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Abstract

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Common Short Selling and Excess Comovement: Evidence from a Sample of LSE Stocks*

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1 Introduction

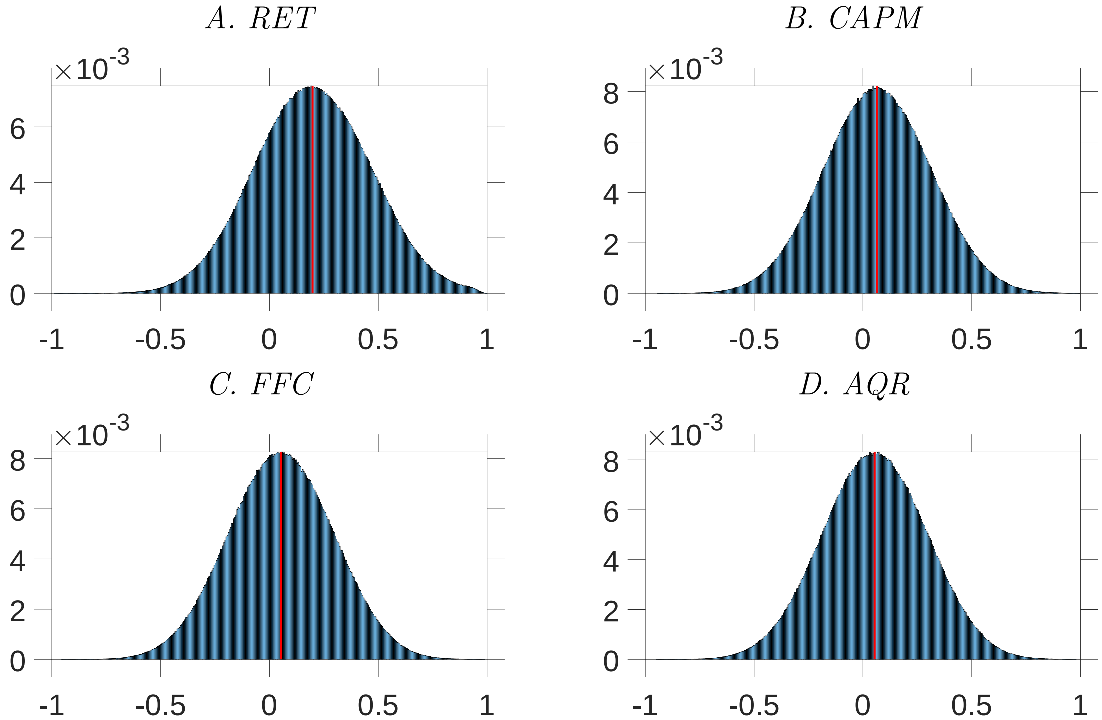
A large part of the cross-sectional variation of stock return correlation can be explained by few fundamental factors. For example, equity returns of companies from closely related sectors and countries tend be more correlated than the equity returns of companies from more distant sectors and countries. Another fundamental factor is firm size—Huberman et al. (1988), among others, have shown that the equity returns of similarly-sized firms are more closely correlated than the equity returns of firms of different sizes.

The part of correlation that cannot be explained by common fundamental factors, such as the Fama and French (1993) value and size factors and the Carhart (1997) momentum factor, is typically termed "excess comovement". Research has shown that supply and demand dynamics of equity markets have a major role in determining the cross-sectional variation of excess comovement. For example, Pindyck and Rotemberg (1993) have shown that excess comovement of equity returns can be in part explained by institutional ownership. More recently, Antón and Polk (2014) and Bartram et al. (2015) have found that excess comovement is linked to mutual fund flows and active reallocations of funds.

Whereas previous studies have focused on the relationship between excess comovement of equity returns and long positions of market agents, in this study, we explore the role of short selling positions. Specifically, we exploit new data on large net short positions, disclosed to the Financial Conduct Authority (FCA) of the United Kingdom (UK), to construct a measure of common short selling. The measure, which is intuitive and easy to compute, captures the strategies of short sellers taking net negative positions against multiple stocks. This can be calculated only if we know the identity of short sellers, which the disclosure data provides. We use this new measure to predict (in-sample) the future excess comovement of equity returns for a sample of 356 stocks listed on the London Stock Exchange (LSE).

We focus on LSE stocks that have at least one public short selling disclosure reported by the UK's FCA. The firms covered in our sample tend to be larger and more liquid than the average LSE firm. For our sample, Figure 1 presents the distribution of the within-month pairwise correlation of daily raw returns, as well as the distribution of excess comovement, computed from the daily residual returns from different factor models. The average correlation of raw returns is 20%, whereas four-factor excess comovement i.e., the correlation of daily residuals from a Fama-French-Carhart factor model, averages 5.4%. Excess comovement remains sizeable and is highly variable across the cross-section of stock pairs.

Figure 1: Distribution of pairwise return correlations, Jan. 2013—Dec.2019



The charts plot the distribution of the monthly realised correlation of daily returns for stock-pairs from an unbalanced sample of 356 LSE-listed stocks that have at least one public short selling disclosure reported by the UK's FCA and sufficient price data. The vertical line denotes the median. Chart A depicts the distribution of monthly realised correlation of raw daily returns. Charts B through D depict the distribution of monthly realised correlation of residual returns from alternative factor models. Specifically, residual returns are computed using: (B) the local CAPM; (C) the local Fama and French (1993) model augmented with the local Carhart (1997) momentum factor (FFC); (D) the local AQR model, which is the FFC model augmented with local betting-against-beta (Frazzini and Pedersen, 2014) and quality-minus-junk (Asness et al., 2018) factors. Local factors are associated to the country (or region) of stocks. Factor data are from AQR's website, whereas stock price data, used to compute returns, are from Refinitiv EIKON.

Because correlation is a key input to the portfolio allocation problem, understanding and trying to anticipate correlations and excess comovement is important for asset managers. Engle and Colacito (2006), among others, have shown that misspecification of correlation can lead to sizeably lower portfolio returns. Further, predicting correlations is important for risk management and hedging purposes, as well as for pricing derivatives such as correlation swaps and index options.

We find that common short sold capital is positively and significantly associated with four-factor residual return correlation one month ahead, controlling for common ownership and common analyst coverage, as well as for similarities in size, book-to-market, momentum, and several other common characteristics. In our most flexible specification, a standard deviation increase in common short sold capital is associated with a future rise of excess comovement equivalent to 2% of its average.

Although restricted to a sample of LSE stocks, the results of our paper are also of interest to regulators. On several occasions, particularly during the aftermath of the financial crisis, short selling has been banned for fears that, in a declining market, it might exacerbate downward price spirals (Finnerty, 2005). For the stocks in our sample, our unique data allows us to verify two hypotheses explaining the uncovered relationship, including the possibility that short sellers induce comovement through price pressure. In the second part of the paper, we analyse these hypotheses and draw implications for financial stability policy.

The effect of illiquidity helps us shed light on the role of price pressure in the relationship between common short selling and excess comovement. According to the theoretical studies of Brunnermeier and Pedersen (2005) and Cont and Wagalath (2013), price pressure by short sellers can induce shifts in correlation and this effect should be stronger the higher the stock pair illiquidity. If the positive relationship that we uncover were stronger for the most illiquid stock pairs, it would bring further evidence in support of the price pressure mechanism.

Quite to the contrary, we find that the association between common short selling and future excess comovement weakens significantly for the most illiquid stock pairs. This result should be somewhat reassuring for regulators, as it does not support, at least directly, the prediction that liquidity conditions could lead to contagion by short selling. Still, we remain cautious about the the global validity of our results, which is restricted by our stock sample, and we cannot completely exclude that the price pressure story occurs in ways that our framework cannot pick up. We discuss alternative interpretations, including the possibility that short sellers adopt stealth trading techniques, in Section 5.2.

Next, we verify the role of informed trading for the relationship between common short selling and excess comovement. Studies have shown that short sellers are sophisticated market agents, who trade on superior information and are able to predict future stock price movements (Boehmer et al., 2008, Diether et al., 2009b, Boehmer et al., 2018). By shorting several stocks, short sellers expect future price declines. As declines occur, they should coincide with higher correlation between the shorted stocks.

We exploit the valuable advantage of our data that allows us to identify short sellers and classify them according to several traits. We find that the effect of common short selling is more predictive of future excess comovement when it originates from informed agents, such as hedge funds, active investors, and short sellers with high past performance. This indicates that, at least for our stock sample, informed trading has a role in explaining the relationship between common short selling and excess comovement.

Finally, we analyse portfolios of stocks that are connected through common short sellers. First, we find that connected portfolios are associated with negative four-factor abnormal cumulative returns that do not revert in the short run and persist for several months after the portfolio construction. Because price declines are non-transitory, this result lends further support to the information hypothesis explaining the link between common short selling and excess comovement. Second, we compare the realised volatility, over 254 trading days, of similar connected and non-connected portfolios, matched by size-deciles. We find that, on average, compared to their matched connected counterpart, portfolios of stocks that do not share any common short sellers have, on average, 12.7% lower volatility. This shows how the uncovered relationship between common short selling and excess comovement can reveal diversification opportunities for portfolio managers.

We contribute to a growing body of literature that makes use of short selling disclosure data (Boehmer et al., 2018, Jones et al., 2016, Jank et al., 2021). Previous studies have used this data to analyse the behaviour of short sellers and the relation between short positions and underlying stock returns. In contrast, we use this data to study the relation between short selling and comovement.

The disclosure data are partially censored, such that only large short positions, above the European regulatory threshold of 0.5% of company capital, are observable. However, compared to alternative short selling data, disclosure data come with at least two advantages. First, rather than proxying for short selling, such as short selling indicators constructed from securities lending data, the disclosure data cover actual net short positions submitted by short sellers to the regulator. Second, the data allow us to identify short sellers taking the short positions, which is crucial for constructing our measure of common short selling and for our analysis of informed trading. Alternative data, such as short interest data, capture the aggregate levels of short selling. This would not allow to retrieve information on common short positions, which we show are useful to explain the commonalities of stock returns.

The rest of the paper is organized as follows. In Section 2, we describe the short selling disclosure data and the sample construction. In Section 3, we outline our regression setting. In Section 4, we present the results uncovering, for our stock sample, the relationship between common short selling and future excess comovement. In Section 5, we investigate the role of illiquidity and informed trading for our results. In Section 6, we analyse price reversals and diversification opportunities for connected portfolios. We draw our conclusions and discuss the validity of our results in Section 7.

2 Data and Sample

2.1 UK Short Selling Disclosure Data

According to EU regulation N. 236/2012, ratified on 14 March 2012 by the European Parliament and the European Council, every financial subject detaining a net short position above 0.2% of issued share capital of a company is required to disclose their position to the competent market authority—for companies listed in the UK, this is the FCA. Furthermore, any short position that passes the threshold of 0.5%, and every change by 0.1% after that, must be publicly disclosed. Public disclosures include the name and ISIN of the shorted share, the name of the short seller, and the quantity short sold as a percentage of issued share capital. Compared to other short selling data, such as short interest data, short disclosures are actual net short positions obligatorily submitted to the regulator and, therefore, are subject to attentive scrutiny. In calculating their net short selling position, short sellers are required to include synthetic short positions obtained through options.

We collected all public disclosures of short positions, published on the FCA's website between the entry into force of the regulation, 1 November 2012, and 31 December 2019.

Table 1: Descriptive statistics of FCA (UK) public short selling disclosures, Nov. 2012—Dec. 2019

Panel A: Number of Disclosed Positions, Stocks, and Short Sellers

Year	Disclosures	Originations	Terminations	Stocks	Short Sellers
2012	793	323	85	165	106
2013	4489	617	582	261	159
2014	5151	717	658	262	162
2015	7167	1008	952	279	185
2016	9301	1232	1181	317	214
2017	10751	1384	1268	321	224
2018	12557	1587	1606	355	229
2019	9890	1148	1248	357	203

Panel B: Summary Statistics for Stocks and Short Sellers

Variable	Year	Mean	Med.	S.D.	Min	Max
# of stocks per short seller	2012	2.9	1	5.6	1	53
	2013	4	2	8.3	1	80
	2014	4.7	2	8.6	1	75
	2015	5.1	2	10	1	89
	2016	5.3	2	11.7	1	116
	2017	5.7	2	13	1	102
	2018	6.5	2	14.4	1	113
	2019	6.3	2	13.5	1	103
# of short sellers per stock	2012	1.8	1	1.7	1	12
	2013	2.5	1	2.4	1	14
	2014	2.9	2	2.7	1	15
	2015	3.4	2	3.4	1	18
	2016	3.6	2	3.7	1	23
	2017	4	2	4.3	1	29
	2018	4.2	2	4.6	1	26
	2019	3.6	2	3.5	1	18

The table reports short selling disclosure public data collected from the website of the UK's FCA between Nov. 2012 and Dec. 2019. Panel A shows the total number of disclosures of net short positions above 0.5% of issued share capital and any position change of 0.1%. Panel A also shows the number of disclosures that were originations (the first disclosure of a net short position above 0.5% of the issued share capital) and those that were terminations (disclosures under the 0.5% threshold). Panel B shows the summary statistics regarding the number stocks and short sellers involved in the disclosure data.

