CAVEAT VENDITOR – CROWDED EXITS!

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ABSTRACT

Crowded exits arise when short positions in a stock are large relative to its usual trading volume, and when a catalyst prompts short-sellers to cover their positions rapidly and simultaneously. Catalysts include, but are not limited to, public news releases by companies. Using a comprehensive dataset of daily stock lending activity across 681 companies on the London Stock Exchange from September 1st, 2003 to May 31st, 2007, we find that crowded exits are associated with positive abnormal returns (i.e. losses to short-sellers), and this result is statistically and economically significant. Our results indicate that short-sellers face an important indirect constraint on short-selling in the form of crowded exits. New, long-only investors would generally be unable to exploit this finding by buying into crowded exits, as by definition these are illiquid stocks; however, incumbent short-sellers, unable to readily cover their positions, suffer losses. As such, the risk of a crowded exit represents an indirect constraint on short-selling, or limit to arbitrage.

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1. Introduction

The study of short-selling constraints and their impact on market efficiency has been a popular area of research for over thirty years. The literature identifies two types of short-selling constraint: 'direct' and 'indirect'. Direct constraints, including legal restrictions on short-selling and additional costs associated with short-selling, are relatively simple to identify and understand. By contrast, indirect constraints have proved to be less tractable. D'Avolio (2002) and Nagel (2005) call for greater research into the nature and impact of indirect short-selling constraints. Geczy *et al.* (2002) argue that if short-selling problems explain the availability of factor portfolio returns to unskilled managers, then these short selling problems are not borrowing costs, but perhaps liquidity constraints. In this paper we consider *crowded exits,* a liquidity problem that is unique to short-sellers. Crowded exits arise in stocks where short-sellers hold large positions relative to normal trading volume, and when a catalyst prompts short-sellers to cover their positions rapidly and simultaneously. Catalysts include, but are not limited to, public news releases by companies. As short sellers unwind positions, the temporary excess demand for stock relative to normal trading volume leads to upward pressure on the stock price and these events are associated with losses to short-sellers that are economically and statistically significant. As such, the risk of a crowded exit represents an indirect constraint on short-selling. We examine the impact how liquidity provides an indirect constraint on short-sellers through a large, new stock lending database for listed UK company stocks.

As part of any anatomy of crowded exits, it is helpful to understand how a short position might become 'crowded' in the first instance. One possible scenario is outlined below. Initially, one or more traders with negative information about a company short-sell the company's stock. This represents informed trading and leads to an increase in the number of shares shorted. In the interest of transparency, most developed stock markets require the publication of data on short-selling or stock lending, and so this increase in short-interest is made public. Note that a substantial body of empirical research shows that heavily shorted stocks perform poorly (for example, Dechow *et al.* (2001), Angel *et al.* (2003), Gopalan (2003), Ackert and Athanassakos (2005), Diether *et al.*, 2007 and Boehmer *et al.*, 2008). Market participants who are aware of this literature can simply short-sell stocks that are already heavily shorted, in an attempt to benefit from other short-sellers' information. In so far as this imitation strategy occurs in markets, it follows that heavily shorted stock positions contain both informed traders and noise traders. Imitation strategies, however, contain the seeds of their own destruction. In this illustration, imitation leads to an increase in the size of the short position relative to the liquidity of the stock. A crowded position develops, based on a mix of informed short-selling and 'rational imitation', where the amount of shorted stock is large relative to the normal liquidity in the stock.

Our research focuses on short positions that are large relative to normal trading volume, which we characterise as 'crowded positions'. With a catalyst, rapid and simultaneous short-covering can commence and the crowded position becomes a 'crowded exit'. The idea is akin to the audience in a crowded theatre rushing to a narrow exit door once the fire alarm sounds…only so many can leave the building in any given interval of time. A variety of catalysts for a crowded exit are possible: a company could release new, positive information to the market; a sell-side analyst could upgrade his earnings forecast or trading recommendation on a stock; informed short-sellers could receive new, private information and start to cover their positions, to be followed by imitators; short-sellers could become unable to hold their short positions (this might arise because of client redemptions, margin calls or internal risk control mechanisms) and be forced to cover their short positions. When this is revealed to the market via public stock-lending data, it could be misconstrued as informed buying and act as a catalyst for short covering by imitators. Finally, manipulators could buy shares in a company so as to prompt short covering amongst traders who misconstrue the manipulative trades to be informed buying. Interviews with practitioners indicate that they perceive short selling to be risky since it can create a crowded exit scenario. In particular, they indicated concern about the difficulty of covering a short position when desired or that the short-seller could suffer losses due to the 'market impact' from quickly moving to cover a short position in the absence of liquidity.

