Short Interest, Crowding and Liquidity Crises*

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Abstract

We use the Short Interest strategy – buying low short interest stocks and shorting high short interest stocks – as a "barometer" for liquidity shocks impacting sophisticated equity investors: we explain why the strategy should exhibit V-shaped drawdowns when short-sellers are affected by liquidity shocks. We show this was the case during the well-documented 2007 Quant Crisis but also, more recently, during the COVID-19 induced 2020 Quant Deleverage that we document in this paper. We then use daily short interest data to infer near real-time crowding levels of quantitative equity long-short strategies and extend the analyses of previous crowding studies. We find that short-sellers have continued to crowd in some of the well-known equity factors such as Momentum, Value and Low Volatility.

*We thank Serge Darolles and Augustin Landier for numerous comments that improved this work, as well as Yonglei Wang and seminar participants at University Paris Dauphine for discussions and feedback.

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"Likely factors contributing to the magnitude of the losses of this apparent unwind were: [...] the enormous growth of assets devoted to long/short equity strategies over the past decade [...]; the general lack of awareness [...] of just how crowded the long/short equity category had become."

Khandani and Lo (2007) on the 2007 Quant Crisis.

"For a broad class of quantitative trading strategies, an important consideration for each individual arbitrageur is that he cannot know in real-time exactly how many others are using the same model and taking the same position as him. This inability of traders to condition their behavior on current market-wide arbitrage capacity creates a coordination problem and [...] can result in prices being pushed further away from fundamentals."

Stein (2009) on the "crowded-trade" effect.

A significant deleverage of quantitative equity strategies, reminiscent of the well documented 2007 Quant Crisis, took place between March 13 and March 18, 2020. The deleverage started the day some European regulators announced short-bans, as a response to the market volatility caused by the COVID-19 pandemic. A mix of factors were likely making any leveraged strategies vulnerable to a sudden shift in expectations: investors hitting their value at risk limits following the sharp increase in volatility, impaired liquidity and losses in other asset classes, the self-fulfilling fear that other investors would deleverage and that it was therefore better to be the first to do so.

This recent deleverage shared a lot of similarities with the 2007 quant crisis. It lasted only a few days, with sharp price reversals thereafter. It spilled-over across regions. The shocks triggering both were likely external, rather than endogenous. Indeed, leading to the recent deleverage, quant equity strategies' performance was not particularly negative; and quant equity investors did not appear to be leverage constrained. Similarly, as pointed out by Khandani and Lo (2007), the 2007 Quant Crisis "was apparently caused by forces outside the long/short equity sector – in a completely unrelated set of markets and instruments [...]".

The main difference between the two episodes is that while the 2007 Quant Crisis happened under relatively benign market conditions (at a time where funding markets had just started to seize and more than a year before the Lehman bankruptcy), the recent deleverage occurred in much more volatile markets, pretty much at the height of the market panic caused by the COVID-19 pandemic. Another difference is that the 2007 Quant Crisis started in US equity markets and then spilled over to Europe, whereas the recent Quant Deleverage seemed to have originated in Europe (and then spilled over to North America).

The Short Interest strategy (buying low short interest stocks and shorting high short interest stocks) is a good indicator for deleveraging activity amongst short sellers (Richardson et al (2017)), an important portion of which are quants. Indeed, if short sellers deleverage their positions, they will sell the stocks they were long and buy back stocks they were shorting: high short interest stocks will therefore rally, and low short interest stocks will sell off, causing the strategy to underperform. The strategy had, in the recent 2020 Quant Deleverage, its largest drawdown over the sample studied in this paper (mid-2006 to mid-2020), larger in fact than the drawdown it suffered during the 2007 Quant Crisis. It rebounded very quickly thereafter (as it did in 2007), highlighting that the price impact generated by large deleverage episodes are mostly temporary. One of the contributions of this paper is to document the recent COVID-19 induced Quant Deleverage, using the Short Interest strategy as a "barometer" for its severity: the Short Interest strategy exhibits sharp but temporary drawdowns when (rare) liquidity crises occur.

Our work is therefore related and contributes to the relatively large literature on short selling and the equity stock lending market. Just to cite a few, Desai et al (2002) study short interest in the Nasdaq market and find that high short interest ratios forecast low future returns. Asquith et al (2005) show that large stocks, given their low level of short interest and high level of institutional ownership are generally not subject to short selling constraints. Saffi and Sigurdsson (2011) establish that price efficiency is hindered by short-sale constraints. More recently, Hong et al (2015) show that days-to-cover (number of stocks shorted divided by daily average number of stocks traded) is a better measure than short interest as it implicitly considers trading costs. Callen and Fang (2015) find that short interest is positively related to one-year ahead stock price crash risk. Richardson et al (2017) show that high short interest stocks experience large positive returns around periods of funding capital scarcity. Finally, Engelberg et al (2018) show that stocks with more short-selling risk have lower returns.

Another important topic related to short interest is crowding. In order to infer trading strategies' crowding levels, a key ingredient is needed: positioning data, preferably focused on a category of investors, and ideally available at daily frequency. In that respect, the short interest data we are using for this paper (IHS Markit[1]) is an ideal candidate. Because short-sellers are generally hedge funds and other arbitrageurs, it is good proxy for the aggregated short single stock positions of sophisticated investors, many of whom implement quant equity strategies. The other advantage is that the data is available daily and with little lag (a few days): the crowding measure inferred from this data is therefore near-real-time.

Hanson and Sunderam (2014, thereafter HS) propose a crowding measure based on short interest, and document that the amount of capital devoted to Value and Momentum strategies has grown significantly since the late 1980s. They then proceed to confirm empirically fact patterns that are consistent with theories of limited arbitrage. In this paper, we look at what has happened since the end of HS' sample (2011). We document some interesting patterns. First, the rise in arbitrage capital, as measured by average short interest

[1]IHS Markit, its Affiliates, or any of its third party data providers shall have no liability whatsoever to recipients of this paper, whether in contract (including under an indemnity), in tort (including negligence), under a warranty, under statute or otherwise, in respect of any loss or damage suffered by such recipient as a result of or in connection with any opinions, recommendations, forecasts, judgments, or any other conclusions, or any course of action determined, by such recipient or any third party, whether or not based on this paper, the data, content, information or materials contained herein.

levels, has not continued since the 2008 global financial crisis and is much lower than the heights reached before 2008. Second, quant equity investors have continued to crowd in well-known equity factors such as Momentum, Value and Low Volatility. Third, we cannot establish as in HS, for our more recent sample, the negative relationship between crowding and future strategy returns – if anything, we find weak evidence of an opposite relationship. This paper contributes to the crowding literature by documenting these patterns. It also contributes by extending the analysis to European equities, where we broadly find similar patterns as in North America.

The topic of crowding received some academic attention in the aftermath of the 2007 Quant Crisis and the 2008 global financial crisis. Khandani and Lo (2007 and 2011) analyse the Quant Crisis of August 2007. They simulate the performance of equity trading strategies likely used by quantitative investors and find evidence of large unwinding of factor-based portfolios and of sharply declining liquidity at that time. Pedersen (2009) also focuses on the Quant Crisis to illustrate the nature of liquidity crises: crowding combined with leverage can generate "liquidity spirals". Stein (2009), when considering whether the increased presence of sophisticated investors in stock market trading would ultimately lead to greater market efficiency, identifies two complicating factors, the first being crowding and the second leverage. For him, the main complication with crowding is that at any point in time, no individual arbitrageur knows exactly how much arbitrage capacity has been taken by others. Pojarliev and Levich (2011) estimate crowdedness of currency strategies by looking at the fraction of currency managers that have significant loadings on several well-known currency strategies. HS, as discussed above, propose a crowding measure based on short interest, and use it to confirm fact patterns that are consistent with theories of limited arbitrage.

More recently, the subject of crowding attracted some further attention, in part because equity factor-based strategies have exhibited lacklustre performance in recent years. Marks and Shen (2019) study the link between crowding and liquidity and show that correlated trading among investors can affect the liquidity and risk of the securities they trade. Brown et al. (2019), use hedge fund long equity holdings data from SEC 13F quarterly filings to measure security level crowdedness (defined as hedge funds' aggregate position in a stock divided by its average daily volume) and show that stocks with higher exposure to crowdedness experience relatively larger drawdowns during periods of market distress. Benzaguen et al. (2020) propose crowding measures by looking at the fluctuations in the imbalance of trades executed in the market. Based on these metrics, they show evidence that Momentum has become more crowded in recent years.

Why are (seemingly sophisticated) quant investors crowding in the same strategies? Perhaps, as explained by Stein (2009), because they cannot measure in real-time how much capital other investors are simultaneously deploying in these strategies. In this paper, we show that near real-time crowding can be inferred from short interest data. Such measures are surely available to sophisticated investors. Maybe, then, are quant investors crowding in the same strategies because these, even crowded, remain good bets? This is possible, as we find no clear empirical link between levels of crowding and future returns: alpha decay, factor timing skills and flow effects probably cancel each other out on average.

Possible alternative explanations, which are outside the scope of this paper but could be the topic of future investigations are the following. Perhaps are quant managers not all that sophisticated. Some might not measure crowding at all. Others might grossly over-estimate the overall capacity available to the strategies they trade. Or maybe there are principal agent issues: as liquidity crises are rare, it might be rational for some managers to crowd in strategies that are well known and fashionable with end-clients. The strategies are therefore easy to implement and sell and will generate fees for the managers until the risk materializes.

The paper is organized as follows. Section I details the data used in this work. Section II documents the 2020 Quant Deleverage, using the performance of the Short Interest strategy as an indicator for its severity, and draws comparisons with the 2007 Quant Crisis. Section III presents the crowding measure and its evolution – over our sample and for some of the better-known equity factors – in both North America and Developed Europe. Section IV analyses the empirical link between crowding and future strategy behaviour. Section V concludes.

1 Data

We combine daily equity finance data from IHS Markit, with equity data from Datascope and stock-level fundamental data from Worldscope, as described in detail below. The study covers a nearly 14-year period from July 1, 2006 through April 23, 2020.

A. Stock Sample Selection

We focus on stocks listed in North America and Developed Europe[2] that are likely to be included in quantitative equity market neutral portfolios. These strategies use leverage, deploy equity anomalies that require frequent rebalancing and, given fixed costs associated (including data, ability to short via prime brokers or derivatives, fund set-up costs. . .), need to have reasonable assets under management – and therefore capacity.

