UNIVERSITY OF CAMBRIDGE
Faculty of Economics

Institute for New Economic Thinking

Cambridge Working Papers in Economics

Cambridge-INET Working Paper Series No: 2020/34

Cambridge Working Papers in Economics: 2066

COMMON SHORT SELLING AND EXCESS COMOVEMENT

Marco Valerio Geraci (University of Cambridge)

Jean-Yves Gnabo (Université de Namur)

David Veredas (Ghent University)

We show that common short sold capital can explain future six-factor excess return correlation one month ahead, controlling for many pair characteristics, including similarities in size, book-to-market, and momentum. We explore the possible mechanisms that could give rise to this relationship. We find that price pressure cannot explain the uncovered relationship. Rather, the relationship is consistent with informed trading, which we identify using additional profiling data for short sellers.

Keywords: short selling, comovement, hedge funds
JEL Classification: G12, G14

Common Short Selling and Excess Comovement*

Marco Valerio Geraci†, **Jean-Yves Gnabo**‡, and **David Veredas**⋆

†*Cambridge-INET Institute and National Bank of Belgium*

‡*CeReFiM, Université de Namur*

⋆*Vlerick Business School and Ghent University*

First version: 29 October 2017

This version: July 24, 2020

Download the latest version: https://www.dropbox.com/s/6dzcdt1i76jnsk7/main.pdf?dl=0

Abstract

We show that common short sold capital can explain future six-factor excess return correlation one month ahead, controlling for many pair characteristics, including similarities in size, book-to-market, and momentum. We explore the possible mechanisms that could give rise to this relationship. We find that price pressure cannot explain the uncovered relationship. Rather, the relationship is consistent with informed trading, which we identify using additional profiling data for short sellers.

Keywords: short selling, comovement, hedge funds

JEL Classification: G12, G14

*The views expressed in this paper are those of the authors and do not necessarily reflect the view of the National Bank of Belgium or of the Eurosystem. The authors gratefully acknowledge the support of the Cambridge-INET Institute and the Communauté française de Belgique (Projet d'Actions de Recherche Concertées grant 13/17-055). We thank Laurent Barras (discussant), Christiane Baumeister, Sophie Béreau, Oscar Bernal, Catherine Dehon, Pelin Ilbas, Oliver Linton, Tarik Roukny, Davy Paindaveine, Pedro Saffi, and Kristien Smedts (discussant), and conference and seminar participants at the University of Cambridge, the 2018 Belgian Financial Research Forum, the 2019 International Forecasting Symposium, the 2018 and 2019 International Association of Applied Econometrics Conference, the 2019 European Economic Association Meeting in Manchester, the 2018 Paris December Finance Meeting, and the 2019 Econometric Society Winter Meeting for helpful comments and suggestions.
Corresponding author email: mvg23@cam.ac.uk.

I Introduction

In this paper, we show that common short sold capital provides explanatory power for the cross-sectional correlation of stock price returns, above and beyond that provided by classic fundamentals (Huberman, Kandel, and Karolyi, 1988, Pindyck and Rotemberg, 1993, Pirinsky and Wang, 2006), common ownership (Antón and Polk, 2014, Bartram, Griffin, Lim, and Ng, 2015), and common analyst coverage (Israelsen, 2016).

Using short positions disclosed to the Financial Conduct Authority (FCA) of the United Kingdom (UK) between Nov. 2012 and Dec. 2019, we construct a measure of common short selling. Our measure connects stocks that are shorted by the same entity. We use these connections to predict (in-sample) the future excess return correlation of equity returns.

Our measure of common short selling predicts excess stock 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 2.3% of the average six-factor excess return correlation for a given stock pair.

Our results show that stocks with high common short sold capital provide less diversification benefits than stocks with low or no common short sold capital. In this sense, investors should consider whether stocks have common short sellers when building their portfolios. Our approach illustrates how to account for this, using publicly disclosed short selling data.

According to the comovement literature, correlated demand and supply of investors or common liquidity shocks drive comovement through price pressure (Barberis, Shleifer, and Wurgler, 2005, Chen, Singal, and Whitelaw, 2016). This could be due to investor choices to allocate funds to stocks that are similar across different dimensions, such as size, sector, or index membership (Greenwood, 2007). Alternatively, comovement through price pressure could be due to different subset of investors trading securities according to specific preferred habitats. Collectively, we refer to these views as the price pressure mechanism.

For common ownership, this mechanism suggests that, by purchasing and selling stocks according to investment categories or "habitats", large institutions *induce* excess comovement. A similar mechanism might explain the result we uncover with common short positions—by short selling (or covering short positions on) stocks according to asset classes, short sellers *induce* higher correlation.

To verify whether the price pressure mechanism is a viable explanation of our results, we exploit the prediction that it prominently occurs when liquidity is scarce (Brunnermeier and Pedersen, 2005). Specifically, we test whether the uncovered association between common short sold capital and future correlation is stronger for less liquid stocks.

We do not find sufficient evidence to confirm this is true. In addition to disproving the price pressure mechanism for common short selling, this result helps shed light on theoretical studies that argue that short sellers can trigger shifts in correlation (Brunnermeier and Oehmke, 2014, Cont and Wagalath, 2013). At least for the frequency and periodicity of our study, our results are not in line with the predictions of these models. Rather, they are consistent with empirical findings that the price pressure of short sellers is weaker than that of long sellers (Shkilko, Ness, and Ness, 2012).

Thus, we turn to an alternative explanation for the relationship between common short selling and excess comovement, based on informed trading by short sellers.

Previous studies have shown that short sellers are sophisticated market agents, who trade on the basis of superior information and are able to predict future stock price movements (Boehmer, Jones, and Zhang, 2008, Diether, Lee, and Werner, 2009, Boehmer, Duong, and Huszaár, 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 verify this view by identifying the short sellers in our sample and classifying them according to several traits. We find that the effect of common short selling is most predictive of future excess correlation when it originates from informed agents, such as hedge funds and active investors, with high turnover and low concentration.

In a similar spirit to Jiao, Massa, and Zhang (2016), by combining long and short positions of investors, we are able to reveal aspects that could not be studied with just one side of the data. Our results reveal a dichotomy—whereas common ownership affects comovement through price pressure, common short selling relates to comovement through informed trading. This concurs with studies evidencing the role of short sellers for price discovery and liquidity provision (Boehmer, Jones, and Zhang, 2013).