We focus on short selling disclosures published by the UK's FCA for three main reasons. First, as will become clear in the next sections, the study involves a large effort to match data across different sources. To keep this exercise manageable, we decided to focus the scope of the paper on a single country of those comprised by the EU short selling disclosure requirement. Second, the UK has a highly recognised and active stock market, guaranteeing reliable stock and company data coverage. Third, as evidenced by Jones et al. (2016), a large part of EU short selling disclosures occurs in the UK.[1]

In the remainder of this section, we briefly describe the raw FCA public short selling disclosure data, whereas in the next section we construct our final matched data sample.

The disclosures involve 664 unique stocks and 454 different short sellers. Most of the stocks are of UK companies of all sectors. Table 1 shows the summary details for the collected disclosure data.

Panel A of Table 1 shows that, between October 2012 and December 2019, there were 60,099 disclosures, of which 8,016 position originations (i.e., the first disclosure of a net short position above 0.5% of issued share capital), 44,503 updates (i.e., any increments or decrements of 0.1% of issued share capital after the 0.5% threshold), and 7,580 position terminations (i.e., disclosures under the 0.5% threshold).

The upper part of Panel B of Table 1 shows that, on average, short sellers take position on about five different stocks per year. The standard deviation is quite large, with some short sellers taking position on as many as 116 different stocks over one year. The average and median duration of disclosed short positions is of, respectively, 81.7 and 28 trading days.[2]

2.2 Stock Sample Construction

We construct the sample for our study from the initial set of 664 stocks that had at least one disclosed short selling position.

First, to compose a sample of comparable and sufficiently liquid stocks, we only consider ordinary shares of companies traded on the London Stock Exchange (LSE).[3] By so doing, we ensure that prices for our stock sample are governed by the same exchange trading rules.[4]

[1]Between November 2012 and December 2019, UK disclosure data involve 664 unique stocks. For the same period, French disclosures cover 173 unique stocks, German disclosures cover 331 stocks, and Italian disclosures cover 168 stocks.

[2]For a sample of European large short position disclosures, Jank and Smajlbegovic (2021) report an average (median) duration of 93 (37) days.

[3]From the initial sample, 137 stocks did not have Refinitiv EIKON data regarding their primary exchange and almost one quarter of these stocks had no price data, making them unusable for our study.

[4]The LSE operates with a price monitoring rule, which is very similarly to a circuit-breaker. See LSE

Table 2: Stock sample construction

Cleaning step	N. Stocks
1. Stocks with at least one FCA short sale disclosure	664
2. Remove non-LSE stocks	470
3. Remove non-common shares	469
4. Remove stocks with more than 50% missing price data	374
5. Match with ownership data	356

Next, for these stocks and for the period covered, we searched for historical price data and company information from Refinitiv EIKON. To compute the control variables for our regression analysis, we also require ownership data from Refinitiv EIKON, and analyst earnings estimates from the Institutional Brokers Estimate System (IBES).

Finally, we require stocks to have a price for 50% of the trading days from Oct. 2007 to Dec. 2019. This criterion selects a homogeneous sample of stocks in terms of the number of time-series observations, without imposing a balanced sample and helps construct our dependent and independent variables that require concomitant returns for stock pairs.

After these restrictions, the final matched sample involves 356 stocks and 43,393 disclosed short selling positions. Figure 2 summarizes the matched sample according to The Refinitiv Business Classification (TRBC) economic sector code.[5] The sector with the most stocks was Industrials with 80 stocks, whereas the Cyclical Consumer Goods & Services sector had the most disclosures and short sellers.[6] As outlined in the next section, sector information is used to control for similarities across stocks in our model.

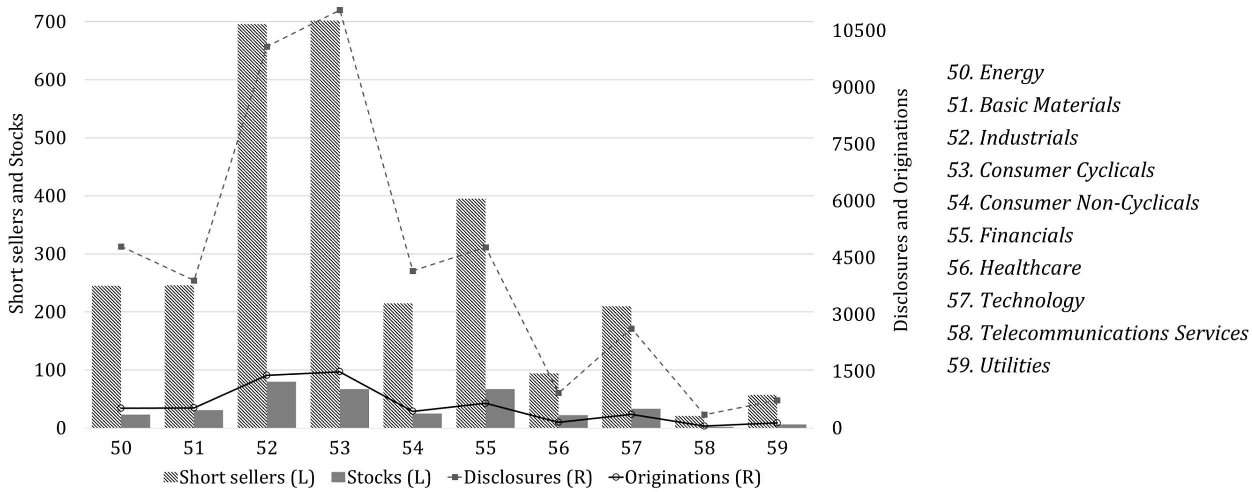
The average total market capitalisation of the firms in our sample is $ 1,924 bn. In comparison, according to data from Refinitiv EIKON, during the same period, the average total market capitalisation of the LSE was of $ 4,912 bn. In terms of trading volume, across

(2020) and FCA (2017) for further information.

[5]The TRBC, formerly called the Thompson Reuters Business Classification, is a classification system based on revenue, similar to the better-known Global Industry Classification Standard (GICS). For our sample, TRBC had a wider coverage than the GICS. For further details on TRBC, see `https://www.refinitiv.com/en/financial-data/indices/trbc-business-classification`

[6]In Section A.2 of the Internet Appendix, we test for significant differences in the size and frequency of disclosed short selling positions between stock sectors. We report that disclosed (net) short positions of financials, healthcare, and, to some extent, technology stocks are, on average, significantly smaller/less frequent than those of the baseline group, consumer cyclicals stocks.

Figure 2: Sample information by company NACE Rev. 2 classification.



The chart shows the distribution, by company classifier following the Economic sector TRBC codes, of our matched sample of 356 LSE-listed stocks that have at least one public short selling disclosure reported by the UK's FCA and sufficient price data. Apart from the number of stocks, the chart illustrates the number of short sellers and the number of short position disclosures associated with the stock sample. To be read against the left axis, the bars depict, for any given sector, the number of stocks in the sample (full) and the number of short sellers taking position against those stocks (hatched). To be read against the right axis, the lines depict the total number of disclosures (dashed) and the number of disclosures that were originations (bold).

the period of study, on average, our sample of stocks accounts for 72.4% of daily value of trades of LSE stocks. Further, over 80% of the stocks in our sample tend to be more liquid than the average LSE stock. Thus, our sample covers a large portion of the LSE, both in terms of market capitalisation and in terms of volume of trades.

The average (median) market capitalisation of companies in our sample is about $5.6 billion ($1.5 billion), whereas, for the same period, the average (median) LSE firm had a market capitalisation of $2.8 billion ($143 million). We present additional descriptive statistics of the stock sample, as well as a more detailed comparison between the average stock in our sample and the average LSE firm, in Section A.3 of the Internet Appendix.[7]

Finally, we note that, on average, every year, 0.89 analysts issue a 1-year ahead earnings forecast on any stock in our sample.[8] According to Refinitiv EIKON, 21.1% of the final sample of stocks have traded options.

[7] Available at: https://www.dropbox.com/s/m08yplsk7wmaxnz/appendix_anon2.pdf?dl=0

[8] Prior to July 2015, our stock sample does not have analyst coverage, likely due to missing data. After June 2015, the average number of analysts covering the stocks in our sample is 3.05 per year. For a sample of stocks from the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ stock Market (NASDAQ), Hameed et al. (2015) report an average coverage of 4.60 analysts.

3 Methodology

3.1 The Model

We follow the approach of Antón and Polk (2014), who studied the impact of common mutual fund holdings on excess comovement. Here, we are interested in the effect of common short selling. We define $SSCAP_{ij,t}$ as the net value of stocks i and j, above the disclosure threshold of 0.5% of issued share capital, shorted by S common short sellers at quarter-end t, scaled by the stock pair's market capitalisation. Specifically,

$$SSCAP_{ij,t} = \frac{\sum_{s=1}^{S}(W_{i,t}^{s} + W_{j,t}^{s})}{MV_{i,t} + MV_{j,t}}, \tag{1}$$

where $W_{i,t}^{s}$ is the value of the net short position held by common short seller s against stock i at quarter-end t and $MV_{i,t}$ is market capitalisation of stock i at quarter-end t. The value of the short position, $W_{i,t}^{s}$, is computed using the publicly disclosed short position weight, multiplied by the market capitalisation of firm i on the reported day of the position. If the short seller reported more than one disclosure during the quarter, then we used the most recent disclosure.

Table 3 summarises the distribution of $SSCAP$. The average common (net) short sold capital of stock pairs is 0.03% but can reach up to 9% of common capital. $SSCAP$ is sparse because, over any given quarter, short sellers tend to take few common positions across several stocks. However, as we will show in the next section, it contains explanatory power for future excess comovement.

As can be noticed from Table 3, $SSCAP$ increases over time. To make the cross-sections comparable and ease interpretability of the regression coefficients, at each quarter, we normalise $SSCAP$ to have zero mean and unit standard deviation. We denote the normalised variable $SSCAP^{*}$.

We use $SSCAP_{ij,t}^{*}$ to forecast the future within-month realised correlation of each stock pair's daily four-factor residual returns, $\rho_{ij,t}^{FFC}$. Specifically, we estimate the following regres-

Table 3: The cross-sectional distribution of SSCAP, Jan. 2013—Dec. 2019

			Percentiles						
Year	Mean	Std	0	25	50	75	95	99	100
All	0.0003	0.002	0	0	0	0	0	0.0095	0.0901
2013	0.0001	0.001	0	0	0	0	0	0.0049	0.0475
2014	0.0001	0.001	0	0	0	0	0	0.0044	0.0455
2015	0.0002	0.0015	0	0	0	0	0	0.0072	0.0666
2016	0.0003	0.002	0	0	0	0	0	0.0095	0.0774
2017	0.0004	0.0025	0	0	0	0	0	0.0123	0.0812
2018	0.0005	0.0027	0	0	0	0	0.0049	0.0132	0.0901
2019	0.0005	0.0025	0	0	0	0	0.0045	0.0122	0.0679

The table reports the cross-sectional distribution of (scaled) common short sold capital. $SSCAP_{ij,t}$ is the net capital of stocks i and j short sold by common short sellers at quarter-end t, scaled by market capitalisation of the stock pair. $SSCAP$ is constructed using public disclosure data, from the UK's FCA, of net short positions larger than the regulatory threshold of 0.5% share capital. Observations relate to stock pairs from an unbalanced sample of 356 LSE-listed stocks that have at least one public short selling disclosure reported by the UK's FCA and sufficient price data.

sion model,

$$\rho^{FFC}_{ij,t+1} = a + b_1 \times SSCAP^{*}_{ij,t} + \sum_{k=2}^{n} b_k \times CONTROL_{ij,k} + \epsilon_{ij,t+1}. \tag{2}$$

To compute monthly realised correlation of residual returns for a given stock pair-month, we require daily residual return observations for at least 50% of the trading days of that month. The four factors used to compute residual returns are the local market excess return, the local size and value factors (Fama and French, 1993), and the local momentum factor (Carhart, 1997).[9] In Section 4.2, we show that results are robust to alternative factor models used to compute residual returns.

Our dependent variable of Equation 2, ρ^{FFC}, captures the part of correlation that isn't explained by the four well-known factors. Table 4 shows that, for our sample of stocks, the average four-factor residual return correlation is 5.35%. This represents over 25% of the average correlation of raw returns. Together with Figure 1, Table 4 shows that both the raw and the abnormal return correlations are highly variable. In some periods, stock pairs have

[9]To compute residual returns, we use local factors i.e., factors associated to the country of a given stock. For six stocks, local factors were not available. For these exceptions, we use regional factors. Excess returns are computed with respect to the daily U.S. T-bill rate. Daily factor data are from AQR's website. Further details on the factor models are provided in Section A.1 of the Internet Appendix.