We thus restrict our attention to stocks that have a certain size and liquidity. Based on an extract from Datascope performed in June 2018, we select stocks based on market capitalisation and turnover (median for the past 3 month) thresholds. The stock selection is performed monthly, on the first day of the month. This results in two regional pools that, after data cleansing detailed in the next paragraphs, average approximately 1,100 stocks for North America and 540 stocks for Developed Europe over the time horizon studied.

A.1. Equity Finance Data

This data comes from the IHS Markit Securities Finance database. It is sourced daily from a variety of industry participants that include beneficial owners, custodian and agents, sell side brokers (such as investment banks' prime brokerage arms) and buy side investors (such as hedge funds who are borrowing stocks to be able to short them). The data is collected globally and covers the largest developed world equity markets, the two largest regions being North America and Developed Europe. It has been collected daily since July 1, 2006.

Many stock-level lending variables are included in this database. We use the following:

- *Share Supply*: number of shares available to be borrowed divided by shares outstanding. This number is an indication of the supply of shares that are available for short sellers to borrow.

- *Short Interest*: number of shares borrowed divided by shares outstanding. This number gives the percentage of shares that are borrowed (the majority of which is likely shorted).

- *Utilization*: Short Interest divided by Share Supply.

- *Daily Cost of Borrow Score (DCBS)*: a number from 1 to 10 indicating the rebate/fee charged by the agent lender based on IHS Markit Securities Finance proprietary benchmark rate, where 1 is the cheapest

[2]North America: Canada and United States. Developed Europe: Belgium, Denmark, France, Finland, Germany, Italy, Ireland, Netherlands, Norway, Portugal, Spain, Sweden, Switzerland, United Kingdom.

and 10 is the most expensive. High DCBS indicate that the corresponding stocks are "Hard-To-Borrow".

To deal with possible outliers, we remove, in each cross-section, observations corresponding to the top and bottom percentile in Short Interest, Share Supply and Utilization. Table 1 displays summary statistics for both the North America (Panel A) and Developed Europe (Panel B) stock samples. For the average North American stock in our sample, around 3% of outstanding shares are on loan and close to 28% are available to be borrowed. The mean utilization is around 12%. The average DCBS is close to 1, which indicates that most stocks in the sample are cheap to borrow. In Developed Europe, both average short interest and share supply are lower at around 1.8% and 18% respectively. Mean utilization is similar at around 12%. The average DCBS is slightly higher than in North America, but still very close to 1.

Panel A of Figure 1 shows that short interest ratios rose significantly at the beginning of the sample and declined significantly during the global financial crisis, stabilising thereafter. This is consistent with what is documented in HS. They use monthly short interest data from Compustat (available since 1988) and show that short interest ratios trended upward during the mid-1990s, rose dramatically from 2001 to 2007 and registered a marked drop in September 2008 when the SEC imposed a ban on the shorts sales of financial stocks. Their sample ends in 2011. Since then, as can be seen from the graph, short interest ratios have remained relatively stable, at around half of the top reached in 2008. Overall, this shows that the rise in arbitrage capital (as measured by short interest ratios) has not continued post crisis. In fact, it is still quite far away from the levels reached in the years immediately preceding the 2008 financial crisis.

In Panel B of Figure 1, we show an alternative measure of arbitrage capital, normalizing by stock liquidity rather than by market capitalization. We define Days to Cover as the number of shares borrowed divided by median 3-month daily number of shares traded[3]. Indeed, turnover as a fraction of market capitalization has declined since the global financial crisis, and it is therefore logical to check how arbitrage capital has evolved as a percentage of market liquidity. Similar trends as in Panel B can be seen. The difference is that average Days to Cover has decreased less than average Short Interest since their peaks in 2008.

In both Panel A and B of Figure 1, equal-weighted short interest ratios are significantly larger than value-weighted ratios, pointing to more short-selling in smaller stocks than in larger stocks. Panel A of Figure 2 shows the relationship between size and short interest and confirms this pattern: smaller stocks have on average higher short interest ratios than larger stocks. Panel B shows the relationship between stock volatility and short interest: higher volatility stocks tend to be more shorted than lower volatility stocks.

[3] Markets have fragmented over the period, with more and more trading taking place outside primary exchanges. For each stock, we use primary exchange turnover, multiplied by a year and country dependent factor to consider this fragmented liquidity. This multiplier is estimated for each year and each regional pool. For example, in the United States, the multiplier is 1.5 for 2008 and 2.1 for 2018, consistent with an increased fragmentation of liquidity.

Table 1

Summary Statistics

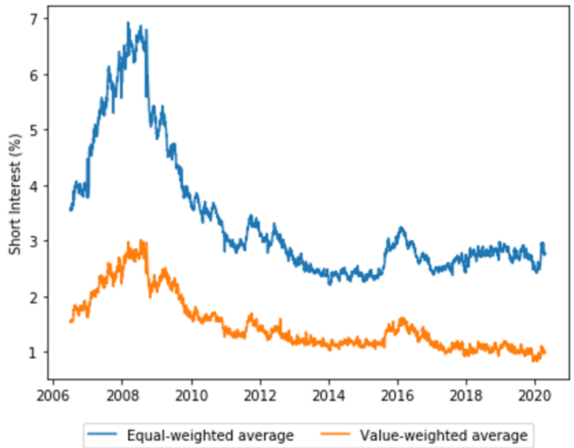
Panel A: North America Sample (firm-days, 2006-2020)

	N	Mean	Median	Min	Max	SD
Short Interest	3,950,044	0.0339	0.0187	0.0000	0.3082	0.0397
Share Supply	3,950,044	0.2780	0.2787	0.0259	0.5671	0.0787
Utilization	3,950,044	0.1259	0.0701	0.0003	0.8747	0.1433
DBCS	3,949,673	1.04	1	1	8	0.33
Market Capitalization	3,950,044	$14.97B	$4.96B	$0.06B	$1,435.26B	$38.82B
Daily Volatility	3,950,044	0.0218	0.0192	0.0072	0.1016	0.0103

Panel B: Developed Europe Sample (firm-days, 2006-2020)

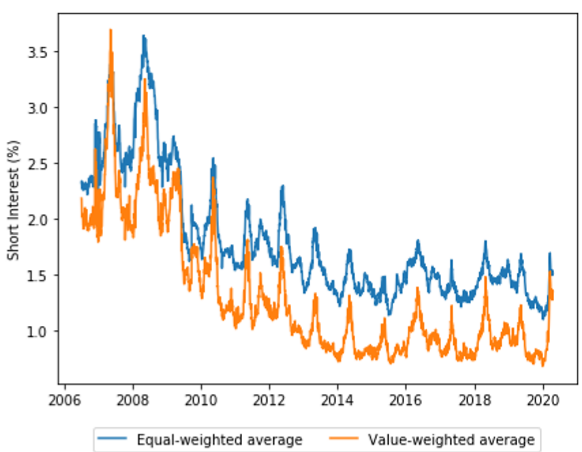
	N	Mean	Median	Min	Max	SD
Short Interest	1,924,673	0.0180	0.0110	0	0.1899	0.0195
Share Supply	1,924,673	0.1715	0.1721	0.0033	0.9870	0.0744
Utilization	1,924,673	0.1252	0.0715	0.0001	0.8917	0.1406
DBCS	1,918,108	1.14	1	1	8	0.54
Market Capitalization	1,924,673	$16.35B	$6.83B	$0.05B	$354B	$26.76B
Daily Volatility	1,924,673	0.0195	0.0175	0.0073	0.0857	0.0078

This table reports summary statistics for stock-level lending variables used in this paper. Share Supply is number of shares available to be borrowed divided by shares outstanding. Short Interest is number of shares borrowed divided by shares outstanding. Utilization is Short Interest divided by Share Supply. DBCS (Daily Cost of Borrow Score) is a number from 1 to 10 indicating the rebate/fee charged by the agent lender based on Data Explorers proprietary benchmark rate, where 1 is the cheapest and 10 is the most expensive. The table also shows Market Capitalization and Daily Volatility, computed as the exponentially-weighted standard deviation of daily stock returns, with a half-life of 126 business days. Panel A shows these summary statistics for our North America sample and Panel B for our Developed Europe sample.

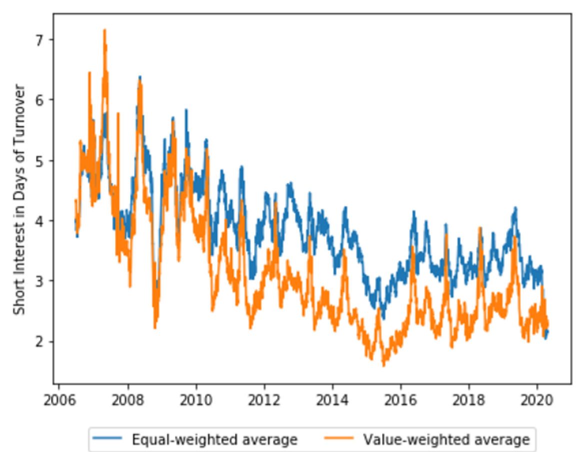


Panel A: Short Interest (North America)

Panel B: Days to Cover (North America)



Panel C: Short Interest (Developed Europe)

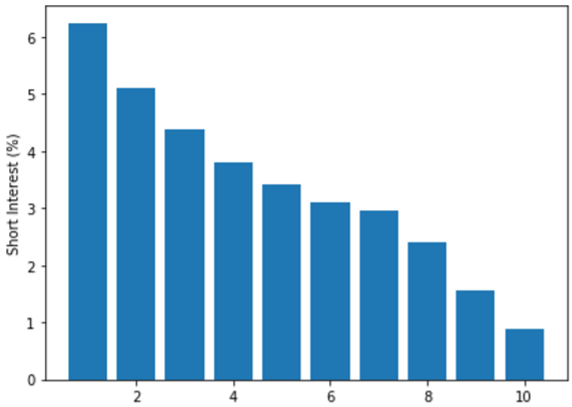


Panel D: Days to Cover (Developed Europe)

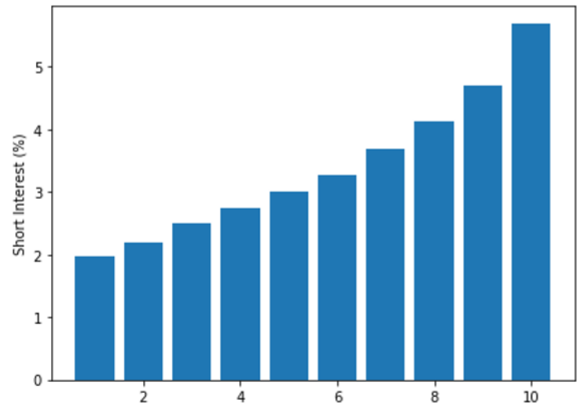
Figure 1

Average Short Interest and Days to Cover, 2006-2020

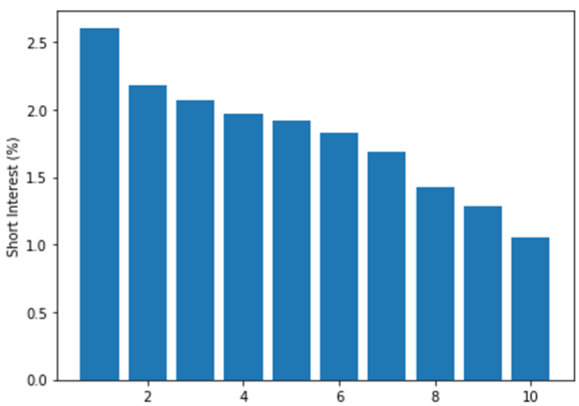
Panel A and C plot the daily equal- and value-weighted average short interest for all stocks in our North America and Developed Europe samples. Short interest is number of shares borrowed divided by shares outstanding. Panel B and D plot the daily equal- and value-weighted average days to cover ratio for all stocks in our North America and Developed Europe samples. Days to cover is the number of shares borrowed divided by median 3-month daily number of shares traded.