Finally, we contribute to a growing body of literature that makes use of short selling disclosure data (Boehmer et al., 2018, Jones, Reed, and Waller, 2016, Jank, Roling, and Smajlbegovic, Forthcoming). This data is partially censored, such that only large short positions are observable. However, compared to previous short selling data, it comes with the invaluable advantage of covering actual net short positions, submitted by short sellers to the regulator.

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. We connect stocks according to common short sellers and show that these connections have informational value for predicting comovement. This would not have been possible with traditional datasets on short interest or securities lending proxying for short selling.

The rest of the paper is organized as follows. In Section II, we describe the short selling disclosure data and in Section III we outline the methodology used. In Section IV, we present the results showing the predictive power of the number of common short sellers for forecasting future excess correlation. In Section V, we investigate the two possible mechanisms that can explain our results. In Section VI, we draw our conclusions.

II Data and Sample

According to EU regulation N. 236/2012, ratified in November 2012 by the European Parliament and the European Council, every financial subject detaining a net short position above 0.2% of shares outstanding of a company is required to disclose their position to the relevant market authority—the FCA, in the UK. Furthermore, any short position that passes the threshold of 0.5%, and every change by 0.1% after that, has to be disclosed publicly on the FCA's website. Public disclosures include the name and ISIN of the shorted share, the name of the short seller, and the quantity short sold, in terms of percentage of shares outstanding. In calculating their net short selling position, short sellers are required to include synthetic short positions obtained through options.

We collected all publicly disclosed short selling positions that were available on the FCA's website, between November 2012 and December 2019. Jones et al. (2016) study the effects of the disclosure regulation for 12 European countries (Austria, Belgium, Finland, France, Germany, Ireland, Italy, the Netherlands, Portugal, Spain, Sweden, and the UK) and find that UK disclosures represent over half of their sample disclosures. Compared to short interest data, short selling disclosures are actual net short positions obligatorily submitted to the regulator and, therefore, are subject to attentive scrutiny.

The disclosures involve 657 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 summarizes the information given by public disclosures of short positions to the FCA. During the sample period, 60,099 disclosures were made, which included 8,026 position originations (i.e., the first disclosure of a net short position above 0.5% of the shares outstanding), 44,493 updates (i.e., any increments or decrements of 0.1% of the shares outstanding after the 0.5% threshold), and 7,580 position terminations (i.e., disclosures under the 0.5% and representing the closing of the short position).

The number of disclosures increased steadily over the years of our sample, with the exception of 2019.[1] This may suggest that, over time, short sellers became more active and/or that they became more accustomed to the new disclosure regulation.

Panel B of Table 1 presents additional descriptive statistics regarding the disclosure data. The upper part of the panel 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 median holding period length of a disclosed short position is of 28 trading days.

On average, the stocks of the disclosure data have around 3 short sellers per year taking position on them. Although the standard deviation of short sellers per stock is not as large as that of stocks per short seller, we observed that some stocks have as many as 29 different short sellers taking position against them.

For all the stocks that had at least one disclosed short selling position, we searched for

[1]Note that we only observe data for the last two months of 2012.

Table 1: Descriptive statistics regarding disclosure data.

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

Year	Disclosures	Originations	Stocks	Short Sellers
2012	793	323	165	106
2013	4489	617	261	159
2014	5151	717	262	162
2015	7167	1008	279	185
2016	9301	1232	317	214
2017	10751	1384	321	224
2018	12557	1590	355	229
2019	9890	1155	357	203

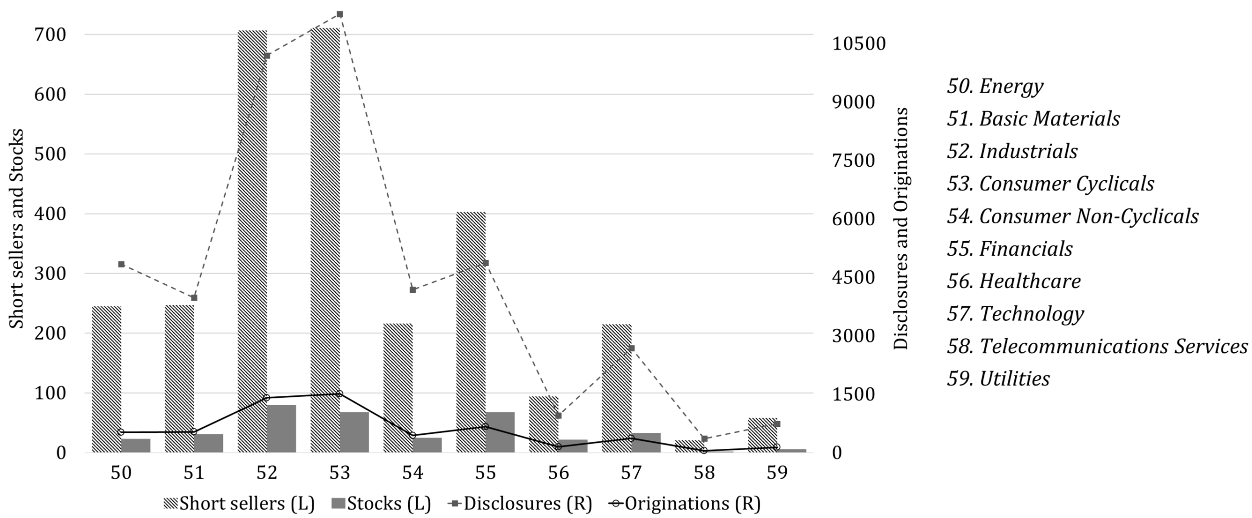
Panel B: Summary Statistics for Stocks and Short Sellers

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

Panel A shows the number of disclosed position and the number of disclosures that were originations of a short position. Panel B shows the summary statistics regarding the number stocks and short sellers involved in the disclosure data.

historical price data and for company information using Refinitiv EIKON. We managed to match the data for 470 stocks. For these stocks and for the time period covered, we also searched for ownership data from Refinitiv Eikon and analyst earnings estimates from the Institutional Brokers Estimate System (IBES). This data is used to build the controls for

Figure 1: Sample information by stock NACE Rev. 2 classification.



The chart shows the matched data sample by company classifier, following the Economic sector TRBC codes. 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 (straight).

pairwise realised correlation.

To compute the variables in our model, we additionally required the stocks in our sample to have a price for 50% of the trading days from Oct. 2007 to Dec. 2019. Moreover, we only consider those stocks that were primary shares of companies traded on the London Stock Exchange (LSE).