Table 4: Summary statistics of stock price return correlation, Jan. 2013—Dec. 2019

Variable	$\bar{N}$	Mean	St. Dev.	P10	P50	P90
ρ^{RET}	62,502	0.200	0.262	0.019	0.198	0.380
ρ^{CAPM}	62,502	0.066	0.243	-0.099	0.066	0.232
ρ^{FFC}	62,502	0.054	0.238	-0.109	0.053	0.217
ρ^{AQR}	62,502	0.054	0.237	-0.108	0.054	0.217
ρ^{ICAPM}	62,502	0.068	0.242	-0.097	0.068	0.234
ρ^{IFFC}	62,502	0.054	0.238	-0.109	0.054	0.217
ρ^{IAQR}	62,502	0.054	0.236	-0.108	0.054	0.216

The table presents summary statistics for the monthly realised correlation of raw and abnormal returns for an unbalanced sample of 356 LSE-listed stocks that have at least one public short selling disclosure reported by the UK's FCA and sufficient price data. To compute monthly realised correlation of raw and abnormal returns for a given stock pair-month, we require daily observations for at least 50% of the trading days of that month. ρ^{RET} is the monthly realised correlation of daily raw returns. ρ^{CAPM}, ρ^{FFC}, and ρ^{AQR} are the monthly correlation of the daily residuals from, respectively, the local CAPM model, the local Fama and French (1993) and Carhart (1997) four-factor model, and the local six-factor AQR model, which is the FFC model augmented with local betting-against-beta (Frazzini and Pedersen, 2014) and quality-minus-junk (Asness et al., 2018) factors. Local factors are associated to the country (or region) of stocks. ρ^{ICAPM}, ρ^{IFFC}, and ρ^{IAQR} are the monthly correlation of the daily residuals from, respectively, the international CAPM model, the international Fama-French-Carhart model, and the international AQR model. International factor models are the local CAPM, FFC, and AQR models augmented with the corresponding global factors. For further details on the factor models, see Section A.1 of the Internet Appendix. Stock price data are from Refinitiv EIKON, whereas daily factors and the Treasury bill rate are from AQR's website. Note that the column headed $\bar{N}$ relates to the average number of observations across cross-sections. All other columns relate to pooled sample statistics.

up to 98.6% of excess comovement.

Given that the unexplained part of correlation remains substantial, we include in Equation 2 a large set of controls, which we present in detail in the next section. All variables on the right-hand side of Equation 2 are updated quarterly.

If common short sold capital is associated with higher future excess comovement, then b_1 will be positive and significant. To limit the effect of serial correlation, we estimate b_1 using the Fama and MacBeth (1973) regressions i.e., we run Equation 2 cross-sectionally for every t and compute the temporal average of b_1. Generally, we find that autocorrelation in our estimates is low and limited to the first lag. We account for autocorrelation up to three lags (one quarter) with Newey and West (1987) robust standard errors.

3.2 Controls

In Equation 2, we include a large set of controls that explain stock return correlations beyond the Fama and French (1993) and Carhart (1997) factors. To avoid potential omitted variable bias, we must control for features associated with short selling that might also influence the comovement of stock returns. To guide us, in Section A.2 of the Internet Appendix, we analyse several drivers of short selling disclosures. We include these variables in our set of controls.[10]

First, we control for common ownership of stock pairs. Let $HCAP_{ij,t}$ be the value of stocks i and j held by common owners, scaled by the market capitalization of the stock pair. $HCAP$ controls for excess comovement created by common owners purchasing and selling stocks. By including $HCAP$ in our specification, we aim to separate the excess comovement due to short selling activity from long strategies of investors. Because our measure of common short selling is constructed using net short positions, $HCAP$ alleviates concerns that movements in $SSCAP$ might be due to changes in long positions.

Next, we control for industry effects using TRBC codes. TRBC offers the widest coverage for the stocks in our sample. It consists of four levels of classification (Economic Sector, Business Sector, Industry Group, and Industry). We created the variable $NUMTRBC_{ij}$, which, for stocks i and j, captures the number of consecutive equal level TRBC codes, starting from the most generic. Alternative definitions of the industry control, based on different classification codes, yield similar results.

Further, we compute a series of additional size, style, and pair characteristic controls.

In terms of size, we control for the size of the two companies i and j using their market capitalisation. Chen et al. (2017) show that stocks of similar size tend to be more highly correlated. Hence, we captured similarity in size using $SAMESIZE_{ij,t}$, which we define as the negative absolute difference in the cross-sectional percentile ranking of the market capitalization of i and j at quarter-end t. As size is a proxy for the number of shares available to short sell (Dechow et al., 2001), it can also control for short selling costs. Thus, we included $GAVSIZE_{ij,t}$, which is the geometric average of the cross-sectional percentile ranking of the market capitalization of i and j at quarter-end t.

[10] We thank the editor and an anonymous referee for suggesting this exercise.

In terms of style, we control for similarities in book-to-market ratio, dividend yield, and momentum. We define $SAMEBM_{ij,t}$, $SAMEDIV_{ij,t}$, and $SAMEMOM_{ij,t}$ as the negative absolute difference in the cross-sectional percentile ranking of, respectively, the book-to-market ratio, the dividend-yield, and the momentum of the two stocks.[11]

Book-to-market ratio is positively associated with a stock's future returns (Fama and French, 1992). Moreover, Curtis and Fargher (2014) show that short sellers tend to concentrate on stocks with high book-to-market. Hence, we control for the geometric average of the cross-sectional percentile rank of the book-to-market of stock pairs, $GAVBM_{ij,t}$. Further, as short sellers might ride on declining prices, which are, by definition, correlated, we include $GAVMOM_{ij,t}$, the geometric average of the percentile rank of the momentum of two stocks.

As highlighted by Dechow et al. (2001), dividend payments represent a real cost for short sellers, whereas they could influence the correlation of stock returns. To capture this, in addition to $SAMEDIV$, we include $GAVDIV_{ij,t}$, which measures the geometric average of the cross-sectional percentile rank of the dividend-yield of the stock pair.

We control for a series of stock pair characteristics. To address concerns for potential reverse causality in our regression model, we control for the past 5-year monthly price return correlation of stock pairs, which we denote $RETCORR_{ij,t}$. As companies with similar profits are expected to have correlated stock returns (Chen et al., 2017), we control for the past 5-year correlation of the return on equity, $ROECORR_{ij,t}$. We include a control variable capturing similarity in abnormal trading volumes, $VOLCORR_{ij,t}$, which measures the monthly correlation in abnormal trading volumes over the past five years.[12] We control for the absolute difference in the price level of the stock pair (Green and Hwang, 2009), which we denote $DIFFPRICE_{ij,t}$, as well as the absolute difference in their leverage, $DIFFLEV_{ij,t}$.

Further, we create variables to control for geographical location (Pirinsky and Wang, 2006). First, $GEODIST$ measures the geographical distance (in km) between the headquarters of two companies. Second, the dummy variable $DCOUNTRY$ captures whether two companies have headquarters in the same country.

[11] Momentum is the cumulative stock return over the last year, excluding the most recent month.

[12] Abnormal trading volume is the residual of a regression of volume on an annual trend and monthly dummies.

Table 5: Summary statistics of stock pair variables, Jan. 2013—Dec. 2019

Variable	$\bar{N}$	Mean	St. Dev.	P10	P50	P90
$SSCAP$	63,190	0.000	0.002	0.000	0.000	0.000
$SSVOL$	63,190	0.159	2.047	0.000	0.000	0.000
$SSFLOAT$	63,190	0.001	0.004	0.000	0.000	0.000
NSS	63,190	0.040	0.234	0.000	0.000	0.000
$HCAP$	63,190	0.102	0.107	0.005	0.074	0.167
$HFCAP$	63,190	0.058	0.063	0.001	0.042	0.095
A	63,190	0.023	0.248	0.000	0.000	0.000
$SAMESIZE$	60,997	-0.335	0.236	-0.503	-0.295	-0.136
$SAMEBM$	60,236	-0.335	0.236	-0.503	-0.295	-0.135
$SAMEMOM$	63,190	-0.335	0.236	-0.501	-0.296	-0.135
$SAMEDIV$	61,409	-0.334	0.237	-0.503	-0.295	-0.136
$GAVSIZE$	60,997	0.444	0.230	0.259	0.432	0.618
$GAVBM$	60,236	0.444	0.230	0.259	0.432	0.618
$GAVMOM$	63,190	0.444	0.230	0.259	0.432	0.618
$GAVDIV$	61,409	0.448	0.222	0.254	0.432	0.618
$DIFFLEV$	52,891	3.102	8.717	0.320	0.852	2.244
$DIFFPRICE$	62,789	1.579	1.332	0.593	1.261	2.197
$NUMTRBC$	63,190	0.256	0.736	0.000	0.000	0.000
$NUMIND$	63,190	1.869	2.938	0.000	1.000	3.000
$RETCORR$	62,712	0.260	0.187	0.143	0.263	0.383
$ROECORR$	60,307	0.057	0.569	-0.445	0.085	0.567
$VOLCORR$	62,789	0.088	0.297	-0.121	0.080	0.299
$GEODIST$	62,835	677.3	677.3	53.48	208.4	398.5
$DCOUNTRY$	63,190	0.789	0.408	1.000	1.000	1.000
$DCITY$	63,190	0.129	0.336	0.000	0.000	0.000

The table presents summary statistics for stock pair variables of an unbalanced sample of 356 LSE-listed stocks stocks that have at least one public short selling disclosure reported by the UK's FCA and sufficient price data. $SSCAP$, $SSVOL$, and $SSFLOAT$ are the net capital shorted by common short sellers, scaled, respectively, by market capitalisation, trading volume, and equity float. NSS is the number of common short sellers. Short selling measures are constructed using public disclosure data, from the UK's FCA, of net short positions larger than the regulatory threshold of 0.5% share capital. $HCAP$ is the (scaled) capital held by common owners. A is the number of common analysts issuing earnings forecast over the past year. $SAMESIZE$, $SAMEBM$, $SAMEDIV$, and $SAMEMOM$ are the negative of the absolute difference in the cross-sectional percentile ranking of, respectively, size, book-to-market, dividend yield, and momentum. $NUMTRBC$ is the number of consecutively equal digits in the TRBC code. $NUMIND$ is the number of shared common indices. $GAVSIZE$, $GAVBM$, $GAVDIV$, and $GAVMOM$ are the geometric average of the cross-sectional percentile ranking of, respectively, size, book-to-market, dividend-yield, and momentum. $RETCORR$, $ROECORR$, and $VOLCORR$ measure the correlation of, respectively, the past 5-year monthly return, the past 5-year return on equity, and the past 5-year monthly abnormal trading volume. $DIFFLEV$ and $DIFFPRICE$ are, respectively, the absolute difference in leverage and price. $DCOUNTRY$ is a dummy capturing common country of headquarters. All variables are updated quarterly. Ownership, company, and market data are from Refinitiv EIKON. Earnings forecast data are from IBES. Note that the column headed $\bar{N}$ relates to the average number of observations across cross-sections. All other columns relate to pooled sample statistics.

Past studies have reported that index membership affects correlation (see, Barberis et al. (2005) and Greenwood (2007)). We construct a variable $NUMIND_{ij,t}$, which is equal to the number of indices, at quarter-end t, of which both stocks i and j are members of. We construct the variable by checking the constituents, over the period of study, of a list of 840 indices.[13] We report summary statistics of the stock pair variables in Table 5.

We update all controls quarterly. To ease interpretation of the regression coefficients of Equation 2, except for the dummy variables, we standardise all independent variables so that, cross-sectionally, they have zero mean and unit standard deviation. Standardised variables are superscripted by $*$.

4 Results

4.1 Main Regression Estimates

Table 6 presents the results of the Fama and MacBeth regression specified in Equation 2. The first column of Table 6 reports the baseline specification with just $SSCAP^*$ and a constant. The coefficient on $SSCAP^*$ is positive and significant, with a coefficient equal to 0.00343. Given that $SSCAP^*$ is standardised to have zero mean and unit standard deviation, the regression constant reflects the average abnormal return correlation when $SSCAP$ is at its mean. Thus, a standard deviation increase in common (net) short sold capital is associated with an increase of predicted excess comovement by about 6.4% of its average.

The second column of Table 6 shows results controlling for common ownership, similarity in sector, size, book-to-market, and momentum. The coefficient on $HCAP^*$ is positive and highly significant, consistent with Antón and Polk (2014) and Bartram et al. (2015).

Recall that the dependent variable is the correlation of the residuals of a four-factor asset pricing model, which includes the size, book-to-market, and the momentum factor. Despite this, similarity in size, book-to-market, and momentum still have a strong positive and significant association with future excess comovement.

[13]The list is determined by the index membership, during the period of study, of the 356 stocks in our sample. Index constituents data are from Refinitiv EIKON.