In this paper we examine crowded exits in detail by making use of a commercial database from September 1st, 2003 to May 31st, 2007 that contains daily stock lending data for up to

681 stocks listed on the London Stock Exchange. The main findings of this research are as follows: crowded exits are associated with positive abnormal returns (that is, losses to short-sellers) of up to 27 per cent over a period of 60 days, and this result is both statistically and economically significant. We infer that short-sellers thus face an important indirect constraint on short-selling in the form of crowded exits. New, long-only investors would generally be unable to exploit this finding by buying into crowded exits, as by definition these are illiquid positions; however, incumbent short-sellers, unable to readily cover their positions, suffer losses.

2. Data

2.1 Data Sources

We create a new dataset for the purposes of this paper by merging data from two sources. The first of these is a commercial database of UK stock lending data from Index Explorers Ltd. This contains daily information on stock lending starting on September 3rd, 2003 when the database came into existence. At inception, this database included stocks from the 350 largest companies traded on the London Stock Exchange. The data is sourced from CREST - the organisation responsible for settlement of all trades on the London Stock Exchange. The amount of stock on loan is updated daily, but with a three day reporting lag (before December 12th, 2005 the lag was five days). Over time, the coverage of companies in the database increases through the addition of smaller capitalization stocks so that by the end date for this sample, May 31st 2007, there is stock lending data for 681 companies. The smallest of these companies have market capitalizations of approximately £25 million (USD 50 million) as of 2007. A number of companies cease to exist at some point during the 45 months (979 trading days) studied. This could be as a result of a merger or acquisition, the lapsing of the company into administrative receivership, or a change to private ownership. Such companies are included in the database until the date of their de-listing, to prevent survivor bias. We make use of all stocks in the database and all dates in the sample for which stock lending data is available - public holidays and weekends are naturally excluded.

The Index Explorers database includes the following daily information for each stock:

- Date
- Name of company
- SEDOL (a unique company identifier code)
- Turnover (defined as the number of shares traded that day)
- Stock Price (defined as the previous day's closing stock price)
- Volume (defined as turnover multiplied by stock price)
- Market Capitalisation (defined as number of shares in issue multiplied by stock price)
- Shares on Loan (defined as the number of shares reported to CREST as being on loan)
- Volume on Loan (defined as shares on loan multiplied by stock price)
- Percentage of Market Capitalization on Loan (defined as the volume of shares on loan divided by the market capitalization)
- Dividend Record Dates (the dates on which the recorded owners of shares on that day become entitled to receive the next dividend payment)
- Stock Utilisation Rate (the percentage of shares available for borrowing that are actually borrowed)
- Weighted Mean Stock Lending Fees (a weighted average of the fees paid by stock borrowers to stock lenders on initiation of the stock loan, measured as a proportion of the value of shares borrowed).

We use Datastream to obtain the following data for all for all FTSE All Share Index constituents from September 1st, 2002 to May 31st, 2007:

- Date
- Name of company
- SEDOL (a unique company identifier code)
- Daily stock returns (defined as the total return for a stock on that date)
- Book value per share (this value is generally updated annually for each UK company and is reported to the public via financial statements that are published up to six month in arrears. Datastream then 'backfills' the new book value to the end of the last financial year. To account for the possible delay in reporting book value per share and

to avoid hindsight bias, we shift the ‘book value per share series’ back by six months for each company)

- Free float percentage of shares (defined as the percentage of the total number of shares in issue that are available to ordinary investors i.e. that are not held away from the market by government or close family interests).

To facilitate the estimation of abnormal stock returns using an asset pricing model, we collect stock returns data for the year before the start of the Index Explorers database. This ‘formation period’ runs from September 1st, 2002 to September 1st, 2003 and is used to estimate the beta of each stock in the study.

Using each company’s SEDOL code as a unique identifier to reconcile stocks across the two databases, we merge the two databases, and construct a data set including trading and fundamental information of up to 681 stocks involved in stock lending activities on the London Stock Exchange, during the period from September 3rd, 2003 to May 31st, 2007. Overall, the dataset is an unbalanced panel of data for between 350 and 681 companies covering 979 trading days with 12 data items per firm day, plus a series of transformations such as the natural logarithms of daily stock returns.

2.2 Stock Lending as a Proxy for Short-Selling

Direct data on short-selling is not publicly available in the UK. Instead, stock lending data is available, on a daily basis. Stock lending acts as a proxy for short-selling, as the process of short-selling generally requires stock to be borrowed to facilitate settlement of the trade. However, there are a number of problems with using stock lending data as a proxy for short-selling.

First, shares do not need to be borrowed to undertake ‘naked’ short-selling (i.e. short-selling where there is no intention of subsequently settling the trade). Naked short-selling for periods of one day or longer is unlikely to be common, however, as it would involve failed settlement. ‘Repeat offenders’ would soon become known to the brokers for such trades, who would cease dealing with them. Intra-day shorting, though, does not require the delivery of stock for settlement at the end of the day, and so would not be revealed by daily stock lending data.

