notice that this measure does not take into account the aggregate level of trading.
APPENDIX 3: CROWDING METRICS - FACTOR BY FACTOR

PROFITABILITY

Exhibit 8: MSCI Crowding Metrics for the Profitability Factor
MOMENTUM

Exhibit 9: MSCI Crowding Metrics for the Momentum Factor
EARNINGS QUALITY

Exhibit 10: MSCI Crowding Metrics for the Earnings Quality Factor
LIQUIDITY

Exhibit 11: MSCI Crowding Metrics for the Liquidity Factor
VALUE

Exhibit 12: MSCI Crowding Metrics for the Value Factor
EARNINGS YIELD

Exhibit 13: MSCI Crowding Metrics for the Earnings Yield Factor
RESIDUAL VOLATILITY

Exhibit 14: MSCI Crowding Metrics for the Residual Volatility Factor

- US Mutual Fund Trading Activity
- Average Pairwise Correlations
- Short Interest (in %)
- Valuation Spread
MANAGEMENT QUALITY

Exhibit 15: MSCI Crowding Metrics for the Management Quality Factor
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