Table 6: Fama-MacBeth regressions of monthly realised pairwise correlation of daily four-factor residual returns on $SSCAP^*$ and controls, Jan. 2013—Dec. 2019

	Dependent Variable: Correlation of 4F Residuals			
	(1)	(2)	(3)	(4)
Constant	0.05344 (13.80)	0.05355 (13.85)	0.05176 (12.76)	0.05289 (13.60)
$SSCAP^*$	0.00343 (7.04)	0.00103 (2.44)	0.00114 (2.71)	0.00105 (2.55)
$HCAP^*$		0.00278 (5.20)	0.00206 (3.63)	0.00044 (0.72)
$SAMESIZE^*$		0.00884 (10.39)	0.00737 (7.79)	0.00533 (6.95)
$SAMEBM^*$		0.00205 (7.50)	0.00146 (5.24)	0.00134 (3.85)
$SAMEMOM^*$		0.00965 (12.15)	0.00743 (9.87)	0.00573 (8.49)
$SAMEDIV^*$		0.00381 (9.84)	0.00296 (7.60)	0.00249 (4.78)
$NUMTRBC^*$		0.01365 (37.89)	0.01140 (34.14)	0.00611 (18.59)
$GAVSIZE^*$		0.01459 (12.68)	0.01171 (10.01)	0.00597 (4.54)
$GAVBM^*$				0.00014 (0.19)
$GAVMOM^*$				0.00540 (4.43)
$GAVDIV^*$				0.00026 (0.24)
$RETCORR^*$			0.01254 (16.74)	0.01154 (16.74)
$ROECORR^*$			0.00205 (5.63)	0.00174 (4.98)
$VOLCORR^*$			0.00602 (6.40)	0.00571 (6.68)
$DIFFLEV^*$			0.00205 (3.47)	0.00215 (3.85)
$DIFFPRICE^*$			0.00092 (1.78)	0.00036 (0.84)
$GEODIST^*$			-0.00110 (-1.81)	-0.00085 (-1.46)
$NUMIND^*$				0.01514 (18.35)

Continued on next page

Table 6—*Continued*

	Dependent Variable: Correlation of 4F Residuals			
	(1)	(2)	(3)	(4)
$DCOUNTRY$			0.00285 (1.66)	0.00103 (0.57)
R^2	0.00039 (4.14)	0.01930 (13.77)	0.02509 (13.44)	0.03065 (12.99)
N. Obs.	62,502 (220.48)	57,518 (107.52)	49,084 (90.38)	49,084 (90.38)
Size controls	No	Yes	Yes	Yes
Firm attributes	No	No	Yes	Yes
Style controls	No	No	No	Yes

The table reports Fama and MacBeth (1973) regression coefficients, computed by running cross-sectional regressions each month between Jan. 2013 and Dec. 2019 (84 months) and then averaging regression coefficients over the sample period. Observations relate to stock pairs from an unbalanced sample of 356 LSE-listed stocks that have at least one public short selling disclosure reported by the UK's FCA and sufficient price data. The dependent variable is the realised pairwise correlation in month $t+1$ of the daily residual returns from a four-factor model. The four factors are: the market excess return, the size and value factors (Fama and French, 1993), and the momentum factor (Carhart, 1997). Factors are local i.e., they are associated to the country (or region) of stocks. Stock price data are from Refinitiv EIKON, whereas daily factors are from AQR's website. Apart from stock pair controls, the independent variables include $SSCAP$, which is the net (scaled) capital of the stock pair shorted by common short sellers at quarter-end t. $SSCAP$ is constructed using public disclosure data, from the UK's FCA, of net short positions larger than the regulatory threshold of 0.5% share capital. $HCAP$ is the (scaled) capital held by common owners. $SAMESIZE$, $SAMEBM$, $SAMEMOM$, and $SAMEDIV$ are the negative of the absolute difference in the cross-sectional percentile ranking of, respectively, size, book-to-market, momentum, and dividend yield for the stock pair. $NUMTRBC$ is the number of consecutively equal digits in the TRBC code for the stock pair. $GAVSIZE$, $GAVBM$, $GAVMOM$, $GAVDIV$ are the geometric average of the cross-sectional percentile ranking of, respectively, size, book-to-market, momentum, and dividend yield for the stock pair. For a given stock pair, $RETCORR$, $ROECORR$, and $VOLCORR$ measure the correlation of, respectively, monthly returns, quarterly return on equity, and monthly abnormal trading volume over the past five years. $DIFFLEV$ and $DIFFPRICE$ are, respectively, the absolute difference in leverage and price of a stock pair. $DCOUNTRY$ is a dummy variable capturing whether both stocks in a stock pair have their headquarters in the same country. $NUMIND$ is the number of common indices of which both stocks of a stock pair are members. Stock-pair controls are constructed using ownership and company data from Refinitiv EIKON. All independent variables are updated quarterly and, except for dummy variables, are cross-sectionally normalised (to have zero mean and unit standard deviation), which we denote by $*$. t-statistics (in parentheses) are computed using Newey and West (1987) robust standard errors, accounting for autocorrelation up to 3 lags (one quarter).

Consistent with early studies of Pindyck and Rotemberg (1993), the similarity in the sector of the two companies is a key determinant of correlation. The coefficient on $NUMTRBC^*$ is statistically significant with a coefficient of 0.01365 and a t-statistic of 37.89.

In the second specification, we also control for stock pair size, with $GAVSIZE^*$, and similarity in dividend yield, with $SAMEDIV^*$. After adding these controls, the size of the coefficient on $SSCAP^*$ decreases, but remains significant at 5% confidence level with a p-value of 1.7%.

In the third specification of Table 6, we include additional controls for pair characteristics. The terms capturing similarities in past correlation, past profits, and past abnormal trading volume are all positive and significant. The coefficient on $DIFFLEV^*$ is positive and significant at 1%, meaning that stocks that have similar leverage have lower correlation of abnormal returns. The coefficient on $GEODIST$ is negative and significant at the 10% confidence level, indicating that stocks of companies that are geographically closer are more strongly correlated. With these additional controls, the coefficient of $SSCAP^*$ is significant at the 1% level of confidence.

In the fourth column of Table 6, we add the book-to-market, dividend yield, and momentum of the stock pairs, $GAVEBM^*$, $GAVDIV^*$, and $GAVMOM^*$. The coefficient estimate on the former two control variables are insignificant, whereas the coefficient on the latter is highly significant. The coefficient on the dummy variables $DCOUNTRY^*$ is positive but insignificant. The effect on $NUMIND^*$, which is positive and highly significant, crowds-out part of the effect of $HCAP^*$. One explanation for this is that investor holdings react to changes of index membership.

Despite the inclusion of many significant controls in the fourth specification, which is the most complete and flexible, the coefficient on $SSCAP^*$ remains significant with an estimate of 0.00105. For our sample of LSE-listed stocks, an increase in one standard deviation in common short sold capital is associated with an increase of excess comovement of about 2% of the average four-factor residual correlation. The effect is strongly significant, with an associated p-value of 1.3%. Notice that $SSCAP^*$ has significant explanatory power for the correlation of the residuals of a four-factor model, even after accounting for many controls and characteristics. As explained in more detail in the next subsection, the results of Table 6 are robust to using alternative factor models to compute the abnormal return correlation.

In untabulated results, we find that the fitted values that are due to $SSCAP^*$ range from an average minimum of 0.0361 to an average maximum of 0.0976, around an average excess comovement of 0.0529.[14] As a mean for comparison, the fitted values due to $HCAP^*$ range from 0.0356 to 0.0701.

Despite the high variability of the correlation of four-factor residual returns, which has an average standard deviation of 0.24, the fourth specification has an average R^2 of 3.06%.[15] The improvement in R^2 attributable to $SSCAP$ is 0.03 percentage points and significant at 1% (t-statistic of 6.00).[16] In line with the relative size of the regression coefficients, this is about half of the improvement in R^2 attributable to common long positions, $HCAP$.

4.2 Robustness

To check the robustness of our results, we carry out a series of alternative specifications of the regressions given in Table 6.

First, we run the regressions of Table 6 using robust regressors, by rank-transforming all right-hand variables, except for the dummy controls, of Equation 2. We denote rank-transformed (and normalised) common short selling as $SSCAP^{\dagger}$. Panel A of Table 7 shows that the coefficient on $SSCAP^{\dagger}$ remains significant across all specifications, with 1% confidence level in the most complete regression.

Second, we use alternative definitions of the main covariate. We define $SSVOL_{ij,t}$ and $SSFLOAT_{ij,t}$ as the (net) common short sold capital of stock pairs i and j at quarter-end t scaled by, respectively, the dollar trading volume and the free float of the stock pair. These measures account for the liquidity of stock pairs, which might limit the capital exposure of short sellers.[17] Additionally, we explore the effect of the number of common short sellers, NSS. Again, as for $SSCAP$, these common short selling variables are constructed using the disclosure data, so account for large (net) short positions, above the disclosure threshold.

Panel B of Table 7 presents the results for the third and fourth specifications of Table 6 with these alternative measures of common short selling. As with the regressions of Sec-

[14] To calculate the range of these fitted values, we first orthogonalise $SSCAP^*$ with respect to all the controls used in the fourth specification. We then forecast the realised correlation of four-factor residual returns using the orthogonalised $SSCAP^*$ and a constant. We save the minimum and maximum forecasted value for each cross-section. Finally, we average these values across time.

[15] This is in line with the R^2 reported by Antón and Polk (2014) for a similar exercise with US stocks.

[16] This is the R^2 obtained from the cross-sectional regression of excess comovement on the orthogonalised $SSCAP^*$. The resulting measure is also known as the semi-partial R^2.

[17] We thank an anonymous referee for suggesting these measures.

tion 4.1, all variables are cross-sectionally normalised to have zero mean and unit standard deviation (denoted by $*$).

Table 7: Fama-MacBeth regressions of monthly realised correlation of daily four-factor residual returns on $SSCAP^{*}$—alternative specifications, Jan. 2013—Dec. 2019

Panel A: Rank Transformed Regressors

	Dependent Variable: Correlation of 4F Residuals			
	(1)	(2)	(3)	(4)
Constant	0.05344	0.05360	0.05060	0.05099
	(13.80)	(13.86)	(13.34)	(13.77)
$SSCAP^{\dagger}$	0.00360	0.00079	0.00086	0.00118
	(6.93)	(1.83)	(2.08)	(3.05)
Other control reported in the Internet Appendix				
Size controls	No	Yes	Yes	Yes
Firm attributes	No	No	Yes	Yes
Style controls	No	No	No	Yes

Panel B: Alternative measures of common short selling

	Dependent Variable: Correlation of 4F Residuals					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.05180	0.05292	0.05176	0.05289	0.05176	0.05289
	(12.77)	(13.61)	(12.77)	(13.60)	(12.76)	(13.59)
NSS^{*}	0.00126	0.00117				
	(2.98)	(2.84)				
$SSVOL^{*}$			0.00051	0.00037		
			(1.81)	(1.35)		
$SSFLOAT^{*}$					0.00087	0.00080
					(2.17)	(2.06)
Other controls reported in the Internet Appendix						
Size controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm attributes	Yes	Yes	Yes	Yes	Yes	Yes
Style controls	No	Yes	No	Yes	No	Yes

Continued on next page

The first two columns of Panel B of Table 7 show that our results continue to hold when we consider the number of common short sellers instead of common (net) short sold capital.

The last two columns of Panel B, Table 7, show the effect of scaling common (net) short sold capital by total free float. The coefficient on $SSFLOAT^*$ is small and significant. Using $SSVOL^*$, the relationship between common short selling and excess comovement remains positive but is statistically insignificant in the most complete specification. This hints that the relationship weakens with illiquidity, a result that we study in more depth in Section 5.2.

Table 7—*Continued.*

Panel C: Alternative correlation measures						
	Dependent Variable: Correlation of 4F Residuals					
	Continuous		Kendall		Spearman	
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.05532	0.05659	0.03987	0.04082	0.05647	0.05780
	(12.55)	(13.38)	(13.92)	(14.79)	(13.97)	(14.85)
$SSCAP^*$	0.00121	0.00108	0.00087	0.00080	0.00125	0.00116
	(2.66)	(2.43)	(3.08)	(2.80)	(3.13)	(2.87)
Other control reported in the Internet Appendix						
Size controls	Yes	Yes	Yes	Yes	Yes	Yes
Firm attributes	Yes	Yes	Yes	Yes	Yes	Yes
Style controls	No	Yes	No	Yes	No	Yes

The table reports Fama and MacBeth (1973) regression coefficients, computed by running cross-sectional regressions each month between Jan. 2013 and Dec. 2019 (84 months) and then averaging regression coefficients over the sample period. Observations relate to stock pairs from an unbalanced sample of 356 LSE-listed stocks that have at least one public short selling disclosure reported by the UK's FCA and sufficient price data. The dependent variable is the realised pairwise correlation in month $t+1$ of the daily residual returns from a four-factor model. The four factors are: the market excess return, the size and value factors (Fama and French, 1993), and the momentum factor (Carhart, 1997). Factors are local i.e., they are associated to the country (or region) of stocks. Stock price data are from Refinitiv EIKON, whereas daily factors are from AQR's website. Apart from stock pair controls, the independent variables include $SSCAP$, which is the net (scaled) capital of the stock pair shorted by common short sellers, at quarter-end t. In Panel A, all independent variables are ranked-transformed and normalised, which we denote by †. Panel B reports results using alternative measures of common short selling. NSS is the number of common short sellers. $SSVOL$ is the net capital of the stock pair shorted by common short sellers, scaled by the stock pair's trading volume. $SSFLOAT$ is the net capital of a stock pair shorted by common short sellers, scaled by the stock pair's equity float. Short selling measures are constructed using public disclosure data, from the UK's FCA, of net short positions larger than the regulatory threshold of 0.5% share capital. Panel C reports results using alternative measures of the correlation of four-factor residual returns as dependent variables. In these specifications we use three measures: a) the continuous transformation of Pearson's pairwise correlation (ρ) proposed by Pindyck and Rotemberg (1993), $c = \tan(\pi\rho/2)$; b) Kendall's rank correlation; and c) Spearman's rank correlation. Estimates for the remaining controls may be found in the Internet Appendix. In Panel B and C, all independent variables (except the dummy variables) are normalised to have zero mean and unit standard deviation, which we denote by $*$. t-statistics (in parentheses) are computed using Newey and West (1987) robust standard errors, accounting for autocorrelation up to 3 lags (one quarter).

Third, we verify robustness of results with different specifications of the dependent variable i.e., with different measures of the comovement of abnormal returns. Panel C of Table 7 presents our two most complete regression specifications using Kendall's and Spearman's measures of rank-correlation as the left-hand side variables. The coefficient on $SSCAP^{*}$ remains significant.