After these restrictions, and after dropping stocks not covered by ownership and analyst estimates data, the final matched sample involves 358 stocks and 44,075 disclosed short selling positions. Figure 1 summarizes the matched sample according to the Thompson Reuters Business Classification (TRBC) economic sector code. 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. As outlined in the next section, sector information is used to control for similarities across stocks in our model.

We present additional descriptive statistics in Panel A of Table A2 in the Internet Appendix.[2] The average (median) market capitalisation of companies in our sample is about \$5.4 billion (\$1.2 billion). For the purpose of comparison, the average market capitalisation of companies listed on the LSE, at the end of 2018, was of \$3.2 billion. We also note that the stocks in our sample appear to have low analyst coverage—on average, every year, only 0.88 analysts issue a 1-year ahead earnings forecast. For a sample of stocks from the New York Stock Exchange (NYSE), American Stock Exchange (AMEX), and NASDAQ stock Market (NASDAQ), Hameed, Morck, Shen, and Yeung (2015) report 4.60 analysts on average.

III Methodology

A The Model

We follow the approach proposed by Antón and Polk (2014), who studied the impact of mutual fund holdings on the correlation of abnormal returns. Here, we are interested in the effect of common short selling. We construct our main covariate, $SSCAP$, from the short selling disclosure data described in Section II.

We define $SSCAP_{ij,t}$ as the total value of stocks i and j, shorted by S common short sellers at the end of the quarter preceding month 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 short position held by common short seller s against stock i at the end of the quarter preceding month t and $MV_{i,t}$ is market value of stock i at the end of the quarter preceding month t. The value of the short position, $W_{i,t}$, is computed using the publicly disclosed short position weight, multiplied by the value of market capital 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 2 summarises the distribution of $SSCAP$. Median common short sold capital of

[2] Available at: https://www.dropbox.com/s/ftyywavevp5eh32/appendix.pdf?dl=0.

Table 2: The Cross-Sectional Distribution of SSCAP

			Percentiles						
Year	Mean	Std	0	25	50	75	95	99	100
All	0.0003	0.0018	0	0	0	0	0	0.0086	0.0901
2013	0.0001	0.0011	0	0	0	0	0	0.0049	0.0475
2014	0.0001	0.001	0	0	0	0	0	0.0049	0.0455
2015	0.0001	0.0013	0	0	0	0	0	0.0061	0.0666
2016	0.0003	0.0018	0	0	0	0	0	0.0089	0.068
2017	0.0004	0.0024	0	0	0	0	0	0.0116	0.0812
2018	0.0005	0.0027	0	0	0	0	0.0045	0.0129	0.0901
2019	0.0005	0.0026	0	0	0	0	0.0047	0.0125	0.0679

This table reports the cross-sectional distribution of (scaled) common short sold capital. $SSCAP_{ij,t}$ is the total value of capital short sold by all common short sellers scaled by total market capitalisation, as of quarter-end. The distributions of $SSCAP$ is shown for the whole sample and for individual years of sample coverage.

stock pairs is 0.18%, but can reach up to 9% of common capital. $SSCAP$ is sparse as, over any given quarter, short sellers tend to take few common positions across several stocks. Nonetheless, as we will show in the next section, it contains explanatory power for future excess correlation.

As can be noticed from Table 2, $SSCAP$ 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 ($\rho_{ij,t+1}$) of each stock pair's daily six-factor excess returns. The six factors we consider are the market, size, and value factors (Fama and French, 1993), momentum (Carhart, 1997), betting-against-beta (Frazzini and Pedersen, 2014), and quality-minus-junk (Asness, Frazzini, and Pedersen, 2018).[3] We include the latter two factors because recent studies have shown that they can explain part of the performance of short sellers (Jank and Smajlbegovic, 2017).

In addition to these six factors, we also control for various pair characteristics, outlined in the next subsection. All variables on the right-hand side of Equation 2 are updated quarterly, meaning that variables relating to month t contain data ending at the end of the last quarter

[3]Daily factors and one-month Treasury bill rate are from AQR's website

preceding t.

$$(2) \qquad \rho_{ij,t+1} = a + b_s \times SSCAP^{*}_{ij,t} + \sum_{k=1}^{n} b_k \times CONTROL_{ij,k} + \epsilon_{ij,t+1}$$

If the number of common short sellers shorting stocks i and j is associated with higher future correlation in the excess returns of stocks i and j, then b_s will be positive and significant.

To limit the effect of serial correlation, we estimate b_s 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_s. 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.

B Controls

In Equation 2, we include a large set of controls that could explain stock return correlations beyond the six factors used to compute excess returns.

First, we control for common ownership of stock pairs. Let $HCAP_{ij,t}$ be the total value of i and j held by common owners, scaled by the market capitalization of the two stocks. Ownership data is from Refinitiv EIKON. $HCAP$ controls for excess correlation created by common owners purchasing and selling stocks. By including $HCAP$ in our specification, we aim to separate the excess correlation due to short selling activity from long strategies of investors.

We control for industry effects using the Thompson Reuters Business Classification (TRBC).[4] The TRBC consists of four levels of classification (Economic Sector, Business Sector, Industry Group, and Industry). We created the variable $NUMTRBC_{ij,t}$, which captures the number of consecutive equal level codes, starting from the most generic, in the TRBC of stocks i and j. We also compute a series of additional size, style, and pair characteristic controls.

[4]TRBC offers the widest coverage for the stocks in our sample. Results do not change with alternative definitions of the industry control.

In terms of size, we control for the size of the two companies i and j using their market capitalisation. Chen, Chen, Chen, and Li (2017) show that stocks of similar size tend to be more highly correlated. Hence, we captured differences 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 the end of the quarter preceding period t. As size is a proxy for the number of shares available to short sell (Dechow, Hutton, Meulbroek, and Sloan, 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 the end of the quarter preceding period t.

In terms of style, we control for similarities in the book-to-market ratio and the momentum of the two stocks. We define $SAMEBM_{ij,t}$ and $SAMEMOM_{ij,t}$ as the negative absolute difference in the cross-sectional percentile ranking of, respectively, the book-to-market ratio, and the momentum of the two stocks.[5]

It is well known that book-to-market ratios are positively associated with future returns (Stattman, 1980, Rosenberg, Reid, and Lanstein, 1985, 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 include the geometric average (of the cross-sectional percentile rank) of the book-to-market of the two stocks, $GAVBM_{ij,t}$. Furthermore, we include the geometric average of the percentile rank of the momentum of the two stocks, $GAVMOM_{ij,t}$. Short sellers might ride on declining prices, which are, by definition, correlated.