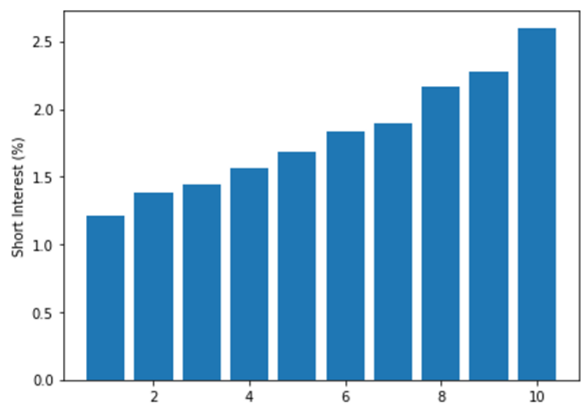
Panel A: Size Deciles (North America)



Panel B: Volatility Deciles (North America)



Panel C: Size Deciles (Developed Europe)



Panel D: Volatility Deciles (Developed Europe)

Figure 2

Mean Short Interest by Size and Volatility Deciles, 2006-2020

Each day, stocks in the North America pool are sorted into size and volatility deciles. For each decile, mean Short Interest are computed. Panel A (C) shows the average over the sample period of the daily mean Short Interest by size decile for our North America (Developed Europe) sample. Panel B (D) shows the average over the sample period of the daily mean Short Interest by volatility decile for our North America (Developed Europe) sample. Short interest is number of shares borrowed divided by shares outstanding.

A.2. Equity Factor Strategies Data

We primarily focus on Momentum, Value, Low Volatility and Return on Assets strategies because of their long histories among both academics and practitioners.

We also study a combination of these four strategies, as a good approximation to how factor-based equity market neutral funds invest[4]. These funds have grown in popularity and assets in the previous decade and have more recently (since 2018) suffered outflows after lacklustre performances[5]. This rise and fall in factor-based equity market neutral funds' assets offer a good data point against which we can test our proposed crowding measure.

We also add the Short Interest strategy given the focus of this paper.

The definitions used for these strategies and the corresponding data sources are as follows:

- *Momentum*: cumulative returns from months $t - 12$ to $t - 1$ (stock returns are taken from Datascope).

- *Value*: common equity divided by market capitalization lagged by 21 business days (Worldscope for common equity and Datascope for market capitalisation).

- *Low Volatility*: 1 divided by stock returns volatility, calculated as the exponentially-weighted standard deviation of daily stock returns, with a half-life of 126 business days (Datascope).

- *Return on Assets*: EBIDTA / Average Total Assets (Worldscope)

- *Short Interest*: minus short interest (IHS Markit, cleaned as described above)

For each of these strategies, every day t, each stock i is ranked in the cross-section according to the measures above. These ranks are then transformed into a strategy score $\mathrm{s_{it}}^{\mathrm{strategy}}$ uniformly distributed on [-1, 1]. For example, the stock with the lowest Momentum measure at date t will be assigned a score $\mathrm{s_{it}}^{\mathrm{momentum}}$ of -1, and the one with the highest Momentum measure a score of 1.

The strategy combination score $\mathrm{s_{it}}^{\mathrm{composite}}$, which we call *composite* is the uniform transformation on [-1, 1] of the following aggregated score:

$$\frac{1}{3}s_{it}^{value} + \frac{1}{3}s_{it}^{momentum} + \frac{1}{6}s_{it}^{lowvolatility} + \frac{1}{6}s_{it}^{roa}$$

It is essentially an equi-weighted strategy combination of Value, Momentum and Defensive (itself an equi-weighted combination of Low Volatility and Return on Assets).

We then compute strategy daily returns, by constructing long-short strategy portfolios following a more

[4] AQR, one of the largest investment managers by assets for this type of funds, describe the investment approach of their Style Premia: Equity Market Neutral UCITS Fund in their prospectus as follows: "The Fund is actively managed and will seek [...] to provide exposure to three separate investment styles [...]: value, momentum, and defensive, using both "long" and "short" positions."

[5] Barrett and al. (2020), in a Kepler industry publication, document the lackluster performance of systematic equity market neutral funds and corresponding outflows.

sophisticated portfolio construction than the traditional quantile sorting methodology. This construction is closer to how real-life arbitrageurs construct their portfolio and described in the following paragraphs.

Each day t, for each stock i in the sample, optimal weights $\mathrm{w_{it}}^*$ are computed by performing the following optimization:

$$Max \sum_i w_{it}^* s_{it}^{strategy}$$

$$s.t. : \sigma_{P,t} = 0.1, and \sum_i w_{it}^* \beta_{it} = 0$$

σ_{it} is the volatility of stock i. $\sigma_{\mathrm{P,t}}$ is the volatility of the portfolio constructed and β_{it} is the beta of stock i.

Essentially, we maximise $\sum_i w_{\mathrm{it}}{}^* s_{\mathrm{it}}{}^{\mathrm{strategy}}$, which can be seen as the expected returns of the portfolio, subject to volatility and beta neutrality constraints. If the strategy indeed generates alpha, a high score stocks should be followed by high excess returns and vice versa. We constrain the volatility of the portfolio to be 10% and the beta of the portfolio (against an equi-weighted basket of the stocks in the portfolio) to be 0.

σ_{it}, $\sigma_{P,t}^2$ and β_{it} are computed from a variance-covariance matrix Ω_t that is estimated over a medium horizon.

Kent et al (2020) tackle a similar problem (instead of maximising returns for a given volatility, they minimize volatility for a given return) and show that this maximisation program has a simple close form solution.

Finally, we smooth turnover in order to consider real-life concerns about trading costs. We follow Garleanu and Pedersen (2013), who show that an optimal dynamic portfolio policy when trading is costly is to trade partially towards the current aim.

Our final weights $\mathrm{w_{it}}$ become:

$$w_{it} = (1 - \tau) w_{it-1} + \tau w_{it}^*$$

We choose a τ equal to 0.1, which is on average close to optimal for the strategies studied. Multiplying these weights by daily stock returns yields the strategy daily returns, gross of any trading costs.

Figure 3 (North America) and 4 (Developed Europe) plot the cumulative returns for Momentum, Value, Low Volatility, Return on Asset, Short Interest and the Composite strategies. These strategies all behave consistently with academic or anecdotal evidence:

- Momentum exhibits the well documented "2009 Momentum Crash" (Daniel and Moskowitz (2016)) and performs relatively well since 2015.

- Value performs poorly over the sample, particularly in the past few years, and experiences a very significant drawdown during the COVID-19 crisis. This poor performance has been the subject of both market commentaries and academic research in the past years and months (Lev et al (2019), Asness (2020)).

- Return on Assets performs well.

- Low Volatility exhibits a strong performance.

- Short Interest, consistent with several papers in the short-selling literature, exhibits positive alpha.