We also re-run regressions using a continuous transformation of Pearson's correlation coefficient as dependent variable. Following Pindyck and Rotemberg (1993), we transform the realised monthly correlation by $c^{FFC} = \tan(\pi\rho^{FFC}/2)$. The first two columns of Panel C of Table 7 show that using c^{FFC} as the dependent variable leaves the result unchanged.

Fourth, we verify whether the result holds for the correlation of alternative specifications of abnormal returns. Specifically, we use the residual returns from the local Capital Asset Pricing Model (CAPM) and the correlation of residual returns from a six-factor asset pricing model (AQR), which is the local FFC model augmented with the local betting-against-beta (BAB) factor of Frazzini and Pedersen (2014) and the local quality-minus-junk (QMJ) factor of Asness et al. (2018).[18] We denote the correlation of the residuals from these factor models as, respectively, ρ^{CAPM} and ρ^{AQR}.

In addition to the local CAPM, FFC, and AQR models, we also test the international versions of these models, which include both local factors (specific to the country or region of the given stock) and global factors. For example, the international FFC includes eight factors: the local and global market, size, value, and momentum factors. We denote the correlation of the residuals from the international CAPM, the international FFC, and international AQR factor models as, respectively, ρ^{ICAPM}, ρ^{IFFC}, and ρ^{IAQR}. Descriptive statistics on these correlations are provided in Table 5, whereas further details on the factor models are outlined in Section A.1 of the Internet Appendix.

Table A.10 of the Internet Appendix reports results from the most complete regression specification, using residual return correlation from these alternative factor models. Overall, results are robust to the factor model choice.

On the other hand, the first column of Table A.10 of the Internet Appendix shows that, when the dependent variable is realised correlation of daily raw returns (RET), the

[18] Jank and Smajlbegovic (2021) find evidence that short sellers trade on the BAB and QMJ factors. By including these factors, we control for the possibility that part of the relationship between common short selling and excess comovement is due to BAB and QMJ.

coefficient estimate on $SSCAP^*$ is positive but insignificant.[19] In our view, this means that, when modelling comovement of non-adjusted raw returns, other features, such as similarity in sector and size, dominate the explanatory power of common (net) short selling. Our covariate of interest remains a significant explanatory variable for the comovement that is not due to the market and to other common risk factors.

Fifth, for the period Jul. 2015 to Dec. 2019, we test the robustness of our results by including the (normalised) number of common analysts, A^*, as an additional control variable in our models. Analysts tend to specialise in stocks that are similar across many different dimensions, some of which might not be easily observable. In this sense, A^* helps us proxy for those unobservable factors that might be driving correlation and that are not captured in our regression specifications.[20]

We define $A_{ij,t}$ equal to the number of analysts issuing earnings forecast of both stocks i and j over the 12-months prior to t. Because analyst coverage for our stock sample is either missing or zero prior to mid-2015, our variable for common analyst coverage is also zero for that period. Therefore, for our robustness checks with A^*, we run the Fama-MacBeth regressions only for the period Jul. 2015—Dec. 2019.

We present results in Table A.11 in the Internet Appendix. The estimates on $SSCAP^*$ remain significant at the 5% level of confidence across all specifications.

Lastly, to address the variability of the sample across the regression specifications, we conducted two additional robustness checks, which we report in the Internet Appendix.

First, we restrict observations to those of specifications 3 and 4 of Table 6. Table A.12 of the Internet Appendix shows that, for this subsample of stock-pairs, the coefficient estimates for specifications 1 and 2 remain similar to those found in Table 6.

Second, we re-run regressions for a subsample of 195 stocks, for which we have complete data for all the controls. This creates an almost perfectly balanced sample of $n \times (n-1)/2 = 18,915$ stock-pairs observations.[21] For this smaller, more balanced, subsample, there is

[19] We report that, for less flexible specifications, when the dependent variable is realised correlation of daily raw returns, the effect of $SSCAP^*$ is positive and significant at 5% level of confidence.

[20] Furthermore, Israelsen (2016) shows common analysts produce correlated forecast errors that propagate to prices, leading to excess comovement.

[21] The sample is not perfectly balanced because for few stock pair-months we miss sufficient daily abnormal returns to compute within-month realised correlation.

substantially less variability in the number of observations across regression specifications. Results are reported in Table A.13 of the Internet Appendix and show that the coefficient on $SSCAP^*$ remains highly statistically significant.

5 Two Explanations

5.1 Hypotheses Development

We put forward two explanations for the uncovered relationship between common short positions and excess comovement.

The first one is that, by taking large short positions on two or more stocks, short sellers exert price pressure, which materialises as comovement.

The price pressure mechanism has been used to explain the relationship between common ownership and excess comovement (Bartram et al., 2015, Antón and Polk, 2014). It has also been illustrated in theoretical studies on short selling and contagion. Brunnermeier and Pedersen (2005) and Cont and Wagalath (2013) suggest that short sellers can drive down prices of several stocks inducing shifts in correlation. They predict that the effect of short selling on comovement inversely depends on the market depth of the stocks short sold—the more illiquid the stocks, the greater should be the impact of short selling.

We draw on these studies to develop our first hypothesis, which we test in Section 5.2.

Hypothesis 1: According to the price pressure mechanism, the relationship between $SSCAP$ and excess comovement should be stronger for more illiquid stock pairs.

Note that the effect does not necessarily have to work in one direction. Positive price pressure might equally explain the relationship between common short selling and excess comovement. In the event of a short squeeze, for example, short sellers would have to buy stocks to cover their positions, driving up prices and correlation. To the extent that a higher level of $SSCAP$ is associated with a higher probability of a short squeeze, the relationship between $SSCAP$ and comovement could also be due to positive price pressure.

Therefore, we do not restrict our analysis to either negative or positive price pressure. Rather, we test the prediction that the relation between $SSCAP$ and excess comovement should be stronger for more illiquid stock pairs. Our goal is not to prove a causal relation, which is outside the scope of this paper, but to verify whether the predictions of the price pressure mechanism are consistent with our results for $SSCAP$.

There are a wide range of alternatives to Hypothesis 1, which we discuss in Section 5.2. These involve, among other, the possibility that short sellers avoid illiquid stocks or adopt stealth trading strategies.

Our second hypothesis is that the uncovered relationship is due to short sellers trading on superior information. There is considerable evidence in the literature that short sellers are informed traders. For example, Boehmer et al. (2008) and Diether et al. (2009b) show that short sellers can correctly predict future returns. Furthermore, studies have found that short sellers tend to focus on overpriced stocks, thus trading in a non-predatory way against market sentiment (Dechow et al., 2001, Curtis and Fargher, 2014).

If common short sellers are informed traders and expect stock prices to decline in the future, as declines materialise, their positions should be associated with higher future correlation. That is, $SSCAP$ predicts future price declines and, as these declines occur, we observe higher correlations. In this sense, the relationship between common short selling and excess comovement is non-causal.

From a temporal perspective, prior evidence of the long-horizon predictability of short selling supports this reasoning. For example, Boehmer et al. (2010) find that heavily shorted stocks display negative monthly abnormal returns for over six months. Jones et al. (2016), show that initial short disclosures are associated with cumulative abnormal returns of -5.23% after 90 days. If, as studies have shown, the predictability of informed short positions persists for several months, this effect should last for the time lag adopted in our regressions.

A counter argument is that informed short positions predict average future stock returns, whereas correlation measures deviations around the average. However, if the overall tendency is for prices of stock pairs to decline, this should result in higher correlation compared to stock pairs for which we do not expect this general tendency. A similar argument has led to the development of unbiased correlation estimators based on opening and closing prices (see, for example, Rogers and Zhou (2008)).

This leads to our second hypothesis explaining the relationship between common short selling and excess comovement.

Hypothesis 2: According to the informative trading mechanism, the relationship between $SSCAP$ and excess comovement should be stronger when common short positions are taken by informed traders.

We test Hypothesis 2 in Section 5.3 by exploiting two additional features of our dataset: 1) short sellers' investor profiles and 2) their past short selling performance.

5.2 Illiquidity and Price Pressure

To verify Hypothesis 1, we construct a dummy variable that captures the illiquidity of a stock pair. Specifically, $DAMIHUD_{ij,t}$ is equal to one if, during quarter t, the Amihud measure of both stocks i and j is above the cross-sectional median.[22] We add the dummy variable and its interaction with $SSCAP^*$ to the two most flexible models of our main regressions. Results, reported in the first two columns of Table 8, show that, for our stock sample, illiquidity is associated with lower future excess comovement.

Contrary to what is predicted by the price pressure mechanism, the interaction term with $SSCAP^*$ is negative and significant, with 10% level of confidence, in the first column and insignificant in the second. For our sample of LSE-listed stocks, the association between common short selling and excess comovement is weaker for more illiquid stock pairs. In fact, the total effect of common short selling for illiquid stock pairs, is statistically irrelevant.

This result is confirmed with alternative liquidity measures. We define the dummy $DTURN_{ij,t}$ as equal to one if, during quarter t, both stocks i and j have an average daily turnover below the cross-sectional median.[23] The third and fourth columns of Table 8 show that the coefficient on the interaction between $SSCAP^*$ and $DTRUN$ is negative and statistically significant, indicating that the effect of common short selling is weaker for the most illiquid stocks. Again, the total effect of common short selling for illiquid stocks is statistically insignificant, meaning that $SSCAP^*$ has an effect only for liquid stock pairs.

[22] The Amihud (2002) measure of stock i is defined as $(\sum_{d=1}^{D_t} |r_{i,t_d}|)/(D_t \sum_{d=1}^{D_t} V_{i,t_d})$, where D_t is the number of trading days in quarter t, $\mid r_{i,t_d} \mid$ is the absolute value of the daily return of stock i on day t_d, and V_{i,t_d} is the daily dollar volume of shares traded.

[23] Turnover is the volume of shares traded, as a percentage of shares outstanding.

We verify results with a third dummy variable of illiquidity, based on the free float of the stock pair. $DFLOAT_{ij,t}$ is equal to one if, during quarter t, both stocks i and j have their free float, as percentage of their shares outstanding, below the cross-sectional median. Columns 5 and 6 of Table 8 indicate the coefficient on interaction term between $DFLOAT$ and $SSCAP^*$ is negative and statistically significant in both specifications, meaning that higher illiquidity is associated with lower levels of excess comovement.

Generally, across all regressions, our results indicate that the association between $SSCAP^*$ and excess comovement holds when at least one of the two stocks is liquid. When the stock pair is illiquid then the effect of $SSCAP^*$ weakens significantly or vanishes. This result, which holds for alternative thresholds used to construct the illiquidity dummies, is consistent with the results of Section 4.2, obtained with the alternative covariate $SSVOL^*$.

We confirm the result with several additional robustness checks. First, we use continuous liquidity measures of the Amihud indicator, turnover, and free float. Results, presented in Table A.15 in the Internet Appendix, show that that the positive association between common short selling and excess comovement continues to hold for liquid stocks, but that this effect weakens as stock pair liquidity decreases.

Second, we use alternative factor models to compute the correlation of residual returns. Table A.16 of the Internet Appendix shows that using residual returns from the AQR six-factor model leaves results unvaried. We obtain comparable outcomes when we use the correlation of residual returns from alternative factor models.

Our results contradict the price pressure mechanism outlined in Hypothesis 1 and are consistent with the findings of Shkilko et al. (2012) that short sales are not the primary drivers of price movements.

We put forward several possible explanations for the result that the effect of $SSCAP^*$ vanishes for the most illiquid stock pairs. First, it could be that short sellers act as liquidity providers for illiquid stocks, alleviating upward price pressure and, hence, reducing excess comovement. Evidence of liquidity provision by short sellers has been found by Boehmer and Wu (2013) and Diether et al. (2009a), among others.