Finally, we control for a series of stock pair characteristics. To address concerns for potential reverse causality in our regression model, we controlled for the past 2-year monthly correlation of stock pairs, which we denote $RETCORR_{ij,t}$. We also control for the past 5-year correlation of the return on equity for every pair, $ROECORR_{ij,t}$. Companies with similar profits are expected to have correlated stock returns (Chen et al., 2017). We also included a control variable capturing similarity in abnormal trading volumes of stock pairs, $VOLCORR_{ij,t}$, which measures the monthly correlation in abnormal trading volumes over the past two years.[6]

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

[6] We compute abnormal trading volumes as the residual of the regression of volume on an annual trend and monthly dummies.

We control for the absolute difference in the price level of the two stocks, which we denote $DIFFPRICE_{ij,t}$, as well as the absolute difference in their leverage, $DIFFLEV_{ij,t}$.

Following Antón and Polk (2014), we also build a control for the difference in sales growth. However, because sales data is only available for half of our sample of stocks, we omit such control from our main regressions. For the subsample for which data is available, we verify that results are unchanged by including difference in sales growth in our model.

Lastly, we create variables to control for geographical location (Pirinsky and Wang, 2006). First, dummy variables $DCOUNT$ and $DCITY$ measure, respectively, whether two companies had their headquarters in the same country and city. $GEODIST$ measures the geographical distance (in Kilometers) between the headquarters of two companies.

Past studies have reported that index membership effects correlation (see, Barberis et al. (2005) and Greenwood (2007)). Since the stocks in our sample are all listed on the London Stock Exchange, we check for their membership to the FTSE100. Throughout the sample period, only one stock was member of the index. Therefore, we did not include controls for index memebership of stock pairs.

With the exception of the dummy variables, we standardise all variables so that they have zero mean and unit standard deviation. This is to ease interpretation of regression coefficients. Moreover, apart for $GEODIST$ and the dummies, we update all controls quarterly. We present summary statistics of the controls in Panel B of Table A2 of the Internet Appendix.

IV Results

A Excess Stock Correlation with Common Short Selling

Table 3 shows the results of the Fama and MacBeth regressions using $SSCAP^*$ to predict the realised correlation of abnormal returns, as specified in Equation 2.

The first column of Table 3 describes the baseline specification using just $SSCAP^*$ with a constant. The coefficient on $SSCAP^*$ is positive and significant, with a coefficient equal to 0.00303. Given that $SSCAP^*$ is standardized to have zero mean and unit standard deviation, the constant term, which is 0.05351, reflects the average abnormal correlation between stock returns, when $SSCAP$ is at its mean. The coefficient on $SSCAP^*$ can thus be interpreted with respect to the average abnormal correlation. A standard deviation increase in the common short sold capital is associated with an increase of the predicted excess return correlation of about 5.7% of the average excess return correlation.

The second column of Table 3 shows results controlling for common ownership, similarity in sector, size, book-to-market, and momentum. The coefficient on $HCAP$ is positive and highly significant. This result is consistent with common owners inducing higher correlation through their trading of stocks held in common (Bartram et al., 2015).

Recall that the dependent variable is the correlation of the residuals of a six factor asset pricing model, which includes the size, book-to-market, and momentum factor of Fama and French (1993) and Carhart (1997). Despite this, similarity in size book-to-market, and momentum still have a strong positive and significant association with future excess correlation.

Consistent with early studies of Pindyck and Rotemberg (1993), the similarity in sector of the two companies is a key determinant of correlation. The coefficient on $NUMTRBC^*$ is statistically significant with a coefficient of 0.01277 and a t-statistic of 33.23.

In the second specification we also include the size control $GAVSIZE^*$, the geometric average of the percentile ranking of the stock pair size. After adding these controls, the size of the coefficient on $SSCAP^*$ decreases, but remains significant at 10% confidence level with a p-value of 5.8%.

In the third specification of Table 3, we add additional controls for pair characteristics. The coefficient estimates for these variables are reported in the Internet Appendix. 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 excess returns. The coefficients on $DIFFPRICE^*$ is also positive, but insignificant. The coefficients on the dummy variables $DCOUNTRY$ is positive and significant at the 5% confidence level, indicating that stocks of companies based in the same country are more strongly correlated. Quite to the contrary, the coefficient on $DCITY$ is negative and significant at the 5%

Table 3: Common short selling and excess correlation

	Dependent Variable: Correlation of 6F Residuals			
	(1)	(2)	(3)	(4)
Constant	0.05351	0.05361	0.05072	0.05383
	(13.22)	(13.28)	(12.08)	(13.3)
$SSCAP^*$	0.00303	0.00074	0.00086	0.00125
	(6.63)	(1.92)	(2.19)	(3.28)
$HCAP^*$		0.00294	0.00226	0.00293
		(5.71)	(3.73)	(4.41)
$SAMESIZE^*$		0.00758	0.00623	0.00605
		(10.73)	(8.52)	(8.43)
$SAMEBM^*$		0.00182	0.00125	0.00116
		(5.63)	(4.17)	(3.44)
$SAMEMOM^*$		0.00964	0.00732	0.00595
		(12.7)	(10.33)	(8.97)
$NUMTRBC^*$		0.01277	0.0111	0.01112
		(33.23)	(32.68)	(32.73)
$GAVSIZE^*$		0.01437	0.0114	0.01071
		(11.52)	(9.99)	(8.91)
Other controls reported in the Internet Appendix				
$R2$	0.05798	0.07386	0.07791	0.07906
	(7.81)	(8.97)	(9.22)	(9.21)
No. Obs.	63,415	59,177	50,899	50,583
	(212.57)	(124.87)	(101.04)	(100.82)
Size controls	No	Yes	Yes	Yes
Pair characteristic controls	No	No	Yes	Yes
Style controls	No	No	No	Yes

This table reports the Fama and MacBeth (1973) cross-sectional regression of the monthly realised correlation of excess returns on common short sold capital and stock pair control variables. The dependent variable is the realised correlation of a stock pair six-factor (Fama and French (1993), Carhart (1997), Frazzini and Pedersen (2014), Asness et al. (2018)) excess returns in month $t+1$. The independent variables are updated quarterly and include $SSCAP^*$, which is the (scaled) capital of the stock pair shorted by common short sellers. $HCAP^*$ is the (scaled) capital held by common owners. $SAMESIZE^*$, $SAMEBM^*$, and $SAMEMOM^*$ are the negative of the absolute difference in the cross-sectional percentile ranking of, respectively, size, book-to-market, and momentum, for the stock pair. $NUMTRBC^*$ is the number of consecutively equal digits in the TRBC code for the stock pair. $GAVSIZE^*$ is the geometric average of the cross-sectional percentile ranking of size for the stock pair. Estimates for the remaining controls may be found in the Internet Appendix. All independent variables (except the dummy variables) are normalised to have zero mean and unit standard deviation. t-statistics (in parentheses) are computed using Newey and West (1987) robust standard errors, accounting for autocorrelation up to 3 lags (one quarter).

confidence level. With these additional controls the coefficient of $SSCAP^*$ is significant at the 5% level (t-statistic of 2.19, p-value of 3.2%).