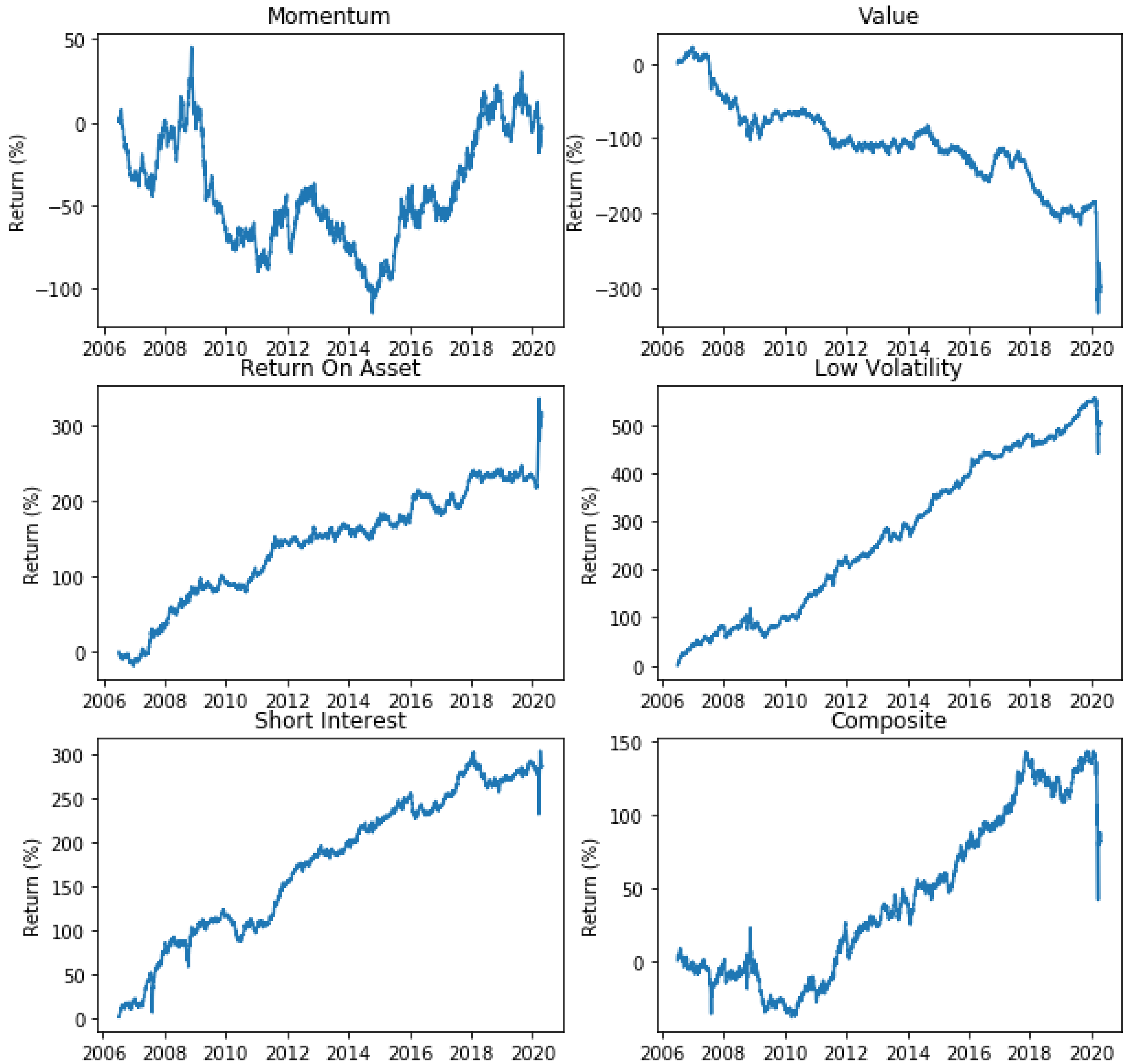


Figure 3

Equity Strategies Cumulative Returns, 2006-2020 (North America)

Momentum, Value, Return on Asset, Low Volatility, Short Interest and Composite cumulative returns for our North America sample. Portfolio target weights are computed daily by optimizing expected returns subject to the following constraints: (i) annual volatility equal to 10% and (ii) beta against an equi-weighted basket of the stocks in the sample equal to 0. Actual weights used to compute returns are a smoothed version of the target weights to approximate turnover control mechanisms used by quantitative equity investors.

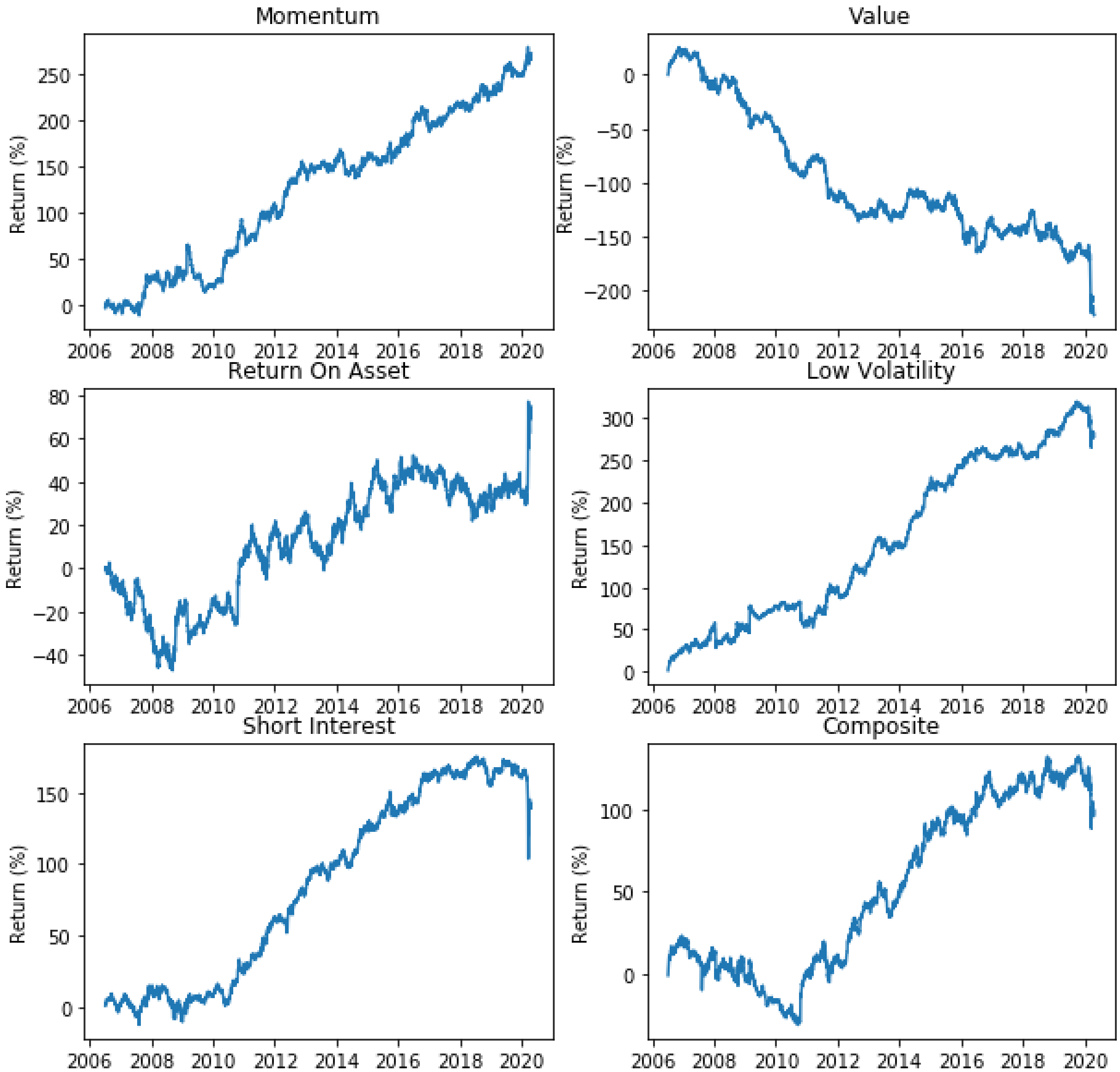


Figure 4

Equity Strategies Cumulative Returns, 2006-2020 (Developed Europe)

Momentum, Value, Return on Asset, Low Volatility, Short Interest and Composite cumulative returns for our Developed Europe sample. Portfolio target weights are computed daily by optimizing expected returns subject to the following constraints: (i) annual volatility equal to 10% and (ii) beta against an equi-weighted basket of the stocks in the sample equal to 0. Actual weights used to compute returns are a smoothed version of the target weights to approximate turnover control mechanisms used by quantitative equity investors.

2 The Short Interest Strategy as an Indicator for Deleverage Episodes

The Short Interest strategy consists in buying low short interest stocks and shorting high short interest stocks – essentially "piggy-backing" on short-sellers' skills in generating alpha. It has been the subject of a relatively large set of papers. One of the perspectives offered to explain the negative relationship between short interest and stock returns (and therefore the profitability of the Short Interest strategy) is the following: given shorting costs, informed traders are more likely to engage in short-selling, leading high short interest to signal adverse information that is not yet reflected in stock prices.

A. Conceptual Framework

In this section, we present a simple model whose aim is to explain the behavior of the Short Interest strategy upon the occurrence of unexpected and exogeneous liquidity shocks on short-sellers (that we call arbitrageurs below). The strategy suffers a V-shaped drawdown. This motivates its later use as a barometer for deleverage activity.

As the Short Interest strategy mimics arbitrageurs' positions, we make the simplifying assumption that its behavior is similar to arbitrageurs' performance. This would imply that one could buy and sell stocks at the same time as the arbitrageurs. In practice, short interest ratios are only observed after the arbitrageurs have traded and with a few days lag. But given the trading horizon of most of the quant equity strategies (few weeks to a few months), we believe this approximation is not too far off the mark.

A.1. Model Settings

The basic settings of the model are largely inspired by HS. A fraction a of agents are arbitrageurs (A) and have correct beliefs about future returns. The remaining 1-a are naïve investors (N) with biased beliefs (that could be explained, for instance, by behavioral biases as documented by the large literature on behavioral finance).

We depart from HS by (i) focusing on a 3-period model (t=0,1,2) and (ii) shocking the arbitrageurs' parameter a at t=1 to see the impact of un-anticipated, exogeneous liquidity shocks on the Short Interest strategy.

Stocks are indexed by i=1,2,...,I and each stock has a fixed positive supply w_i, where $\sum_i w_i = 1$. At time 2, stocks pay terminal dividends. The variance-covariance matrix of terminal dividends is known by both type of agents. At time 0, investors trade and returns between time 0 and time 2 are determined. We use time 1 solely to shock parameter a and understand the impacts such a shock has. Note that in the absence of any changes in a, no trading would happen in t=1, as we make the simplifying assumption that agents take a as a fixed parameter and do not anticipate the shock.

Arbitrageurs correctly believe that expected excess returns on stock i are $E_t^*[r_i]$, whereas naïve investors incorrectly believe that $E_t[r_i] = E_t^*[r_i] + b_i$.

b_i represents the naïve investors biases: their over-estimation of stock i expected return. For simplicity, we assume no aggregate mispricing, $\sum_i w_i b_i = 0$. This assumption has no impact on our results as we are focused on the cross-section of expected stock returns. It implies that both arbitrageurs and naïve investors expect the same excess returns r_M on the market portfolio.

A.2. Equilibrium

Stock demands of arbitrageurs are, at time 0 and in vector notation, $\mathbf{q}_{A,0} = \gamma(Var[\mathbf{r}])^{-1}E_0{}^*[\mathbf{r}]$. Those of the naïve investors are $\mathbf{q}_{A,0} = \gamma(Var[\mathbf{r}])^{-1}(E_0{}^*[\mathbf{r}] + \mathbf{b})$.

At equilibrium, supplies and demands for all stocks are equal: $\mathbf{w} = a\mathbf{q}_{A,0} + (1-a)\mathbf{q}_{N,0}$, which implies that:

$$E_0{}^*[\mathbf{r}] = -(1-a)\mathbf{b} + \frac{Cov[\mathbf{r}, r_M]}{Var[r_M]} E_0{}^*[r_M] = \alpha + \beta E_0{}^*[r_M]$$

Each stock has a CAPM alpha of -(1-a) b_i. The alpha is negative for positive b_i and is decreasing in b_i. This makes intuitive sense: the higher the bias of the naïve investors on a stock, the more they will over-demand this stock and push its time 0 price up, thereby reducing its excess return. The CAPM alpha's absolute value is decreasing in a. It tends to 0 as a tends to 1. Again, this makes sense: the more arbitrageurs (higher a), the less alpha there will be and if there are only arbitrageurs and no naïve investors, the canonical CAPM result of no alpha should hold.