Table 8: Fama-MacBeth cross-sectional regressions of monthly realised pairwise correlation of daily four-factor residual returns on the interaction of $SSCAP^*$ with illiquidity dummies, Jan. 2013—Dec. 2019

	Dependent Variable: Correlation of 4F Residuals					
	(1)	(2)	(3)	(4)	(5)	(6)
Constant	0.05378	0.05454	0.05028	0.05183	0.05308	0.05399
	(12.88)	(13.52)	(12.30)	(13.05)	(12.59)	(13.40)
$SSCAP^*$	0.00115	0.00105	0.00136	0.00123	0.00152	0.00137
	(2.45)	(2.27)	(3.18)	(2.93)	(3.36)	(3.16)
$DAMIHUD$	-0.00933	-0.00767				
	(-5.01)	(-4.01)				
$SSCAP^* \times DAMIHUD$	-0.00126	-0.00089				
	(-1.99)	(-1.45)				
$DTURN$			0.00601	0.00439		
			(4.51)	(3.35)		
$SSCAP^* \times DTURN$			-0.00174	-0.00192		
			(-2.38)	(-2.71)		
$DFLOAT$					-0.00379	-0.00313
					(-3.53)	(-2.86)
$SSCAP^* \times DFLOAT$					-0.00145	-0.00118
					(-3.22)	(-2.50)
Other controls reported in the Internet Appendix						
Tot. $SSCAP^*$ effect for illiquid pairs	-0.00011	0.00016	-0.00038	-0.00069	0.00007	0.00019
	(-0.19)	(0.30)	(-0.54)	(-0.97)	(0.15)	(0.39)

Continued on next page

Table 8—*Continued*

	Dependent Variable: Correlation of 4F Residuals					
	(1)	(2)	(3)	(4)	(5)	(6)
R^2	0.02553	0.03104	0.02567	0.03115	0.02548	0.03101
	(13.22)	(12.83)	(13.66)	(13.16)	(13.61)	(13.15)
N. Obs.	49,084	49,084	49,084	49,084	49,074	49,074
	(90.38)	(90.38)	(90.38)	(90.38)	(89.71)	(89.71)
Size controls	Yes	Yes	Yes	Yes	Yes	Yes
Pair characteristic controls	Yes	Yes	Yes	Yes	Yes	Yes
Style controls	No	Yes	No	Yes	No	Yes

The table reports Fama and MacBeth (1973) regression coefficients, computed by running cross-sectional regressions each month between Jan. 2013 and Dec. 2019 (84 months) and then averaging regression coefficients over the sample period. Observations relate to stock pairs from an unbalanced sample of 356 LSE-listed stocks that have at least one public short selling disclosure reported by the UK's FCA and sufficient price data. The dependent variable is the realised pairwise correlation in month $t+1$ of the daily residual returns from a four-factor model. The four factors are: the market excess return, the size and value factors (Fama and French, 1993), and the momentum factor (Carhart, 1997). Factors are local i.e., they are associated to the country (or region) of stocks. Stock price data are from Refinitiv EIKON, whereas daily factors are from AQR's website. Apart from stock pair controls, the independent variables include $SSCAP$, which is the net (scaled) capital of the stock pair shorted by common short sellers at quarter-end t, as well as the interaction of $SSCAP$ with three illiquidity dummies: $DAMIHUD$, $DTRUN$, $DFLOAT$. $SSCAP$ is constructed using public disclosure data, from the UK's FCA, of net short positions larger than the regulatory threshold of 0.5% share capital. $DAMIHUD$ is equal to one if both stocks in a stock pair have an Amihud (2002) measure above the cross-sectional median, and zero otherwise. $DTRUN$ is equal to one if both stocks have an average daily turnover below the cross-sectional median. $DFLOAT$ is equal to one if both stocks have free float (as percentage of shares outstanding) below the cross-sectional median. Stock data used to compute the illiquidity measures are from Refinitiv EIKON. Estimates for the remaining controls may be found in the Internet Appendix. All independent variables are updated quarterly and, with the exception of dummy variables, are cross-sectionally normalised (to have zero mean and unit standard deviation), which we denote by $*$. t-statistics (in parentheses) are computed using Newey and West (1987) robust standard errors, accounting for autocorrelation up to 3 lags (one quarter).

Another possibility is that short sellers avoid illiquid stock pairs because of high transaction costs or to reduce risks of being caught in a short squeeze (Dechow et al., 2001). Boehmer et al. (2010) find that lightly shorted stocks are less liquid, whereas factor models have less explanatory power for these stocks. Although our regression specifications account for the difficulty to short through firm size (i.e., market capitalisation) controls, this remains an alternative explanation for our liquidity results.

Lastly, the result could be due to short sellers trying to trade illiquid stocks less aggressively than liquid stocks to either conceal information or to minimise price impact. While this type of stealth behaviour is known to occur among long traders, evidence of it occurring among short sellers is less conclusive. With US shorting flow data, for example, Boehmer et al. (2008) find that informed short sellers will favour large trades over many small or medium-sized trades. With European disclosure data, Jank et al. (2021) note that short sellers bunch positions under the disclosure threshold. However, they find that bunching is motivated by disclosure avoidance and unrelated to short sellers' stock liquidity concerns.

To shed light on these alternative hypotheses, we would require short positions under the 0.5% disclosure thresholds. This would allow us to examine whether the relationship between $SSCAP^*$ and correlation strengthens or weakens for illiquid stocks under the threshold and, accordingly, to exclude some of the different possible interpretations.

5.3 Informed Trading

Hypothesis 2 posits that the effect of $SSCAP^*$ should be stronger for informed short sellers. With this in mind, we investigate common short positions originating from different types of short seller.

From Refinitiv EIKON, we obtain the investor profiles for 323 of the 454 short sellers in our sample. We collect the following information: investment orientation, investor type, portfolio turnover (%), and number of instruments held.[24]

As hedge funds are considered highly informed agents (Aragon and Martin, 2012, Agarwal et al., 2013), we identify the hedge funds short sellers in our sample.[25] We consider a short

[24]Investor profiles are not available historically, so they refer to the date of collection (March 2020).

[25]We do not explicitly make the distinction between hedge funds and hedge fund managers.

seller a hedge funds if, according to their Refinitiv EIKON investor profile, their investor type is either "Hedge Fund" or "Investor Advisor/Hedge Fund". According to this classification, our sample of short sellers comprises 234 hedge funds and 89 non-hedge funds.[26]

The first two columns of Table 9 show, for our LSE-listed stock sample, the effect of $SSCAP^*$ for hedge fund and non-hedge fund short sellers. The regression coefficient on $SSCAP^*$ for hedge funds is substantially larger than that on non-hedge funds, but this difference is not statistically significant.

We obtain similar results when we distinguish short sellers based on their investment orientation. Refinitiv EIKON classifies investors' investment orientation as either active or passive. Active investors are more prone to stock-picking and using proprietary trading strategies, whereas passive investors involve less buying and selling and more long-haul investments. Our sample of short sellers includes 276 active investors and 47 passive investors.

The third and fourth columns of Table 9 show that, for our data, common short positions of active investors are more strongly associated with future excess comovement than those of passive investors. Although the difference between coefficient estimates is not statistically significant, it is in line with the informed trading explanation.

Our sample of short sellers is skewed towards hedge funds and active investors. This could lead to an unbalanced comparison between $SSCAP^*$ for hedge funds (active investors) against $SSCAP^*$ for non-hedge funds (passive investors). To mitigate this issue, we use an alternative definition of activeness. We separate short sellers according to their (long) portfolio turnover and concentration, keeping the size of groups balanced.[27]

We define a short seller as a high (low) turnover investor if it ranks above (below) the cross-sectional median in terms of portfolio turnover. Similarly, we say entities have high (low) concentration if they rank below (above) the cross-sectional median in terms of number of stocks in their investment portfolio.[28]

The fifth and sixth columns of Table 9 show that the relationship between common short

[26]Using SEC ADV forms paired with the methodology of Brunnermeier and Nagel (2004) and Griffin and Xu (2009), we obtain a similar classification, with 75% concordance.

[27]The issue remains a concern if hedge funds, active investors, or investors with high turnover are more active in the shorting market than non-hedge funds, passive investors, or investors with low turnover. In Table A.6 of the Internet Appendix, we verify that, except for high/low concentration groups, the number and size of short positions does not vary significantly between the groups of short sellers.

[28]We obtain similar results if we use terciles, rather than medians, to group short sellers.

selling and future excess comovement is stronger for short sellers that often re-balance their portfolios. The effect of common (net) short selling of high concentration investors is initially significant, but the effect statistically vanishes when we include additional controls.

These results point towards common short positions of informed short sellers having a stronger association with future excess comovement. However, this rests on the implicit assumption that hedge funds, active investors, or investors with high turnover and high concentration are more informed than non-hedge funds, passive investors, or investors with low turnover and low concentration.

An alternative explanation consistent with our results could be that $SSCAP^*$ signals agreement between short sellers and hence greater overall disagreement between short sellers and long investors. Higher disagreement can lead to more volatility and hence greater covariation in stock returns. This disagreement mechanism might be strongest when short sellers are "opinionated" agents, such as active investors or ones with high turnover.

To address this concern, we repeated the analysis with a different measure of informativeness, that should be less susceptible to the disagreement mechanism—short sellers' past performance. The informativeness of short positions is often measured by their ability to predict future returns (see, for example, Christophe et al., 2004). In first instance, opinionatedness should not be related to performance.

At each period, we computed short sellers' performance over the previous 12 months based on the disclosure data.[29] We say that short sellers have high (low) performance if, over the preceding 12 months, their short portfolio returns were above (below) the cross-sectional median.[30] Then, using these two groups, we constructed $SSCAP^*$ for high performance and low performance short sellers.

The seventh and eighth columns show that, for our stock sample, common short positions of short sellers with high past performance are better able to predict future excess comovement. The difference between high and low performance short sellers is significant at the 1% confidence level in both specifications. Furthermore, the size of coefficient of $SSCAP^*$ for high performance short sellers is larger than that of hedge funds and for active investors.

[29]To construct the short portfolio based on disclosure data, we followed the conservative equally-weighted approach of Greppmair et al. (2020).

[30]We obtain similar results if we use terciles, rather than medians, to group short sellers.

Table 9: Fama-MacBeth cross-sectional regressions of monthly realised pairwise correlation of daily four-factor residual returns on $SSCAP^{*}$ by short seller type, Jan. 2013—Dec. 2019

	Dependent Variable: Correlation of 4F Residuals							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Hedge Funds	0.00092	0.00086						
	(2.26)	(2.24)						
Non-Hedge Funds	0.00039	0.00030						
	(1.93)	(1.48)						
Active			0.00094	0.00089				
			(2.24)	(2.19)				
Passive			0.00036	0.00025				
			(2.10)	(1.58)				
High Turnover					0.00028	0.00047		
					(1.82)	(3.26)		
Low Turnover					0.00057	0.00031		
					(1.27)	(0.75)		
High Concentration					0.00029	0.00018		
					(2.24)	(1.52)		
Low Concentration					0.00055	0.00064		
					(1.01)	(1.27)		
High Performance							0.00125	0.00117
							(3.35)	(3.24)
Low Performance							0.00002	0.00000
							(0.08)	(-0.01)
Other controls reported in the Internet Appendix								
Group Difference	0.00052	0.00056	0.00059	0.00063			0.00123	0.00117
	(1.17)	(1.38)	(1.24)	(1.41)			(3.61)	(3.53)

Continued on next page

Table 9—*Continued*

	Dependent Variable: Correlation of 4F Residuals							
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
R^2	0.02513	0.03069	0.02512	0.03068	0.02523	0.03078	0.02513	0.03069
	(13.44)	(12.99)	(13.44)	(12.98)	(13.45)	(13.00)	(13.46)	(13.00))
N. Obs.	49,084	49,084	49,084	49,084	49,084	49,084	49,084	49,084
	(90.38)	(90.38)	(90.38)	(90.38)	(90.38)	(90.38)	(90.38)	(90.38)
Size controls	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Pair characteristics	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Style controls	No	Yes	No	Yes	No	Yes	No	Yes

The table reports Fama and MacBeth (1973) regression coefficients, computed by running cross-sectional regressions each month between Jan. 2013 and Dec. 2019 (84 months) and then averaging regression coefficients over the sample period. Observations relate to stock pairs from an unbalanced sample of 356 LSE-listed stocks that have at least one public short selling disclosure reported by the UK's FCA and sufficient price data. The dependent variable is the realised pairwise correlation in month $t+1$ of the daily residual returns from a four-factor model. The four factors are: the market excess return, the size and value factors (Fama and French, 1993), and the momentum factor (Carhart, 1997). Factors are local i.e., they are associated to the country (or region) of stocks. Stock price data are from Refinitiv EIKON, whereas daily factors are from AQR's website. Apart from stock pair controls, the independent variables include $SSCAP$ by short seller type, which is the net (scaled) capital of the stock pair shorted by common short sellers of a given type at quarter-end t. $SSCAP$ by short seller type is constructed using public disclosure data, from the UK's FCA, of net short positions larger than the regulatory threshold of 0.5% share capital. Each row reports the coefficient on $SSCAP^*$ for different types of short sellers. Short sellers are classified as hedge funds/non-hedge funds, active/passive investors, high/low turnover investors, and high/low concentration investors according to their Refinitiv EIKON investor profile. Categorisation of short sellers according to high/low performance is based on their past 12-month equally-weighted portfolio returns, constructed using their disclosed short positions. Estimates for the remaining controls may be found in the Internet Appendix. All independent variables are updated quarterly and, with the exception of dummy variables, are cross-sectionally normalised (to have zero mean and unit standard deviation), which we denote by $*$. t-statistics (in parentheses) are computed using Newey and West (1987) robust standard errors, accounting for autocorrelation up to 3 lags (one quarter).

We verified the robustness of results to alternative specifications.

First, similarly to the approach using NSS of Section 4.2, we re-run results using alternative covariates, based on the number of common short sellers, rather than common short sold capital, by short seller type. In line with the results of Table 9, Table A.18 of the Internet Appendix shows that the number of common short sellers is more strongly associated with excess comovement when short sellers are highly-informed traders.

Second, Table A.19 of the Internet Appendix reports regressions using, as dependent variable, the correlation of six-factor residual returns from the local AQR model. Results are unchanged and alternative factor models, such as those presented in Section 4.2, obtain similar outcomes.

6 Further Evidence

6.1 Price Reversals

The informative content of common short positions can be also assessed by analysing the evolution of returns after the positions are taken. Particularly, we would expect non-informative short positions to be associated with price reversals (Boehmer and Wu, 2013). This is because, generally, price reversals are transient and not information based. Thus, informed short sellers should, in theory, not position themselves against these events.