In the fourth column of Table 3, we add book-to-market and momentum measures for the stock pairs, $GAVEBM^*$ and $GAVMOM^*$. Also, we replace both dummy variables with the continuous variable $GEODIST^*$. Again, coefficient estimates for these controls are given in the Internet Appendix. In this specification, which is the most complete and flexible, the coefficient on $SSCAP^*$ gains in significance (t-statistic of 3.28 and p-value of 0.2%). The coefficient equals 0.00125, which underlines that an increase in one standard deviation in common short sold capital is associated with an increase of the predicted correlation of excess returns of about 2.3% of the average abnormal correlation.

The coefficients reported in Table 3 show that the effect of a standard deviation increase in common short selling is smaller than the effect of a standard deviation increase in common ownership. To some extent, this difference reflects the fact that it is much easier to "go long" than to "go short" and that long positions are generally much larger than short positions.

Consider interpreting results in terms of stock pair capital, using the standard deviation of $SSCAP$ given in Table 2. In the most complete specification, a 1% increase in common short sold capital is associated with an increase of excess correlation of 0.00679, equivalent to 12.6% of the average excess correlation. Taking into account the standard deviation of $HCAP$ given in Panel B of Table A4 of the Internet Appendix, a 1% increase in common ownership is associated with an increase of excess correlation of 0.00028, that is 0.5% of its average. Hence, if common short positions were as large as common long positions, they would likely have a stronger association with correlation.

In untabulated results, we find that fitted values that are due to $SSCAP^*$ range from an average minimum of 0.0395 to an average maximum of 0.1039, around an average abnormal correlation of 0.0538.[7] As a mean for comparison, the fitted values due to $HCAP^*$ range from 0.0389 to 0.0753, showing that common short positions have similar explanatory power to common long positions.

Overall, despite the high variability of the correlation of excess returns, which have an average standard deviation of 0.24, in the fourth specification, the regression has an an

[7]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 6-factor excess returns using the orthogonalised $SSCAP^*$ and save the minimum and maximum forecasted value for each cross-section. Finally, we average these values across time.

average R^2 of 7.91% and the association between $SSCAP^*$ and the future correlation of excess returns is significant at 1% confidence level.

Notice that $SSCAP^*$ explains excess returns of a six factor model, even after accounting for many controls and characteristics. As explained in more detail in the next subsection, the results of Table 3 are even stronger if we use excess returns from a four factor or one factor model.

B Robustness

To check the robustness of our results, we carry out a series of alternative specifications of the regressions given in Table 3.

First, we include the (standardised) number of common analysts, A^*, as an additional control variable in our models.

Including A^* in our regressions helps us control for factors that might contaminate the effect of common short selling. According to Israelsen (2016), common analysts produce correlated forecast errors that propagate to prices, leading to excess correlation.

We define $A_{ij,t}$, equal to the number of analysts issuing an earnings forecast of both stocks i and j over the past year. The distribution of A, presented in Panel C of Table A4 of the Internet Appendix, shows that, especially for early cross-sections, our sample of stocks has low (common) analyst coverage.[8] For this reason, we run these additional robustness regressions with A^* for a subsample starting in July 2017.

We present results in Table A6 in the Internet Appendix. Although, across all specifications, the coefficients on $SSCAP^*$ are higher than for the full sample shown in Table 3, significance decreases for the second and third specification, (p-values of, respectively, 13.6% and 9.1%). Nonetheless, the estimate remains significant at the 5% level of confidence (p-value of 1.6%) in the most complete specification.

The coefficient on common analyst coverage is also positive and highly significant. This confirms the relation between common analyst coverage and excess correlation that has been uncovered in several studies e.g., Antón and Polk (2014) and Israelsen (2016).

[8] For the more recent part of the sample, A appears to have a similar sparse distribution as $SSCAP$.

As a second robustness check, we verify results with different specifications of the dependent variable. First, to have a continuous dependent variable, we follow Pindyck and Rotemberg (1993) and transform correlation to $c = \tan(\pi\rho/2)$.

This transformation pushes high (absolute) correlation values towards minus/plus infinity. However, the transformation is mild for values of correlation close to zero, which is our case (see Figure A1 given in the Internet Appendix). For this reason, our results are basically unchanged if we consider this continuous measure of excess correlation. Panel A of Table A7 in the Internet Appendix reports the same regressions of Table 3 using as regressand the continuous measure of excess correlation, c, instead of ρ.

We also verify whether the result holds for different specifications of excess return correlation. Specifcally, we regress $SSCAP^*$ and controls on the correlation of simple returns (RET), the correlation of excess returns from the classic Capital Asset Pricing Model (CAPM), and the correlation of excess returns from the asset pricing model with Fama and French (1993) and Carhart (1997) factors (FFC). Results are displayed in Panel B of Table A7 in the Internet Appendix and show that, if anything, the association between $SSCAP^*$ and correlation is stronger when we account for less factors, reinforcing the validity of results in Table 3.

Lastly, we run the regressions in Table 3 using alternative and robust regressors. First, we verify that replacing common short sold capital, $SSCAP^*$, with the (standardised) number of common short sellers, NSS^*, does not alter our main results (see Panel A of Table A8 of the Internet Appendix). Second, we rerun all the regressions of Table 3 with rank-transformed (and standardised) regressors. Although this decreases the significance of the estimate on $SSCAP$, in the most complete specification, the estimate remains significant at 1% confidence level. These results are available in Panel B of Table A8 in the Internet Appendix.

V An Explanation

Different mechanisms can explain the positive relationship between common short selling and future excess return correlation. In this section, we distinguish between two main mechanisms and we test their predictions.