Total positions of arbitrageurs in equilibrium are therefore $a\mathbf{q}^*{}_{A,0} = a\mathbf{w} - a(1-a)\gamma(Var[\mathbf{r}])^{-1}\mathbf{b}$.

These positions are decreasing in b_i. Indeed, arbitrageurs, who have correct beliefs, know that naive investors have biases and tend to over-value high b_i stocks (and vice versa). They underweight these stocks (assign less weights than the market portfolio) as they have lower expected excess returns. For some parameters (large enough b_i, small enough a), they even short-sell some of these overvalued stocks.

These total arbitrageur positions in ratios of market capitalization, are:

$$\mathbf{P}^*{}_0 = a\mathbf{1} - a(1-a)\frac{\gamma(Var[\mathbf{r}])^{-1}\mathbf{b}}{\mathbf{w}}$$

To get short interest ratios $\mathbf{SI}_0{}^*$, we simply multiply the above by -1 and consider only positive numbers $\mathbf{SI}_0{}^*$=Max(0,-$\mathbf{P}_0{}^*$).

A.3. Results

In the below and as discussed above, we make the simplifying assumption that the Short Interest strategy mimics exactly the arbitrageurs' performance.

Result 1: arbitrageurs and the Short Interest strategy generate positive "alpha" (positive expected market beta adjusted returns):

$$\mathbf{q}_{\mathrm{A},0}{}^{*\prime}\alpha = \gamma \sum_i \frac{(1-a)^2 b_i^2}{Var[\mathbf{r}]} > 0$$

Arbitrageurs who, in this setting, have un-biased beliefs, exploit unsophisticated investors' predictable biases. They actually generate positive alpha for each single stock position: the single stock alpha $\gamma(1-a)^2 b_i^2 (Var[\mathbf{r}])^{-1}$ is positive, increasing in the bias $\mathrm{b_i}$, decreasing in the proportion of arbitrageurs a and increasing in the ratio of risk aversion to stock return variance.

Result 2: when there is an un-anticipated, exogenous liquidity shock on the arbitrageurs in time 1, arbitrageurs suffer losses (the Short Interest strategy crashes). From Result 1, one can see that each stock shorted by the strategy has alpha $\gamma(1-a)^2 b_i^2 (Var[\mathbf{r}])^{-1}$. This alpha is strictly decreasing in a. Upon liquidity shock, the alpha of each stock shorted therefore increases, which, combined with the fact that expected terminal value for stocks are unchanged, means that prices for the stocks that are shorted go up. Over-valued stocks become even more over-valued and the Short Interest strategy suffers. The performance rebounds in time 2 as stock prices converge to their terminal values.

B. 2007 Quant Crisis and 2020 Quant Deleverage

The 2007 Quant Crisis was described at length by Kadani and Lo (2007 and 2011). Here is the abstract of their 2007 paper for reference: "During the week of August 6, 2007, a number of quantitative long/short equity hedge funds experienced unprecedented losses. [...] we hypothesize that the losses were initiated by the rapid "unwind" of one or more sizeable quantitative equity market-neutral portfolios. Given the speed and price impact with which this occurred, it was likely the result of a forced liquidation [...]. These initial losses then put pressure on a broader set of long/short and long-only equity portfolios, causing further losses by triggering stop/loss and deleveraging policies. A significant rebound of these strategies occurred on August 10^{th}, which is also consistent with the unwind hypothesis. This dislocation was apparently caused by forces outside the long/short equity sector – in a completely unrelated set of markets and instruments [...]."

More than a decade later, a large quant equity deleverage episode occurred again. In March 2020, financial markets became extremely volatile. Investors started to understand the negative economic impact of the COVID-19 pandemic related lock-downs. Governments and central banks, surprised themselves, had not yet announced the massive shock-offsetting monetary and fiscal measures that would later ease the panic. In the first two weeks of March, quant equity market neutral funds were resisting quite well to the market turmoil (they were only slightly negative for the year)[6]. Then, on March 13, regulators in some European countries announced short ban measures. Between that day and March 18, a large deleverage by quant equity hedge

[6] According to a Goldman Sachs daily report, they were down -2.7% year to date as of March 12, 2020.

funds followed[7].

The likely triggers for this sudden large unwind could be the following: investors hitting their value at risk limits following the sharp increase in volatility, impaired liquidity and losses in other asset classes, increased probability of generalized short bans, the self-fulfilling fear that other investors would deleverage and that it was therefore better to be the first to do so. Once it started, quant equity managers started experiencing severe losses and a liquidity spiral followed.

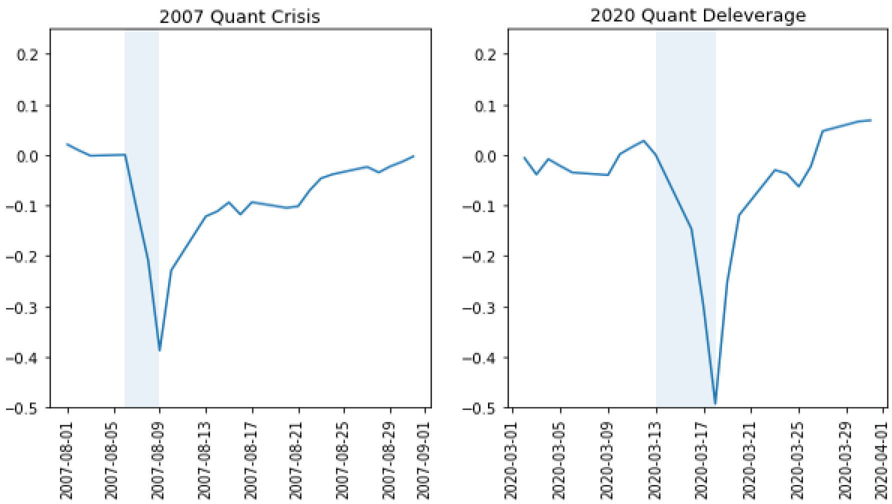
Figure 5 plots the cumulative performance of the Short Interest strategy (our unwind "barometer") for North America and Europe, during both the 2007 Quant Crisis and the 2020 Quant Deleverage. We can see the following:

• As expected, the Short Interest strategy exhibits a V-shape cumulative performance during both these crises and in both regions: the strategy suffers sharp drawdowns and rebounds quickly right after, consistent with the unwind hypothesis (temporary large price pressures that are not linked to fundamentals).

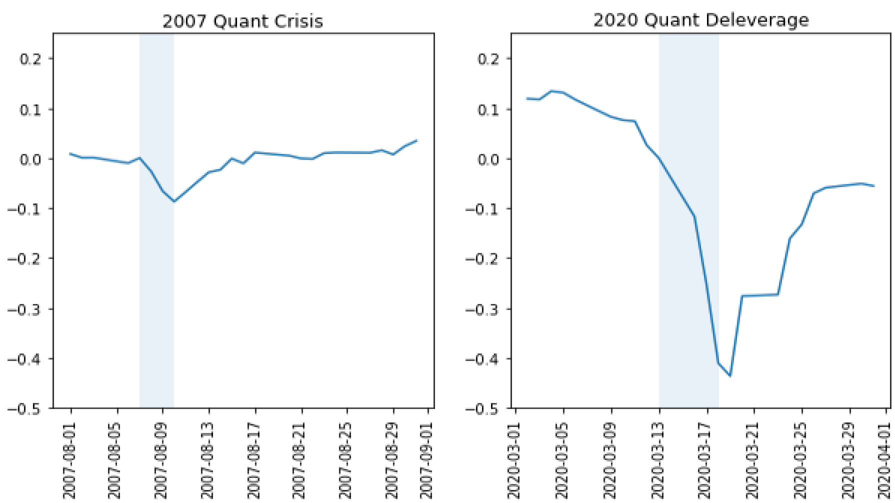
• In 2007, the drawdown starts earlier and is more severe in North America. Europe does get affected, but to a lesser extent and a day later. This is consistent with what has been documented for the 2007 episode: triggered in the US, with some contagion to other international markets.

• For both regions, the drawdown is more severe in 2020 than in 2007, showing how violent the shock was. There is one caveat. Markets were very volatile during the 2020 episode. In contrast, the 2007 Quant Crisis happened at the onset of the global financial crisis, at a time where equity markets were less volatile.

[7] According to a Goldman Sachs weekly report published on March 20, 2020, Systematic Equity Long/Short managers reduced significantly their gross equity exposures during the preceding week.



Panel A: Short Interest Cumulative Returns (North America)



Panel B: Short Interest Cumulative Returns (Developed Europe)

Figure 5

Short Interest Strategy Cumulative Returns, 2007 Quant Crisis and 2020 Quant Deleverage

Short Interest strategy cumulative returns for our North America (top, panel A) and Developed Europe (bottom, panel B) samples, during both the 2007 Quant Crisis (left) and the 2020 Quant Deleverage (right). Portfolio target weights are computed daily by optimizing expected returns subject to the following constraints: (i) annual volatility equal to 10% and (ii) beta against an equi-weighted basket of the stocks in the sample equal to 0. Actual weights used to compute returns are a smoothed version of the target weights to approximate turnover control mechanisms used by quantitative equity investors.

3 Crowding Measure

A. Crowding Measure Methodology

HS develop a methodology to infer from short interest data the amount of capital allocated to quantitative arbitrage strategies. Their key insight is that "each cross-section of short interest reveals how intensely arbitrageurs are using a quantitative equity strategy at a given time".

Indeed, if a lot of arbitrageurs are allocating capital to a long-short equity strategy, short interest should be higher for the stocks shorted by that strategy (in our setting, those with negative $\mathrm{s_{it}}^{\mathrm{strategy}}$).

Largely inspired by HS, we run daily cross-sectional regressions of stock-level short interest $\mathrm{SI_{it}}$ on strategy scores $\mathrm{s_{it}}^{\mathrm{strategy}}$, controlling for stock volatility[8] and size (as we have shown above, both are correlated to short interest):

$$SI_{it} = k_t^{strategy}(\text{-}s_{\mathrm{it}}{}^{\mathrm{strategy}}) + controls + \epsilon_{it}$$

The coefficient obtained through this regression, $\mathrm{k_t}^{\mathrm{strategy}}$, is the estimated difference in short interest between the most shorted stock (that has a score of -1) and the median score stock (that has a score of 0). It can be interpreted as a proxy for crowdedness or the strategy-level capital arbitrage.