To adopt such an analysis in our context of common short positions, we define, at the beginning of month $t+1$, the connected portfolio i as the portfolio of stocks that are connected, through one or more common short seller, to stock i at quarter-end t. The return on the equally-weighted connected portfolio of stock i is computed as the average of all the connected stocks of i. That is,

$$r^{EQ}_{iC,t+1} = \frac{\sum_{j=1}^{J} \mathbb{I}(SSCAP_{ij,t}) r_{j,t+1}}{\sum_{j=1}^{J} \mathbb{I}(SSCAP_{ij,t})}, \tag{3}$$

where $\mathbb{I}(\cdot)$ is the indicator function, which is equal to one if its argument is positive and zero otherwise, and J is the number of stocks connected through common short positions to i. With the goal of verifying whether portfolios of connected stocks are associated with price reversals, we analyse the cumulative buy-and-hold abnormal returns of the connected portfolios over the 12 months after portfolio creation—$t+1, t+2, ..., t+12$.

We retrieve the abnormal returns of the connected portfolio by regressing excess portfolio returns on the global excess-market return and on global FFC factors. To avoid weighing our results on the more recent part of the sample, during which more stocks are present, we focus on a subsample of 195 stocks for which there is a balanced number of observations.

Figure 3 presents the average abnormal cumulative returns for the connected portfolios, selected from the balanced sample of 195 LSE-listed stocks.

Chart A shows that equally-weighted portfolios of connected stocks earn, on average, negative abnormal returns that persist for over one year. These cumulative returns reach -0.30% after six months, and then appear to stabilise. Rather than revert, cumulative abnormal returns persist. This lends evidence to the informative trading story of Hypothesis 2. For our LSE sample, stocks connected through common short positions are associated with permanent, rather than transient, price shifts.

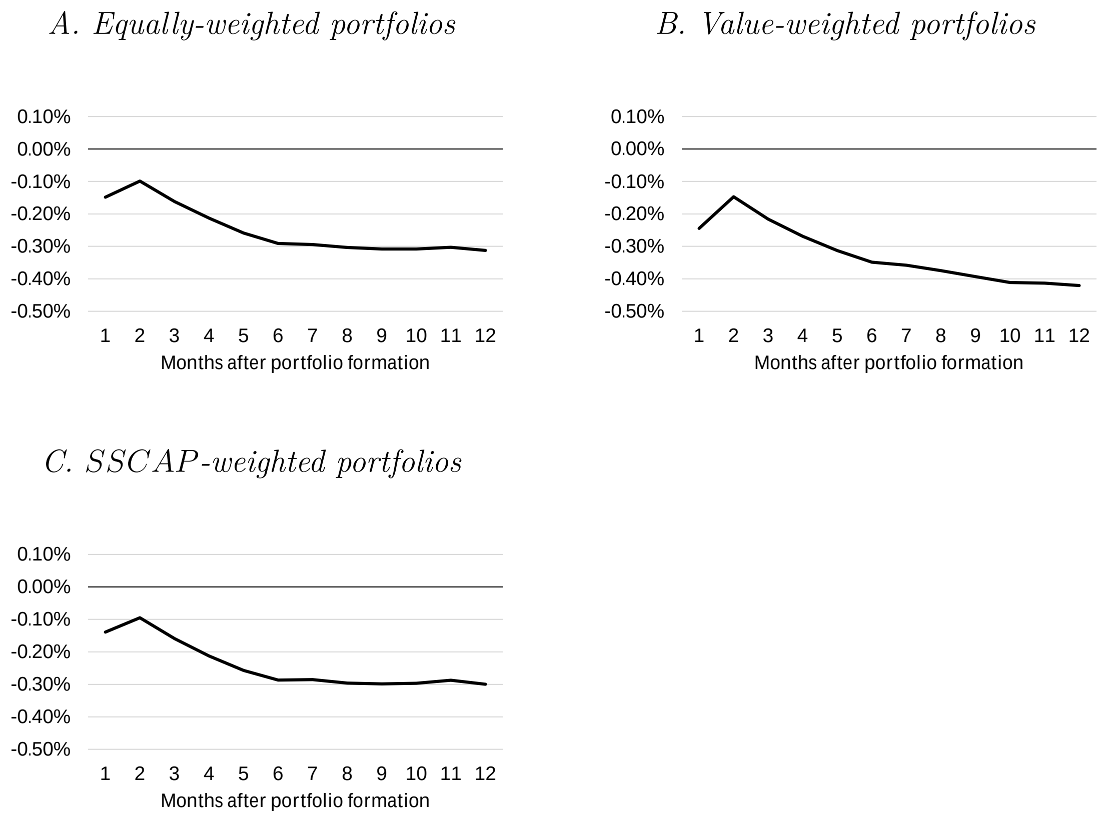
These results continue to hold when we use alternative portfolio weights for the connected stocks. Chart B of Figure 3 shows the average monthly four-factor abnormal returns of connected portfolios constructed using value weights, whereas Chart C depicts the same measure for portfolios constructed using $SSCAP$ weights. In the latter case, the return on connected portfolio of stock i is computed as

$$r_{iC,t+1}^{SSCAP} = \frac{\sum_{j=1}^{J} SSCAP_{ij,t} r_{j,t+1}}{\sum_{j=1}^{J} SSCAP_{ij,t}}. \tag{4}$$

In both cases, cumulative abnormal returns are negative and persistent.

In Figure A.2 of the Internet Appendix, we present robustness of this result to alternative definitions of abnormal returns. If we use simple cumulative excess returns above the U.S. T-bill rate, we observe reversal after about nine months. If we look at cumulative returns in excess of the market using the CAPM model, we obtain a much flatter picture, indicating even slower reversion. Paired with Figure 3, these results indicate that, when benchmarked against the market and FFC factors, connected portfolio returns are associated with persistently negative cumulative returns that are slow to revert. This result is further confirmed when abnormal returns are defined using the six-factor AQR model.

Figure 3: Average monthly cumulative abnormal returns of connected portfolios, Jan. 2013—Dec. 2019



The charts present the average monthly abnormal cumulative returns of connected portfolios, between January 2013 to December 2019 (84 months). Connected portfolios are selected from a balanced sample of 195 LSE-listed stocks that have at least one public short selling disclosure reported by the UK's FCA and sufficient price data. At the beginning of every month $t + 1$, we define connected portfolio i as the portfolio of stocks that, at quarter-end t, are connected, through one or more common short seller, to stock i. Buy-and-hold cumulative abnormal returns of these portfolios are computed over the twelve months after portfolio formation. Abnormal returns are retrieved by regressing portfolio returns in excess of the U.S. T-bill rate on the global market excess return, the global size and value factors (Fama and French, 1993), and the global momentum factor (Carhart, 1997). Price data are from Refinitiv EIKON, whereas factor data are from AQR. Chart A depicts the monthly abnormal cumulative return of connected portfolios computed using an equal weighting of stocks within each portfolio. Chart B and Chart C depict the monthly abnormal cumulative return of connected portfolios computed using, respectively, value weighting and weights based on common short sold capital. Common short sold capital is constructed using public disclosure data, from the UK's FCA, of net short positions larger than the regulatory threshold of 0.5% share capital.

6.2 Portfolio Diversification

Finally, we explore the possibility of using the results on common short selling and comovement to improve the diversification of portfolios.

We study the volatility of daily excess returns of equally-weighted connected portfolios for the successive 254 days after portfolio creation (without re-balancing). As in Section 6.1, connected portfolios are defined at the beginning of each month $t + 1$, using the non-zero entries of $SSCAP_{ij,t}$, with our balanced sample of 195 LSE-listed stocks. As a mean of comparison, every month, we construct non-connected portfolios of matching stocks.

Our non-connected portfolios contain stocks that, according to the disclosure data, at quarter-end t, had no common short sellers. As a matching criterion, we impose that the stocks in the non-connected portfolios belong to the same size deciles as the stocks in the corresponding connected portfolio.[31] For the connected and non-connected portfolios, we compute the realised yearly volatility of the equally-weighted daily excess returns.

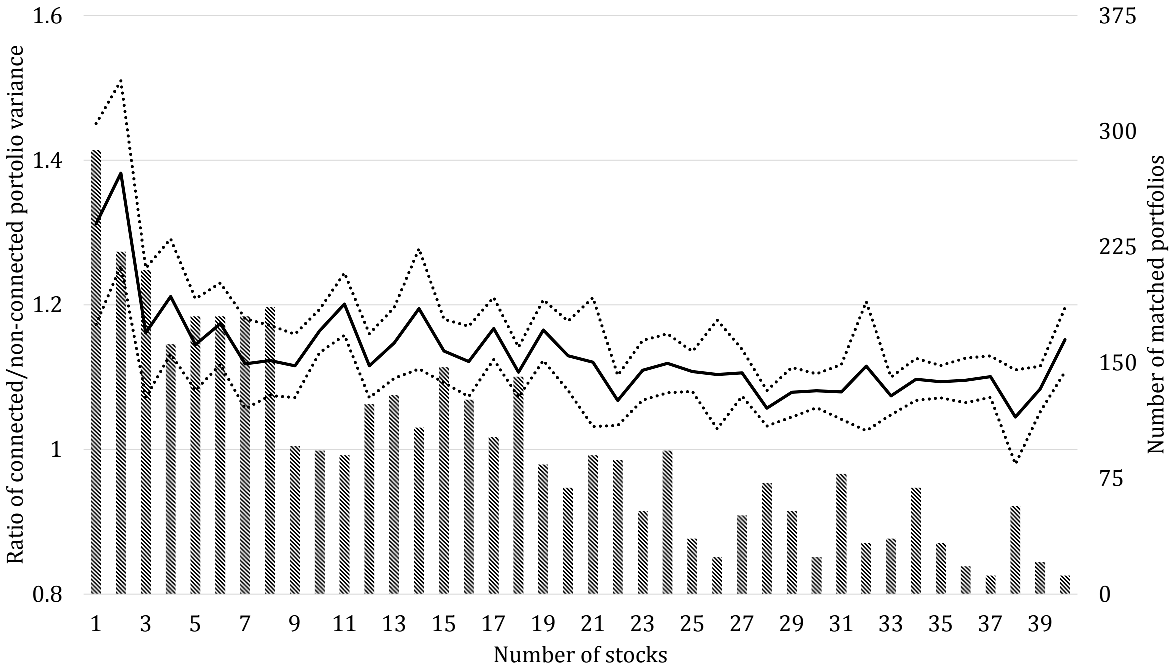
Figure 4 depicts the average of the ratio of the connected and non-connected portfolio excess return volatilities. As the size of the portfolio increases i.e., as the number of (matched) stocks in the portfolios grows, diversification of connected portfolios strengthens, and the average ratio tends towards one. However, when both portfolios include 40 stocks, the ratio of the volatilities still hovers around 1.1. This means that, for our stock sample, choosing stocks without common short sellers obtains substantial diversification benefits.

The chart also depicts the number of portfolios used to compute the average ratio. Because it becomes more difficult to fulfil the matching criteria for large portfolios, the number of portfolios declines as portfolio size increases. Inevitably, this means that results are less precise for large portfolios. However, for small portfolios, the result hints that there are diversification benefits to grouping stocks with no common short sellers.

Table 10 reports the average and median volatilities across 3,870 connected and non-connected portfolios, constructed using our balanced stock sample. The non-connected portfolio has, on average, a 12.7% smaller volatility than connected portfolios. This difference is statistically significant at 1% confidence level.

[31] Attempting to match over more characteristics, does not return a sufficient number of matches. However, we note that size may act as a proxy for other characteristics.

Figure 4: Ratio of yearly realised excess return volatility of equally-weighted connected and non-connected portfolios, Jan. 2013—Dec. 2019



The chart plots the average ratio of yearly realised volatilities of the returns of matched connected portfolios and non-connected portfolios (bold solid, left axis), between January 2013 to December 2019 (84 months), as well as the uncertainty bands (light dashed, left axis) representing 2.5 standard deviations from the average. At the beginning of every month $t+1$, we define connected portfolio i as the portfolio of stocks that, at quarter-end t, are connected, through one or more common short seller, to stock i. At the same, for each connected portfolio, we defined a matching non-connected portfolio of stocks that belong to the same size deciles as those in the connected portfolio and do not share any common short seller at quarter-end t. We computed the daily equally-weighted excess return of these portfolios and compared their realised volatility over the successive 254 trading days. The figure also plots the number of matched portfolios over which the average volatility ratio is calculated (bars, right axis). Portfolios are selected from a balanced sample of 195 LSE-listed stocks that have at least one public short selling disclosure reported by the UK's FCA and sufficient price data. Excess returns are computed using price data from Refinitiv EIKON and the U.S. Treasury bill rate. We determine common short selling connections using public disclosure data, from the UK's FCA, of net short positions larger than the regulatory threshold of 0.5% share capital. Uncertainty bands are computed using Newey and West (1987) robust standard errors, accounting for autocorrelation up to 12 lags (one year).

We verified the difference in riskiness between connected and non-connected portfolios by conducting tests on the equality of variances. We used Levene's (1960) absolute deviation test, which is more robust to departures from normality than the classic F-test. The alternative hypothesis to the test is that the connected portfolio variance is not equal to that of the matching non-connected portfolio.