A The Price Pressure Mechanism

To explain the excess comovement associated with common ownership, Antón and Polk (2014) and Bartram et al. (2015) rely on the price pressure mechanism. According to Antón and Polk (2014), mutual fund flows induce these funds to buy/sell stocks in their portfolios, which leads to higher observed correlation of these stocks. On the other hand, according to Bartram et al. (2015), it is active reallocations of funds, rather than flows, which drives comovement.

A similar effect is foreseeable for common short sellers—by taking short positions against several stocks, short sellers apply negative price pressure, inducing higher correlation.

Rather than applying negative price pressure and eroding liquidity, short sellers have been found to help price discovery by acting as liquidity providers (Diether et al., 2009, Boehmer and Wu, 2013). Nonetheless, short selling price pressure has been discussed in several theoretical studies on liquidity crises.

Brunnermeier and Pedersen (2005) suggest that short sellers with predatory intentions can cause contagion i.e., shifts in correlation (Forbes and Rigobon, 2002). Cont and Wagalath (2013) argue that common short sellers can drive down prices of several stocks, inducing high correlation. Both models predict that the effect of short selling on correlation inversely depends on market depth of the stocks short sold—the more illiquid the stocks, the greater should be the impact of common short sellers on correlation.

Note that the effect does not necessarily have to work in only 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 in order 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 future short squeeze, the positive relationship between $SSCAP$ and future excess correlation 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 would be outside the scope of this paper, but to verify if the predictions of the price pressure mechanism are consistent with our results for $SSCAP$.

We construct a dummy variable that captures the illiquidity of a stock pair. Specifically, $DAMIHUD_{ij,t}$ is equal to one if the Amihud measure for both stocks i and j is in the upper cross-sectional quartile at quater-end t.[9]

We add the dummy variable and its interaction with $SSCAP^*$ to the most flexible model of our baseline regressions (corresponding to column 4 of Table 3).[10] Results, reported in the first column of Table 4, show that illiquidity is associated with lower future excess return correlation, when controlling for size, style, and common characteristics.

Contrary to what is predicted by the asset class effect, the interaction term with $SSCAP^*$ is negative and insignificant. The positive association between common short selling and excess comovement appears weaker for more illiquid stocks. In fact, the total effect of common short selling for illiquid stock pairs, is statistically insignificant.

This result is confirmed by further checks, using alternative measures of liquidity, based on turnover and equity float.

We define turnover as volume traded as a percentage of shares outstanding. Then, the dummy $DTURN$ is equal to one if, over the prior quarter, both stocks have average daily turnover below the lower cross-sectional quartile.

The second column of Table 4 shows that the interaction between $SSCAP^*$ and the turnover dummy is negative and significant at the 5% confidence level, indicating that the effect of common short selling is less strong 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.

Contrary to the results of Column 1, Column 2 shows that illiquidity, measured by $DTURN$, is positively associated with future excess comovement. Both the Amihud measure

[9]The Amihud (2002) measure of stock i is defined as $\frac{1}{Di,t}\frac{\sum_{d=1}^{D_t}|r_{i,t_d}|}{\sum_{d=1}^{D_t}V_{i,t_d}}$, 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.

[10]For the sake of brevity, the other specifications are omitted but give similar conclusions. These results are available from the authors upon request.

Table 4: Common short selling and excess correlation: The effect of illiquidity

	Dependent Variable: Correlation of 6F Residuals		
	(1)	(2)	(3)
Intercept	0.05612 (13.38)	0.05255 (13.16)	0.05703 (13.26)
$SSCAP^*$	0.00125 (2.92)	0.00144 (3.66)	0.00126 (2.87)
$DAMIHUD$	-0.00897 (-4.9)		
$SSCAP^* \times DAMIHUD$	-0.001 (-1.63)		
$DTURN^*$		0.00558 (4.53)	
$SSCAP^* \times DTURN$		-0.00168 (-2.22)	
$DFLOAT$			-0.01314 (-5.68)
$SSCAP^* \times DFLOAT$			-0.00072 (-1.46)
Other controls reported in the Internet Appendix			
Tot. $SSCAP$ effect for illiquid pairs	0.00025 (0.46)	-0.00023 (-0.32)	0.00054 (1.29)
$R2$	0.0796 (9.27)	0.0797 (9.29)	0.07969 (9.26)
No. Obs.	50513 (102.84)	50513 (102.84)	50572 (99.96)
Size controls	Yes	Yes	Yes
Pair characteristic controls	Yes	Yes	Yes
Style controls	Yes	Yes	Yes

This table reports the Fama and MacBeth (1973) cross-sectional regression of the monthly realized correlation of excess returns on common short sold capital and stock pair control variables. The dependent variable is the realized correlation of a stock pair 6-factor (Fama and French (1993), Carhart (1997), Frazzini and Pedersen (2014), Asness et al. (2018)) excess returns in month $t + 1$. The table shows the result of adding illiquidity dummies $DAMIHUD$, $DTRUN$, $DFLOAT$ and their interaction with $SSCAP^*$ to the regression carried out in Column 4 of Table 3. $DAMIHUD$ is equal to one if both stocks in a stock pair have an Amihud (2002) measure in the upper cross-sectional quartile during the previous quarter, and zero otherwise. Similarly, $DTRUN$ is equal to one if both stocks have an average daily turnover in the lower cross-sectional quartile during the previous quarter. $DFLOAT$ is equal to one if both stocks have percentage equity float capital in the lower cross-sectional quartile during the previous quarter. Estimates for the remaining controls may be found in the Internet Appendix. All independent variables are updated quarterly and normalised to have zero mean and unit standard deviation. t-statistics (in parentheses) are computed using Newey and West (1987) robust standard errors, accounting for autocorrelation up to 3 lag (one quarter).

and turnover are built with the volume of shares traded over the previous quarter. However, the former also takes into account price impact, by using the daily average absolute returns. The discording results are puzzling, and have lead us to verify the results with a third measure of liquidity, equity float.

We construct an additional dummy variable of illiquidity based on the percentage of equity float of the stock pair. $DFLOAT$ is equal to one if, for a stock pair, both stocks have equity float in the lower cross-sectional quartile over the previous quarter.