Our crowding measure differs from HS' in the following aspects:

1. Short Interest Data: we use IHS Markit, available daily and based on aggregating data from various institutions involved in the equity finance market. HS use Compustat which is monthly and based on exchange data.

2. We focus on a tradeable stock sample. HS study a larger sample that includes a lot of smaller stocks.

3. HS regress short interest on strategy decile dummies, omitting the 5_{th} decile, whereas we regress on a uniformly distributed strategy score.

B. Results

Figure 6 (North America) and 7 (Developed Europe) show the evolution over time of $\mathrm{k_t}^{\mathrm{strategy}}$ for Value, Momentum, Low Volatility, Return on Assets and the Composite as well as the corresponding t-statistics.

• Low Volatility seems to be the most significantly crowded strategy with $\mathrm{k_t}^{\mathrm{low\ volatility}}$ showing a steady increase over the past 8 years or so, in both regions.

• At the other end of the spectrum, Return on Assets is not very crowded over the sample, except on the lead up to the global financial crisis.

[8] For the low volatility strategy, we do not control for volatility. All other strategies, including the composite, are controlled for both size and volatility.

- Value and Momentum are in between, with average $k_t^{strategy}$ that are positive but not always significant. Value is more crowded in North America than in Developed Europe while Momentum is more crowded in Developed Europe than in North America.

- $k_t^{composite}$ is generally positive and significant. It increased a lot since 2016 and peaked at the end of 2017 before decreasing meaningfully, quite consistently with the rise and fall in assets of factor-based equity market neutral strategies.

- Most strategies were crowded pre financial crisis and experienced large drops in crowding in September 2008 (Lehman default, SEC short ban). One exception is Value, which was not crowded in the build up to the crisis.

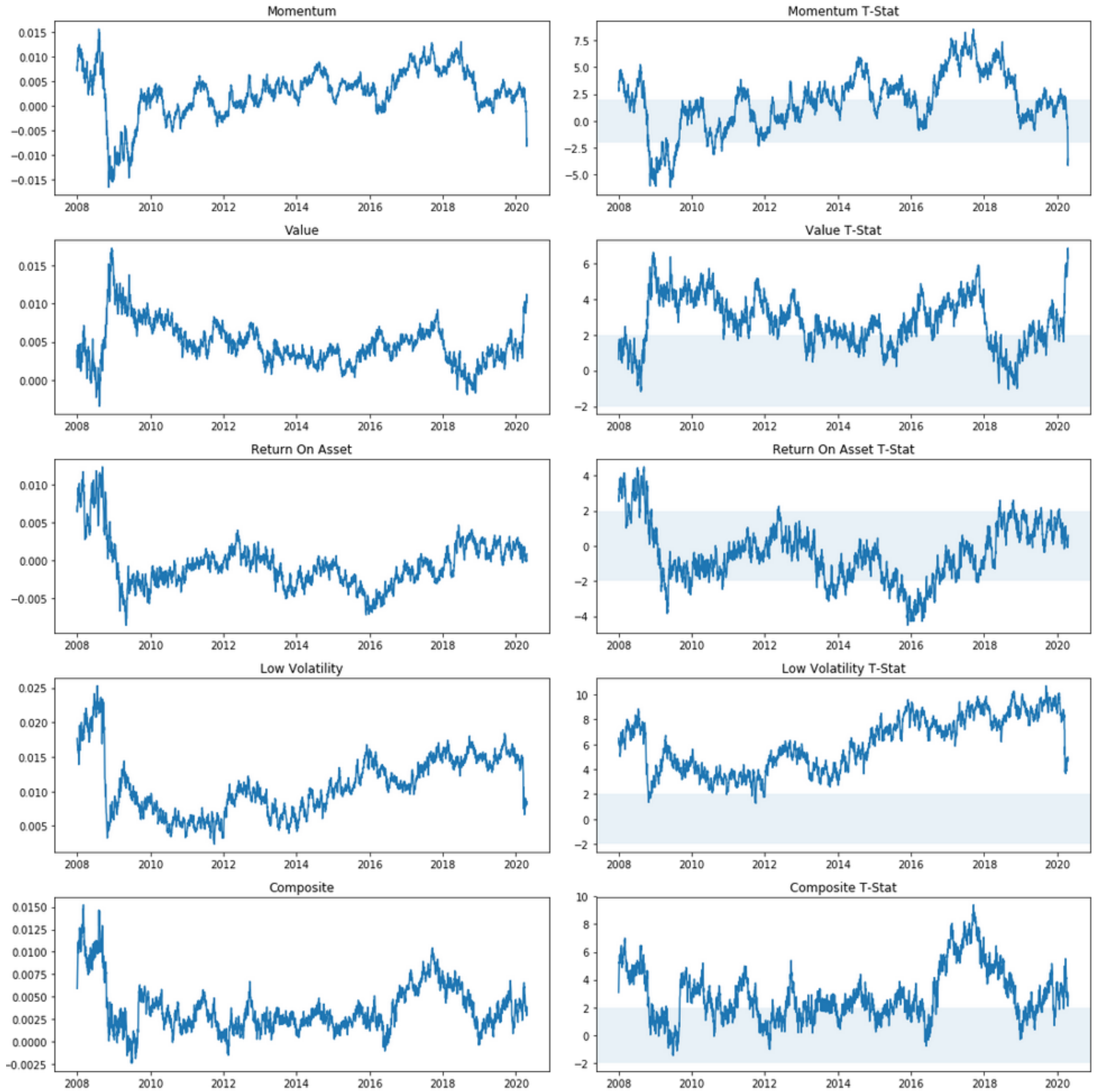


Figure 6

Evolution of Crowding Measures $k_t^{strategy}$, 2008-2020 (North America)

The crowding measure $k_t^{strategy}$ is estimated daily via the following cross-sectional regression: $SI_{it}=k_t^{strategy}(-s_{it}^{strategy})+$ controls$+\ \epsilon_{it}$ where SI_{it} is the short interest for stock i and $s_{it}^{strategy}$ is the score for the quantitative equity strategy studied, uniformized on [-1, 1]. strategy include Value, Momentum, Low Volatility, Return on Assets and the Composite. The regression is controlled for size (log of market capitalization) and volatility. The evolution though time of the coefficient $k_t^{strategy}$ is shown on the left-hand side, that of the t-statistic of the regression on the right-hand side.

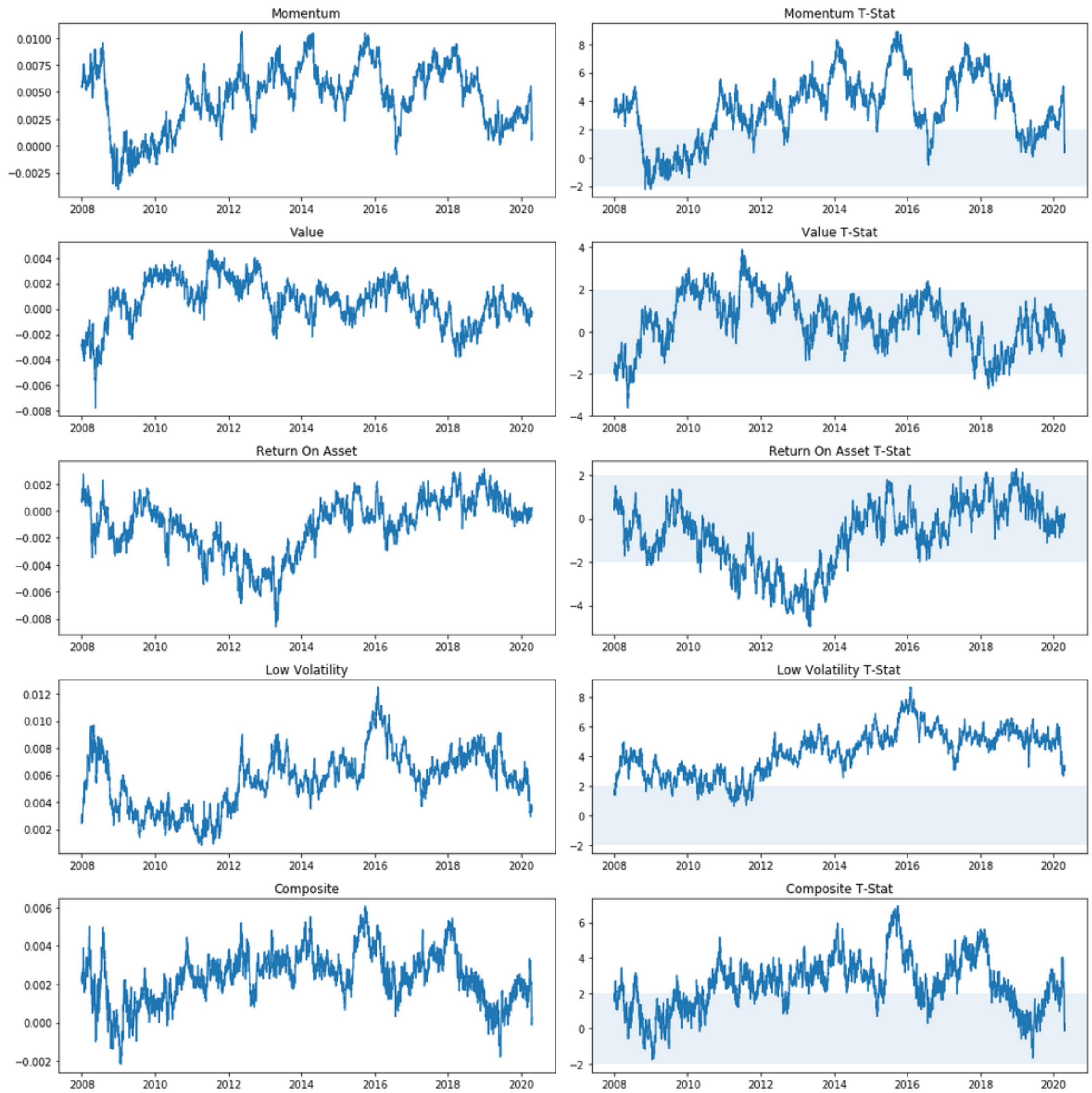


Figure 7

Evolution of Crowding Measures $k_t^{strategy}$, 2008-2020 (Developed Europe)

The crowding measure $k_t^{strategy}$ is estimated daily via the following cross-sectional regression: $SI_{it}=k_t^{strategy}$ $(-s_{it}^{strategy})+$ controls$+\ \epsilon_{it}$ where SI_{it} is the short interest for stock i and $s_{it}^{strategy}$ is the score for the quantitative equity strategy studied, uniformized on [-1, 1]. textitstrategy include Value, Momentum, Low Volatility, Return on Assets and the Composite. The regression is controlled for size (log of market capitalization) and volatility. The evolution though time of the coefficient $k_t^{strategy}$ is shown on the left-hand side, that of the t-statistic of the regression on the right-hand side.