Table 10: Summary statistics of yearly realised volatilities of matching connected and non-connected portfolios, Jan. 2013—Dec. 2019

	Portfolio Yearly Realised Volatilities		
	Connected Portfolios	Non-Connected Portfolios	% of Rejections
Mean	0.0138	0.0121	24.83
	(65.81)	(61.53)	(22.64)
Median	0.0118	0.0105	

The table reports the mean and median volatilities for 3,870 matched connected and non-connected portfolios, between January 2013 to December 2019 (84 months), as well as the rejection frequency of Levene's (1960) absolute deviation test on equality of variances. Rejection frequency is computed controlling for false discovery rate at the 10% level using Benjamini and Hochberg (1995) method. At the beginning of every month $t+1$, we define connected portfolio i as the portfolio of stocks that, at quarter-end t, are connected, through one or more common short seller, to stock i. At the same, for each connected portfolio, we defined a matching non-connected portfolio of stocks that belong to the same size deciles as those in the connected portfolio and do not share any common short seller at quarter-end t. We computed the daily equally-weighted returns of these portfolios in excess of the U.S. T-bill rate and computed the realised volatility of excess returns over the 254 trading days after portfolio formation. Portfolios are selected from a balanced sample of 195 LSE-listed stocks that have at least one public short selling disclosure reported by the UK's FCA and sufficient price data. Daily stock price data are from Refinitiv EIKON. We determine common short selling connections using public disclosure data, from the UK's FCA, of net short positions larger than the regulatory threshold of 0.5% share capital. t-statistics (in parentheses) are computed using Newey and West (1987) robust standard errors, accounting for autocorrelation up to 12 lags (one year).

Table 10 shows that, for almost 25% of the matched portfolios, the test rejected the null hypothesis of equality of variances controlling for false discovery rate at 10%.[32]

These results are robust to various alterations to our analysis. First, we repeated the analysis with alternative matching criteria, based on TRBC Economic Sector. Second, we varied the weights in the connected and non-connected portfolios. We adopted value-weights and weights based on common short sold capital, $SSCAP$. Third, we varied the length of holding period, increasing it to two years and decreasing it to six-months. Lastly, we repeated the analysis using residual returns from different factor models.

These robustness results are presented in Figure A.3 and Table A.20 of the Internet Appendix. Results are in line with those presented in this section. In particular, the rejection frequencies for the tests on the equality of variances across connected and non-connected portfolios vary between 17% and 30%.

[32] Using the classical F-test, with the alternative that the connected portfolio volatility is greater than that of the matching non-connected portfolio, the same rejection frequency increases to 53.5%.

7 Conclusion

For a sample of LSE-listed stocks, we show that stocks connected by common short sellers have stronger excess comovement than stocks that are not connected by common short sellers. This result can be used to obtain portfolio diversification benefits. We explore two hypotheses that explain our findings. The weight of the evidence tends towards an informed trading hypothesis more than a price pressure hypothesis.

Our analysis is not immune to some key limitations. First, despite the wealth of our controls and our robustness checks, we cannot completely exclude that our results are not related to fundamental comovement. It is still possible that short sellers trade according to some unobserved stock characteristics that we do not capture in our framework. To exclude this possibility completely, we would ideally have an exogenous event that induces a change in $SSCAP$, without directly affecting comovement. However, due to our brief sample period, and the nature of our data, we lack this sort of setting.

This does not change the significance of our results and the predictive power of $SSCAP$ for future excess comovement. In fact, it would mean that $SSCAP$ proxies for some unobserved fundamental factor not captured by other measures widely used in the literature. Future work could then focus on determining the drivers of common short positions and analysing whether these are related to discount rates or cashflow news. In this sense, the evidence we gathered on hedge funds and informed trading would prove a useful starting point.

Second, the fact that our data is restricted to large short position disclosures covering just one market leads to some additional considerations. Our sample covers large and highly liquid stocks listed on the LSE. Although sample restrictions undoubtedly limit the global validity of the results, we have presented several robustness specifications that strengthen their local validity for an important European stock exchange, such as the LSE. Recently Boehmer et al. (2021) have uncovered cross-country differences in the predictive power of short selling data for stock price returns. Given these findings, future extensions could verify the results of our study across different countries, industries, and types of firms (e.g., export-oriented vs. domestic-oriented firms).

Furthermore, despite we capture a good portion of the short selling picture, due to the European disclosure rule, we are missing a large number of smaller short positions below the 0.5% threshold. In its 2018 Report on Trends, Risks and Vulnerabilities, ESMA notes that EU positions above the 0.5% threshold represent less than one third of all positions above the 0.2% threshold (above which institutions privately report to national authorities). The literature has found that large short positions are generally informed, and that the informativeness increases with position size (Avramov et al., 2006, Boehmer et al., 2008, Easley and O'Hara, 1987). This is in line with our result that common short selling relates to excess comovement through informed trading. Thus, a further path for future work would be to verify our results with smaller short positions, using data exclusively disclosed to national regulators.

References

V. Agarwal, W. Jiang, Y. Tang, and B. Yang. Uncovering hedge fund skill from the portfolio holdings they hide. *Journal of Finance*, 68(2):739–783, 2013. doi:10.1111/jofi.12012.

Y. Amihud. Illiquidity and stock returns: cross-section and time-series effects. *Journal of Financial Markets*, 5(1):31–56, 2002. doi:10.1016/s1386-4181(01)00024-6.

M. Antón and C. Polk. Connected stocks. *Journal of Finance*, 69(3):1099–1127, 2014. doi:10.1111/jofi.12149.

G. O. Aragon and J. S. Martin. A unique view of hedge fund derivatives usage: Safeguard or speculation? *Journal of Financial Economics*, 105(2):436–456, 2012. doi:10.1016/j.jfineco.2012.02.004.

C. S. Asness, A. Frazzini, and L. H. Pedersen. Quality minus junk. *Review of Accounting Studies*, 24:34–112, 2018.

D. Avramov, T. Chordia, and A. Goyal. The impact of trades on daily volatility. *Review of Financial Studies*, 19(4):1241–1277, 2006.

N. Barberis, A. Shleifer, and J. Wurgler. Comovement. *Journal of Financial Economics*, 75 (2):283–317, 2005. doi:10.1016/j.jfineco.2004.04.003.

S. M. Bartram, J. M. Griffin, T.-H. Lim, and D. T. Ng. How important are foreign ownership linkages for international stock returns? *Review of Financial Studies*, 28(11):3036–3072, 2015.

Y. Benjamini and Y. Hochberg. Controlling the false discovery rate: A practical and powerful approach to multiple testing. *Journal of the Royal Statistical Society. Series B (Methodological)*, 57(1):289–300, 1995. doi:10.1111/j.2517-6161.1995.tb02031.x.

E. Boehmer and J. Wu. Short Selling and the Price Discovery Process. *Review of Financial Studies*, 26(2):287–322, 2013. ISSN 1465-7368. doi:10.1093/rfs/hhs097.

E. Boehmer, C. M. Jones, and X. Zhang. Which Shorts Are Informed? *Journal of Finance*, 63(2):491–527, 2008. doi:10.1111/j.1540-6261.2008.01324.x.

E. Boehmer, Z. R. Huszár, and B. D. Jordan. The Good News in Short Selling. *Journal of Financial Economics*, 96(1):80–97, 2010. doi:10.1016/j.jfineco.2009.12.002.

E. Boehmer, T. X. Duong, and Z. R. Huszár. Short covering trades. *Journal of Financial and Quantitative Analysis*, 53:723–348, 2018.

E. Boehmer, Z. R. Huszár, Y. Wang, X. Zhang, and X. Zhang. Can shorts predict returns? A global perspective. *Review of Financial Studies*, 35:2428–2463, 2021. doi:10.1093/rfs/hhab079.

M. K. Brunnermeier and S. Nagel. Hedge funds and the technology bubble. *Journal of Finance*, 59(5):2013–2040, 2004. doi:10.1111/j.1540-6261.2004.00690.x.

M. K. Brunnermeier and L. H. Pedersen. Predatory trading. *Journal of Finance*, 60(4): 1825–1863, 2005.

M. M. Carhart. On Persistence in Mutual Fund Performance. *Journal of Finance*, 52(1): 57–82, 1997.

H. Chen, S. Chen, Z. Chen, and F. Li. Empirical investigation of an equity pairs trading strategy. *Management Science*, 2017. doi:10.1287/mnsc.2017.2825.

S. E. Christophe, M. G. Ferri, and J. J. Angel. Short-selling prior to earnings announcements. *Journal of Finance*, 59(4):1845–1875, 2004.

R. Cont and L. Wagalath. Running for the exit: Distressed selling and endogenous correlation in financial markets. *Mathematical Finance*, 4:718–741, 2013.

A. Curtis and N. L. Fargher. Does short selling amplify price declines or align stocks with their fundamental values? *Management Science*, 60(9):2324–2340, 2014.

P. M. Dechow, A. P. Hutton, L. Meulbroek, and R. G. Sloan. Short-sellers, fundamental analysis, and stock returns. *Journal of Financial Economics*, 61:77–106, 2001.

K. B. Diether, K. Lee, and I. M. Werner. It's SHO time! Short–sale price tests and market quality. *Journal of Finance*, 64:37–73, 2009a.

K. B. Diether, K.-H. Lee, and I. M. Werner. Short-sale strategies and return predictability. *Review of Financial Studies*, 22(2):575–607, 2009b.

D. Easley and M. O'Hara. Price, trade size, and information in securities markets. *Journal of Financial Economics*, 19:69–90, 1987.

R. Engle and R. Colacito. Testing and valuing dynamic correlations for asset allocation. *Journal of Business & Economic Statistics*, 24(2):238–253, 2006.

E. F. Fama and K. R. French. The cross-section of expected stock returns. *Journal of Finance*, 47:427–465, 1992.

E. F. Fama and K. R. French. Common risk factors in the returns on stocks and bonds. *Journal of Financial Economics*, 33:3–56, 1993.

E. F. Fama and J. D. MacBeth. Risk, Return, and Equilibrium: Empirical Tests. *Journal of Political Economy*, 81(3):607–636, 1973.

FCA. Catching a falling knife: an analysis of circuitbreakers in UK equity markets. Technical report, 2017. URL `https://www.fca.org.uk/publications/research/analysis-circuit-breakers-uk-equity-markets`.

J. D. Finnerty. Short selling, death spiral convertibles, and the profitability of stock manipulation. SEC working paper, 2005. URL `https://www.sec.gov/comments/s7-08-08/s70808-318.pdf`.

A. Frazzini and L. H. Pedersen. Betting against beta. *Journal of Financial Economics*, 111: 1–25, 2014.

T. C. Green and B.-H. Hwang. Price-based return comovement. *Journal of Financial Economics*, 93(1):37–50, 2009. doi:10.1016/j.jfineco.2008.09.002.

R. Greenwood. Excess comovement of stock returns: Evidence from cross-sectional variation in Nikkei 225 weights. *Review of Financial Studies*, 21(3):1153–1186, 2007. doi:10.1093/rfs/hhm052.

S. Greppmair, S. Jank, P. A. C. Saffi, and J. Sturgess. Securities lending and information acquisition. Working paper, July 2020. URL `https://papers.ssrn.com/sol3/papers.cfm?abstract_id=3604977`.

J. M. Griffin and J. Xu. How smart are the smart guys? A unique view from hedge fund stock holdings. *Review of Financial Studies*, 22(7):2531–2570, 2009. doi:10.1093/rfs/hhp026.

A. Hameed, R. Morck, J. Shen, and B. Yeung. Information, analysts, and stock return comovement. *Review of Financial Studies*, 28(11):3153–3187, 2015.

G. Huberman, S. Kandel, and G. A. Karolyi. Size and industry-related covariations. IIBR Working Paper No. 960/88, February 1988.

R. D. Israelsen. Does common analyst coverage explain excess comovement? *Journal of Financial and Quantitative Analysis*, 51(4):1193–1229, 2016. doi:10.1017/S002210901600051X.

S. Jank and E. Smajlbegovic. Dissecting short-sale performance: Evidence from large position disclosures. July 2021. URL https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2631266.

S. Jank, C. Roling, and E. Smajlbegovic. Flying under the radar: The effects of short-sale disclosure rules on investor behavior and stock prices. *Journal of Financial Economics*, 139:209–233, 2021.

C. M. Jones, A. V. Reed, and W. Waller. Revealing shorts: An examination of large short position disclosures. *Review of Financial Studies*, 29(12):3278–3320, 2016.

H. Levene. Robust tests for equality of variances. In I. Olkin and H. Hotelling, editors, *Contributions to Probability and Statistics: Essays in Honor of Harold Hotelling*, pages 278–292. Stanford University Press, 1960.

LSE. Maintaining orderly markets: circuit breakers explained. Technical report, 2020. URL https://docs.londonstockexchange.com/sites/default/files/documents/maintaining-orderly-markets.pdf.

W. K. Newey and K. D. West. A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. *Econometrica*, 55(3):703–708, 1987.

R. S. Pindyck and J. J. Rotemberg. The comovement of stock prices. *Quarterly Journal of Economics*, 108(4):1073–1104, 1993.

C. Pirinsky and Q. Wang. Does corporate headquarters location matter for stock returns? *Journal of Finance*, 61(4):1991–2015, 2006. doi:10.1111/j.1540-6261.2006.00895.x.

L. C. G. Rogers and F. Zhou. Estimating correlation from high, low, opening and closing prices. *Annals of Applied Probability*, 18(2):813—823, 2008.

A. Shkilko, B. Van Ness, and R. Van Ness. Short selling and intraday price pressures. *Financial Management*, 41(2):345–370, 2012. doi:10.1111/j.1755-053x.2012.01189.x.