The third column of Table 4 presents results using $DFLOAT$. Similar to the results using $DAMIHUD$, Column 3 indicates that higher illiquidity is associated with lower levels of excess comovement. The regression in Column 3 of Table 4 also shows that the coefficient on interaction term with $SSCAP^*$ is positive, although insignificant at the 10% confidence level. This is consistent with previous results using Amihud and turnover as liquidity measures.

In unreported robustness checks, we obtain similar results using continuous liquidity measures based on the Amihud indicator, turnover, and equity float of stock pairs. Overall, these results point to a positive association between common short selling and excess return comovent for liquid stocks. This effect weakens as stock pair illiquidity increases.

Overall, these results do not provide sufficient evidence to confirm that the positive relationship between $SSCAP$ and excess comovement is due to price pressure mechanism of short selling.

If the price pressure mechanism does not explain the association between common short selling and excess comovement, how do our results reconcile with the work of Antón and Polk (2014) and Bartram et al. (2015)? One possibility is that the price pressure mechanism underlines the relationship between common ownership and comovement, but not that between common short selling and comovement.

This could occur if, for example, long sales (buys) drive prices more than short sales (covers). Some evidence of this asymmetry has been provided by Shkilko et al. (2012). In this case, price pressure remains a viable explanation for the relationship between common ownership and excess comovement, but is insufficient to explain the relationship between common short selling and excess comovement. Hence, we propose an alternative mechanism below.

B Informed Trading

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

The association between common short selling and future correlation might be the product of informed trading by short sellers. Short sellers trading according to information expect stock prices to decline in the future. As these declines realise, they should lead to higher observed correlation across the shorted stocks.

We verify this explanation by using additional data to isolate the effect highly informed common short sellers on future excess return correlation.

We obtain the investor profiles for 323 out of the 454 short sellers in our data from on Refinitiv EIKON. From these profiles, we collect the following information: investment orientation, investor type, portfolio turnover (%), and number of instruments held.[11]

First, we explore the differential impact of $SSCAP$ for hedge funds.[12] Hedge funds are considered highly informed agents (Aragon and Martin, 2012, Agarwal, Jiang, Tang, and Yang, 2013). For this reason, we would expect common short sellers that are hedge funds to be more informed than short sellers that are not hedge funds.

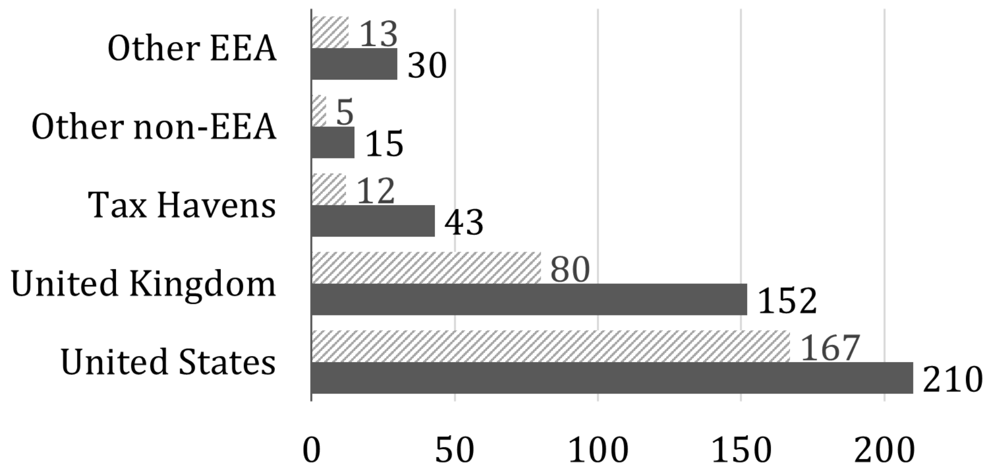
We classify short sellers in our sample as hedge funds if, according to their Refenitiv EIKON investor profile, their investor type is either "Hedge Fund" or "Investor Advisor/Hedge Fund". According to this classification system, our sample comprises 234 short sellers as hedge fund and 89 as non-hedge funds. Figure 2 depicts the classification of the short sellers in our sample according to their location.

Further, we double check that this hedge fund classification is consistent with others employed in the literature. In particular, using the SEC ADV forms filed by the short sellers in our sample, we obtain consistent classifications following the methodology of Brunnermeier

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

[12] We do not explicitly make the distinction between hedge funds and hedge fund managers. Simply, we refer to both types of entities as hedge funds.

Figure 2: Sample of Short Sellers



The charts show the number of short sellers identified as hedge funds or hedge fund managers (hatched/grey) and their country of location (solid/bold). Short sellers located in Switzerland were grouped within the "Other EEA" category, whereas the "Other non-EEA" category contains short sellers from Australia, Canada, and Hong Kong. The category "Tax Havens" groups short sellers located in tax haven countries, as defined by the OECD (2000).

and Nagel (2004) and Griffin and Xu (2009).

Table 5 presents the Fama and MacBeth (1973) cross-sectional regressions of excess return correlation on $SSCAP$ for different types of common short sellers. Results are shown for the fourth and most complete specification of Table 3. Alternative specifications present similar results and are available upon request.

The first column of Table 5 shows the effect of $SSCAP$ for short sellers that classify as hedge funds and non-hedge funds. The regression coefficient on $SSCAP$ for hedge funds is larger than that on non-hedge funds, and this difference is statistically significant at the 10% significance level (p-value at 8%).

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 involves less buying and selling and more long-haul investments. Our sample of short sellers includes 276 active investors and 47 passive investors.

Results, reported in the second column of Table 5, show that common short positions

Table 5: Common short selling and excess correlation by entity type

	Dependent Variable: Correlation of 6F Residuals			
	(1)	(2)	(3)	(4)
Hedge fund	0.00103 (2.88)			
Non-hedge fund	0.00036 (1.95)			
Active		0.00106 (2.77)		
Passive		0.00028 (1.95)		
Tax haven			0.00019 (1.72)	
Non-tax haven			0.00111 (2.92)	
High turnover				0.00034 (2.36)
Low turnover				0.00049 (1.15)
High concentration				0.00035 (2.8)
Low concentration				0.00071 (1.42)
Other controls reported in the Internet Appendix				
Difference between groups	0.00067 (1.77)	0.00078 (1.78)	0.00092 (2.25)	
$R2$	0.07909 (9.22)	0.07909 (9.22)	0.07908 (9.22)	0.07919 (9.22)
No. Obs.	50,583 (100.82)	50,583 (100.82)	50,583 (100.82)	50,583 (100.82)
Size controls	Yes	Yes	Yes	Yes
Pair characteristic controls	Yes	Yes	Yes	Yes
Style controls	Yes	Yes	Yes	Yes