D. Case Study: 2007 Quant Crisis and 2020 Quant Deleverage

Figure 8 (North America) and 9 (Developed Europe) plot, for both events, strategy level crowding and strategy cumulative returns for Momentum, Value, Low Volatility, Return on Asset. Here are some observations:

• Markets were very volatile during the 2020 episode. In contrast, the 2007 Quant Crisis happened at the onset of the global financial crisis, at a time where equity markets were less volatile. This can be seen in the range of strategy returns, which is much larger in 2020 than in 2007.

• Strategies that were crowded generally drew down in 2020. Momentum and Low Volatility were crowded and under-performed in both regions, Return on Asset was not crowded and performed. Value is less clear, it suffered the most in both regions but was only crowded in North America. Given the volatility at the time, other factors than crowding were likely at play and added noise in the strategy returns.

• In 2007, crowded strategies under-performed in North America: Momentum, Low Volatility, Return on Assets were all crowded and suffered. Value was not crowded but suffered as well. In Europe where the Quant Crisis was much less pronounced, the picture is less clear: Value and Momentum both suffered but only Momentum was crowded. Low Volatility was crowded but did not under-perform. One possible explanation is that quants were crowding in Value but that non quant short sellers such as fundamental equity long short hedge funds had a short value bias. This illustrates one limitation of the crowding measure: short interest aggregates short positions across all short-sellers (quants and non-quants).

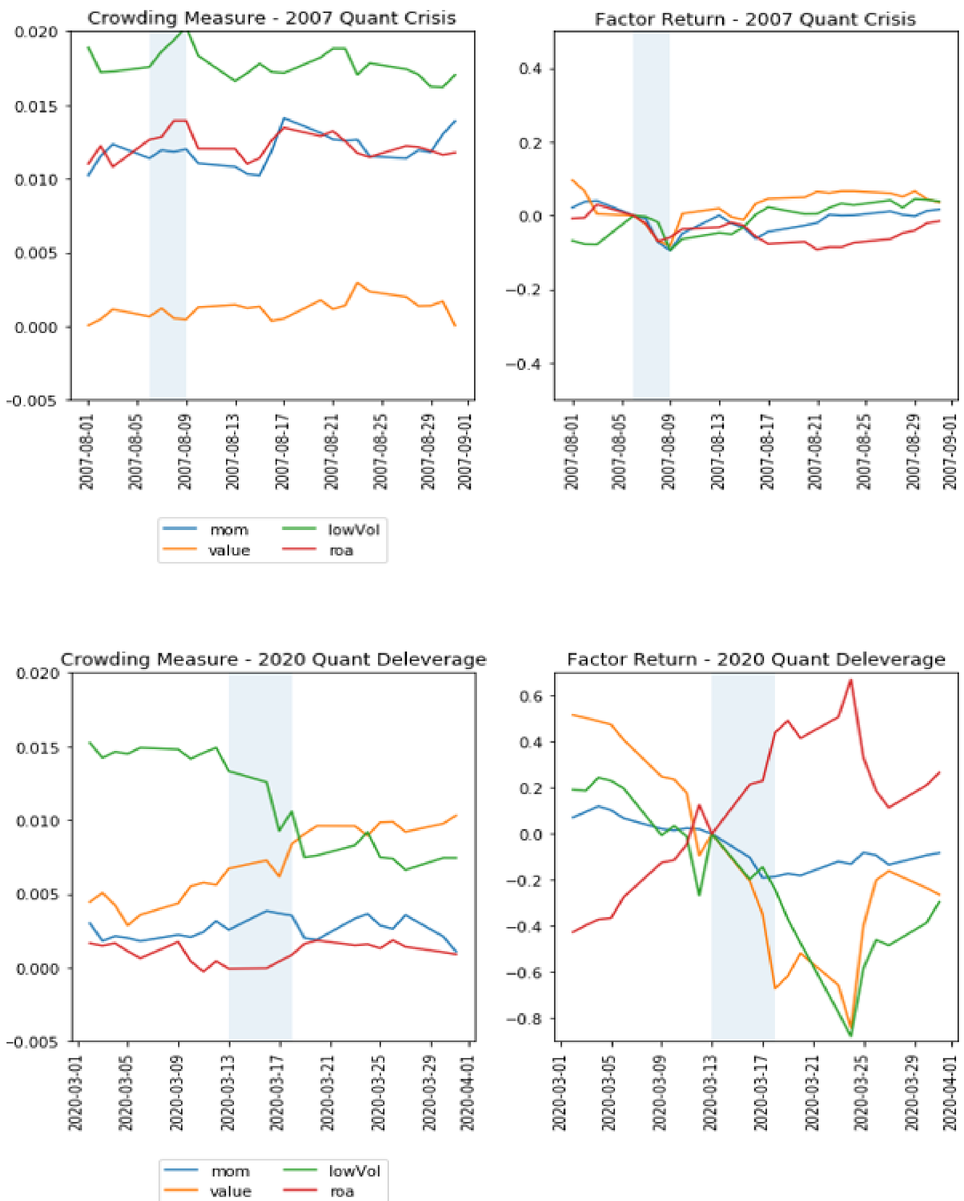


Figure 8

Crowding and Factor Performance, 2007 Quant Crisis and 2020 Quant Deleverage (North America)

Crowding measures (left) and factor (Momentum, Value, Low Volatility, Return on Asset) cumulative returns (right) for our North America sample, during both the 2007 Quant Crisis (left) and the 2020 Quant Deleverage (right). Portfolio target weights are computed daily by optimizing expected returns subject to the following constraints: (i) annual volatility equal to 10% and (ii) beta against an equi-weighted basket of the stocks in the sample equal to 0. Actual weights used to compute returns are a smoothed version of the target weights to approximate turnover control mechanisms used by quantitative equity investors.

Figure 9

Crowding and Factor Performance, 2007 Quant Crisis and 2020 Quant Deleverage (Developed Europe)

Crowding measures (left) and factor (Momentum, Value, Low Volatility, Return on Asset) cumulative returns (right) for our Developed Europe sample, during both the 2007 Quant Crisis (left) and the 2020 Quant Deleverage (right). Portfolio target weights are computed daily by optimizing expected returns subject to the following constraints: (i) annual volatility equal to 10% and (ii) beta against an equi-weighted basket of the stocks in the sample equal to 0. Actual weights used to compute returns are a smoothed version of the target weights to approximate turnover control mechanisms used by quantitative equity investors.

4 Impact of Crowding on Strategy Returns and Drawdowns

In this section, we analyse the impact of strategy-level crowding on future strategy returns and drawdowns.

A. Impact of Crowding on Future Strategy Returns

We first investigate whether a higher level of crowding is followed by lower strategy returns. In Table 2, we regress strategy returns over the following d business days $\mathrm{r_{t,t+d}}^{\mathrm{strategy}}$ on the initial level of crowding. We look at various values for d: 63, 126 and 252 business days. The equation for the regression is:

$$r_{\mathrm{t,t+d}}{}^{\mathrm{strategy}} = \alpha + \beta k_{\mathrm{t}}{}^{\mathrm{strategy}} + \epsilon_{\mathrm{t,t+d}}{}^{\mathrm{strategy}}$$

The t-statistics are calculated using Newey-West standard errors because of overlapping returns, allowing for d+2 daily lags. We also show results when we control for the increase in the crowding measure during the period for which the returns are computed: $\Delta k_{\mathrm{t,t+d}}{}^{\mathrm{strategy}} = k_{\mathrm{t+d}}{}^{\mathrm{strategy}} - k_{\mathrm{t}}{}^{\mathrm{strategy}}$. Indeed, strategy inflows and outflows could have some contemporaneous impact on strategy returns.

Results are generally robust to various values of d and to controlling for $\Delta k_{\mathrm{t,t+d}}{}^{\mathrm{strategy}}$, but no clear pattern emerge across strategies and regions. High levels of crowding seem to be followed by higher returns in North America for Momentum, Value and Return on Assets but by lower returns for Low Volatility and the Composite. Developed Europe shows no significant pattern, except for Composite where high levels of crowding are very significantly followed by higher returns, opposite to what we see in North America. Overall and on balance, although the results are mixed, it seems that crowding is associated in more cases to higher future returns, which is at odds with what is found by HS on their 1973-2011 sample: they showed a negative relationship between crowding and future strategy returns.

A possible explanation is that offsetting effects are at play. On the one hand, more arbitrage capital chasing the same strategy will, all else equal, lead to alpha decay. But on the other hand, some sophisticated investors might have skills in timing factors: these skilled investors increase exposure to a factor when they (correctly) believe it will have attractive future returns. This increased exposure shows up in short interest data and our crowding measure.

Table 2

Crowding and Future Strategy returns

Panel A: North America Sample 2006-2020

	Momentum		Value		Return on Assets		Low Volatility		Composite	
d=63										
Intercept	-0.03	-0.04	-0.07	-0.06	0.05	0.05	0.12	0.11	0.01	0.02
	[-2.01]	[-2.04]	[-2.64]	[-2.24]	[3.69]	[3.73]	[3.47]	[3.29]	[0.84]	[0.93]
$k_t^{strategy}$	10.16	10.96	5.03	3.96	4.99	3.88	-2.59	-2.09	1.2	0.65
	[3.68]	[3.51]	[1.26]	[0.77]	[1.87]	[1.34]	[-0.97]	[-0.8]	[0.41]	[0.18]
$\Delta k_{t,t+d}^{strategy}$		2.24		-2.74		-6.51		2.14		-1.55
		[0.55]		[-0.32]		[-1.83]		[0.47]		[-0.38]
d=126										
Intercept	-0.06	-0.07	-0.12	-0.13	0.09	0.09	0.27	0.26	0.06	0.05
	[-1.88]	[-1.95]	[-2.93]	[-2.53]	[4.29]	[4.26]	[5.05]	[4.66]	[2.57]	[1.63]
$k_t^{strategy}$	19.55	21.81	8.96	11.59	10.91	9.77	-7.34	-6.64	-4.39	-2.16
	[4.03]	[3.58]	[1.28]	[1.32]	[2.75]	[2.08]	[-1.85]	[-1.57]	[-1.01]	[-0.32]
$\Delta k_{t,t+d}^{strategy}$		3.82		4.12		-3.61		1.86		4.1
		[0.81]		[0.42]		[-0.76]		[0.44]		[0.55]
d=252										
Intercept	-0.08	-0.1	-0.25	-0.31	0.18	0.18	0.63	0.6	0.18	0.18
	[-1.30]	[-1.44]	[-3.44]	[-2.99]	[5.43]	[5.48]	[8.58]	[6.78]	[4.17]	[3.39]
$k_t^{strategy}$	29.24	36.13	20.17	32.71	18.84	22.52	-23.27	-20.27	-20.02	-21.82
	[4.24]	[3.17]	[1.56]	[1.94]	[3.31]	[3.71]	[-3.78]	[-2.75]	[-2.81]	[-1.68]
$\Delta k_{t,t+d}^{strategy}$		7.69		15.98		6.95		6.2		-1.88
		[1.08]		[0.83]		[1.4]		[0.92]		[-0.17]

Panel B: Developed Europe Sample 2006-2020

	Momentum		Value		Return on Assets		Low Volatility		Composite	
					d=63					
Intercept	0.06	0.05	-0.03	-0.03	0.01	0.01	0.03	0.02	-0.01	-0.02
	[2.20]	[1.92]	[-2.83]	[-2.75]	[0.72]	[0.53]	[1.05]	[0.63]	[-0.93]	[-1.79]
$\mathrm{k_t}^{\mathrm{strategy}}$	-2.19	-1.62	-4.57	-11.17	-1.82	-3.44	3.46	5.71	13.15	18.72
	[-0.49]	[-0.32]	[-0.72]	[-1.82]	[-0.47]	[-0.74]	[0.77]	[1.22]	[2.72]	[3.26]
$\Delta k_{\mathrm{t,t+d}}{}^{\mathrm{strategy}}$		1.72		-17.59		-4.63		7.96		12.57
		[0.38]		[-3.37]		[-0.83]		[1.08]		[2.61]
					d=126					
Intercept	0.09	0.1	-0.07	-0.06	0.01	0.01	0.08	0.04	-0.01	-0.04
	[1.72]	[1.63]	[-3.38]	[-3.37]	[0.85]	[0.67]	[1.50]	[0.62]	[-0.45]	[-1.68]
$\mathrm{k_t}^{\mathrm{strategy}}$	1.43	-0.8	2.37	-13.13	-3	-5.75	4.04	12.24	21.13	35.51
	[0.16]	[-0.07]	[0.22]	[-1.06]	[-0.47]	[-0.76]	[0.49]	[1.34]	[2.27]	[3.35]
$\Delta k_{\mathrm{t,t+d}}{}^{\mathrm{strategy}}$		-3.89		-26.16		-6.16		18.26		22.31
		[-0.69]		[-3.24]		[-0.74]		[1.79]		[4.08]
					d=252					
Intercept	0.2	0.17	-0.15	-0.13	0.04	0.03	0.16	0.06	-0.04	-0.12
	[2.38]	[1.75]	[-4.30]	[-4.40]	[1.23]	[0.89]	[1.59]	[0.68]	[-0.82]	[-2.69]
$\mathrm{k_t}^{\mathrm{strategy}}$	-1.67	4.94	16.04	-7.45	-3.05	-12.82	9.39	26.48	50.53	85.42
	[-0.12]	[0.27]	[1.31]	[-0.45]	[-0.42]	[-1.2]	[0.59]	[1.63]	[3.44]	[5.42]
$\Delta k_{\mathrm{t,t+d}}{}^{\mathrm{strategy}}$		8.04		-38.57		-18.3		27.97		40.53
		[0.82]		[-2.82]		[-1.6]		[1.89]		[4.16]

This table reports coefficients and t-statistics for the regression $r_{\mathrm{t,t+d}}{}^{\mathrm{strategy}} = \alpha + \beta k_{\mathrm{t}}{}^{\mathrm{strategy}} + \epsilon_{\mathrm{t,t+d}}{}^{\mathrm{strategy}}$ where $\mathrm{r_{t,t+d}}^{\mathrm{strategy}}$ is the cumulative strategy return between days t and t+d, $\mathrm{k_t}^{\mathrm{strategy}}$ is the strategy-level crowding measure calculated as described in section 3 and strategy include Value, Momentum, Return on Asset, Low Volatility and the Composite strategies. T-statistics are shown in brackets and calculated using Newey-West standard errors, allowing for serial autocorrelations up to d+2 daily lags. We show results for both our North America (Panel A) and Developed Europe (Panel B) samples.

B. Impact of Crowding on Future Strategy Skewness

Next, we study whether high positive levels of strategy-level crowding are followed on average by more negative skewness. In Table 3, we regress strategy skewness computed over the following d business days on the initial level of crowding. We look at various values for d: 63, 126 and 252 business days. The equation for the regression is:

$$Skew_{t,t+d}^{strategy} = \alpha + \beta k_t^{strategy} + \epsilon_{t,t+d}^{strategy}$$

The t-statistics are calculated using Newey-West standard errors because of overlapping returns, allowing for d+2 daily lags.

For the Composite strategy in North America, high levels of crowding are followed by more negatively skewed returns. In Developed Europe, the coefficient is negative as well, but the result is not significant. For other strategies, there are no clear patterns in North America, with all coefficients insignificant. In Developed Europe, Momentum and Return on Assets seem to exhibit more negatively skewed returns when they are crowded, but Value and Low Volatility show an opposite behaviour. Overall, the results are quite mixed but, if anything, slightly tilted towards the expected link: crowding is weakly associated with more negatively skewed returns.

Table 3

Crowding and Future Strategy returns

Panel A: North America Sample 2006-2020

	Momentum	Value	Return on Assets	Low Volatility	Composite
			d=63		
Intercept	-0.27	0.07	-0.08	-0.05	0.02
	[-4.73]	[0.77]	[-2.16]	[-0.39]	[0.29]
$Skew_{t,t+d}^{strategy}$	-0.12	2.32	-0.75	-0.63	-1.87
	[-0.02]	[0.15]	[-0.09]	[-0.06]	[-0.14]
			d=126		
Intercept	-0.32	0.08	-0.07	0.02	0.07
	[-4.96]	[0.79]	[-1.89]	[0.17]	[0.96]
$Skew_{t,t+d}^{strategy}$	-1.94	3.37	-1.36	-10.55	-15.99
	[-0.33]	[0.24]	[-0.18]	[-0.73]	[-1.21]
			d=252		
Intercept	-0.35	0.08	-0.08	0.1	0.13
	[-5.36]	[0.79]	[-1.57]	[0.55]	[1.57]
$Skew_{t,t+d}^{strategy}$	-0.2	0.98	-3.91	-17.66	-30.84
	[-0.03]	[0.08]	[-0.59]	[-1]	[-2.11]

Panel B: Developed Europe Sample 2006-2020

	Momentum	Value	Return on Assets	Low Volatility	Composite
			d=63		
Intercept	0.18	0.01	0	-0.14	0.13
	[0.86]	[0.28]	[-0.07]	[-0.53]	[0.86]
$Skew_{t,t+d}^{strategy}$	-62.99	-0.06	-18.66	33.98	-32.59
	[-1.79]	[0]	[-1.57]	[0.9]	[-0.66]
			d=126		
Intercept	0.35	-0.02	0.06	-0.3	0.28
	[1.16]	[-0.49]	[0.70]	[-0.64]	[1.20]
$Skew_{t,t+d}^{strategy}$	-85.28	6.7	-16.36	62.02	-65.5
	[-1.63]	[0.38]	[-1.05]	[0.99]	[-0.85]
			d=252		
Intercept	0.46	-0.06	0.18	-0.61	0.35
	[1.28]	[-1.33]	[1.30]	[-1.00]	[1.10]
$Skew_{t,t+d}^{strategy}$	-75.85	24.18	4.63	123.72	-54.29
	[-1.28]	[1.54]	[0.18]	[1.54]	[-0.46]

This table reports coefficients and t-statistics for the regression $Skew_{t,t+d}^{strategy} = \alpha + \beta k_t^{strategy} + \epsilon_{t,t+d}^{strategy}$ where $Skew_{t,t+d}^{strategy}$ is the strategy's skewness between days t and t+d, $k_t^{strategy}$ is the strategy-level crowding measure calculated as described in section 3 and *strategy* include Value, Momentum, Return on Asset, Low Volatility and the Composite strategies. T-statistics are calculated using Newey-West standard errors, allowing for serial autocorrelations up to d+2 daily lags. We show results for both our North America (Panel A) and Developed Europe (Panel B) samples.

5 Conclusion

In this paper, we use sophisticated equity investors' positioning data for two purposes. First, by approximating their portfolios, as an indicator for liquidity shocks impacting these investors. Second, through cross-sectional regressions, as inputs to calculate crowding levels of various quant equity strategies. In that respect, equity finance data is particularly well adapted. It enables to compute short interest ratios for each stock. Although these ratios are aggregated stock-level short position measures across all short-sellers, they are good proxies for short single stock positions of sophisticated investors, many of whom implement quant equity strategies. This is because short-sellers are typically sophisticated investors such as hedge funds.

Our analysis of the Short Interest strategy shows that, consistent with several papers in the short-selling literature, high short interest predicts low future returns. In other words, a strategy that shorts high short interest stocks and buys low short interest stocks exhibits positive alpha. But we also show that this strategy exhibits large V-shaped drawdowns during "liquidity crises", times during which quant arbitrageurs simultaneously unwind their positions. The largest drawdowns for the Short Interest strategy occurred during the 2007 Quant Crisis and, more recently, during the 2020 Quant Deleverage.

Next, we use short interest data to infer near real-time levels of crowdedness for some of the best-known quantitative equity strategies, by regressing cross-sectionally short interest on strategy-level scores. Such a method can be used for any other type of quant equity strategy. We show that quantitative investors are still crowding significantly in some of these, though there is important time variation in the levels of crowding.

The consequences of crowding on future strategy returns are mixed in our sample, with on balance higher levels of crowding leading to higher future returns. We believe this is the case because there are competing effects. On the one hand, more crowding for a trading strategy should lead to lower returns as the strategy's capacity becomes saturated, but on the other hand, sophisticated investors might be skilled at timing strategy returns, thereby increasing their positions on strategies that will perform better. Perhaps the second effect is slightly more important on the sample studied. We also find a mixed relationship between levels of crowding and subsequent negative skew, with perhaps a slight tilt towards a negative relationship: highly crowded strategies, if anything, tend to exhibit more negative subsequent skew.

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