This table reports the Fama and MacBeth (1973) cross-sectional regression of the monthly realized correlation of abnormal returns on common short sold capital and stock pair control variables. The dependent variable is the realized correlation of a stock pair 6-factor (Fama and French (1993), Carhart (1997), Frazzini and Pedersen (2014), Asness et al. (2018)) abnormal returns in month $t+1$. Each row reports the coefficient on $SSCAP^*$, the (scaled) capital of the stock pair shorted by common short sellers, computed for different types of short sellers. Estimates for the remaining controls may be found in the Internet Appendix. All independent variables are updated quarterly and normalised to have zero mean and unit standard deviation. t-statistics (in parentheses) are computed using Newey and West (1987) robust standard errors, accounting for autocorrelation up to 3 lags (one quarter).

of active investors are more strongly associated with future excess correlation than those of passive investors. As active investing requires processing extensive information rapidly, these results are in line with the informed trading explanation.

Next, we explore whether the association between common short selling and excess return correlation varies with the location of short sellers. We determine the location of the short sellers according to their country of incorporation, given by Refinitiv EIKON. If the country of incorporation is unavailable, we use the short sellers' country of headquarters. In turn, if the country of headquarters is unavailable, we use the country of principle business, as reported in the short sellers' ADV form.

Figure 2 shows that the short sellers are mainly located in the United States and United Kingdom. About 27.9% of the short sellers in our sample are domiciled in countries considered as tax haven by the OECD (2000).

The third column of Table 5 shows the differential effect of common short selling for entities located in tax havens. Compared to short sellers located in non-tax haven countries, short sellers located in tax haven countries tend to be more opaque (Jank et al., Forthcoming). The coefficient attached to common short selling is weaker for sellers that are located in tax haven countries than for those located in non-tax haven countries. The difference with is significant at 1%. Our results suggest that common short sellers located in tax haven countries take less informative positions in terms of predicting future excess return correlation.

In untabulated results, we have also verified whether the effect of $SSCAP$ was different for short sellers located in the United States compared to the effect for short sellers located in the United Kingdom. Although, the coefficient on $SSCAP$ for US short sellers was larger than that of UK short sellers, this difference was not statistically significant.

In the fourth column of Table 5, we present the effect of $SSCAP$ for common short sellers with different levels of portfolio turnover and portfolio concentration.

We define a short seller as a high (low) turnover short seller if it ranks in the upper (lower) cross-sectional tercile in terms of portfolio turnover. Similarly, we define high (low) concentration short sellers those short sellers that rank in the lower (upper) cross-sectional tercile in terms of number of stocks dealt.

The fourth column of Table 5 shows that the relationship between common short selling and future excess return correlation is stronger for short sellers that are high turnover and low concentration investors. These type of agents are likely to be highly informed, as they often re-balance their portfolios and invest in few specific stocks.

Overall, our results show that common short selling is predictive of future excess correlation especially when the common short sellers are informed agents, such as active hedge-funds, with high turnover and low concentration.

VI Conclusion

Our results have two main implications.

First, stocks with higher common short sellers are more correlated than stocks without common short sellers. For investors, this means that accounting for common short sellers provides diversification benefits. Accordingly, our new approach to interpreting publicly available data on short selling disclosures offers a useful tool to portfolio and risk managers.

Second, our analysis using illiquidity measures and short seller types shows that the association between common short selling and excess comovement can be primarily ascribed to the informed trading of short sellers rather than price pressure. For financial stability policy, this offers additional evidence that short sellers are informed agents, unlikely to act predatorily and trigger contagion.

Short selling disclosure data allows us to connect stocks according to their common short sellers. However, the European legislation sets the disclosure threshold at 0.5% of company capital, which means that we cannot observe potentially smaller common short positions that might have additional explanatory power for excess return comovement.

According to Easley and O'Hara (1987) and Avramov, Chordia, and Goyal (2006), large positions are more likely to be informed than small positions. This is in line with our result that common short selling relates to excess comovement through the informed trading. Future work could verify whether our conclusions continue to hold for smaller short positions, which are, as by EU Regulation N. 236/2012, 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. *The Journal of Finance*, 68(2):739–783, mar 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, jan 2002. doi:10.1016/s1386-4181(01)00024-6.

M. Antón and C. Polk. Connected stocks. *The Journal of Finance*, 69(3):1099–1127, may 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, aug 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, feb 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? *The Review of Financial Studies*, 28(11):3036–3072, 2015.

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

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

E. Boehmer, C. M. Jones, and X. Zhang. Shackling short sellers: The 2008 shorting ban. *Review of Financial Studies*, 26(6):1363–1400, Jun 2013. ISSN 1465-7368. doi:10.1093/rfs/hht017. URL `http://dx.doi.org/10.1093/rfs/hht017`.

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

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

M. K. Brunnermeier and M. Oehmke. Predatory Short Selling. *Review of Finance*, 18: 2153–2195, 2014. doi:10.1093/rof/rft043.

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, V. Singal, and R. F. Whitelaw. Comovement revisited. *Journal of Financial Economics*, 121(3):624–644, sep 2016. doi:10.1016/j.jfineco.2016.05.007.

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

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. Short-sale strategies and return predictability. *Review of Financial Studies*, 22(2):575–607, 2009.

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

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.

K. Forbes and R. Rigobon. No contagion, only interdependence: Measuring stock market comovements. *Journal of Finance*, 62(5):2223–2261, 2002.

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

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

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, may 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, Feb. 1988.

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

S. Jank and E. Smajlbegovic. Dissecting short-sale performance: Evidence from large position disclosures. 2017.

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*, Forthcoming.

Y. Jiao, M. Massa, and H. Zhang. Short selling meets hedge fund 13f: An anatomy of informed demand. *Journal of Financial Economics*, 122(3):544–567, dec 2016. doi:10.1016/j.jfineco.2016.09.001.

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

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

OECD. Towards global tax co-operation. Technical report, Report to the 2000 Ministirial Council Meeting and Recommendations by the Committee on Fiscal Affairs, 2000.

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

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

B. Rosenberg, K. Reid, and R. Lanstein. Persuasive evidence of market inefficiency. *Journal of Portfolio Management*, 11:9–17, 1985.

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

D. Stattman. Book values and stock returns. *The Chicago MBA: A Journal of Selected Papers*, 4:25–40, 1980.