Second, stock lending occurs for a number of reasons other than short-selling. In general, borrowing shares results in the temporary receipt of legal ownership of the securities and so the borrower is entitled to dividends, voting rights, and so forth. Strategies exist to benefit from such arrangements. These include borrowing stock so as to exercise a vote at a firm’s General Meeting. Such a strategy would be illegal in the US, but is merely regarded as unethical in the UK. To prevent this practice, stock lenders are recommended to recall their shares prior to voting dates (see Myners, 2001)[1]. Another strategy involving stock borrowing is ‘dividend tax arbitrage’, a strategy that is feasible when a ‘borrower’ has a tax advantage over the ‘lender’. Christoffersen *et al.* (2001) demonstrate increases in securities lending around dividend record dates. As a result of these various practices, the dataset can become obfuscated. Christophe *et al.* (2005) discuss the problem of obfuscation in short-interest data arising from the aggregation of short positions from market participants with differing motivations (e.g. market makers, option-market arbitrageurs, traders expecting stock price declines). They provide evidence that some of the component parts that are aggregated in short interest data are negatively correlated with one another. One of the crucial issues for this study concerns the time around the dividend dates, since dividend tax arbitrage is common in practice. To minimize the risk that stock lending for dividend tax arbitrage is confounded with borrowing to facilitate short-selling, we remove data from three weeks before until three weeks after the dividend record date for each stock in this study of stock lending data. This is consistent with the method employed by Saffi & Sigurdsson (2007). In studies that use stock lending data, but that do not adjust for dividend tax arbitrage (e.g. Au *et al.*, 2007), results have not been consistent with those found in the bulk of the literature.

Third, the extent to which market practitioners fulfil their obligations to report stock lending to the market authorities is a further limitation on the use of stock lending data as a proxy for

[1] Myners Report, 2001. http://www.hmtreasury.gov.uk/media/DCB/53/myners_principles_web.pdf

short-selling. Discussions with practitioners involved in stock lending suggest that this problem is rare, but unavoidable.

Finally, derivatives can be used to effect transactions that are economically equivalent to short-selling (see, for example, Ofek *et al*., 2004). These trades are referred to as ‘synthetic short-sales’. The extent to which the use of derivatives to facilitate short-selling is transmitted into the stock lending market influences the usefulness of stock lending data as a proxy for short-selling. Discussions with stock-lending practitioners suggest that the majority, but not all, synthetic short-sales are ultimately hedged by the counter-parties to those trades, through borrowing stock and selling short.

2.3 Advantages and Limitations of the Dataset

A number of studies into short-selling make use of monthly data (e.g. Senchack and Starks, 1993 and Dechow *et al.*, 2001, Gamboa-Cavazos and Savor, 2007). However, Christophe *et al.* (2005) criticise the use of monthly short-selling data, as it “represents only a snap-shot of total shorted shares on one day during the month.” Cohen *et al.* (2007) find that almost half the securities lending contracts they study are closed out within two weeks, while the median contract length is 11 days. This suggests that monthly data could be inadequate for understanding the trading practices of short-sellers. The dataset used for this study incorporates daily data on borrowed shares (as proxy for shares shorted). This higher frequency data allows for an appropriate degree of granularity for the study of manipulative short squeezes, crowded exits, and the use of stop losses.

Some studies obtain trade-by-trade (or ‘flow’) data on stock lending or short-selling. These same studies tend to investigate shorter time periods. There is a balance to be had, though: although flow data provides the highest degree of granularity, it would be arduous to study flow data for long periods of time. However, studies over longer periods could reveal trends and cycles not found in shorter periods. Christophe *et al.* (2005) themselves take flow data for a ten month period and aggregate it into daily data.

Due to differences in regulatory and institutional frameworks, evidence from studies using US data are not necessarily representative of behaviour outside the US markets. For example, in the United Kingdom at the time of our study, the Financial Services Authority did not impose specific restrictions or controls on short-selling, unlike in the USA. Instead, short-sellers are subject to general market and regulatory arrangements, including market abuse principles. In addition, studies on non-US data can be used to counter the criticism that observed regularities in empirical studies are simply due to data mining. A limited number of studies investigate short-selling and its impact on stock prices outside the US (e.g. Aitken *et al.*, 1998, Biais *et al.*, 1999, Poitras, 2002, Ackert and Athanassakos, 2005, and Au *et al.*, 2007). However, these studies do not involve an investigation of crowded exits, as considered in this paper.

Geczy *et al.* (2002) examines shares available for borrowing (and thus available for shorting), based on a single lender of stock for a twelve month period. D'Avolio (2002) examines an eighteen month period of data from one stock lender. This paper draws on a longer time period than either Geczy *et al.* or D'Avolio, and uses market-wide data on stock lending, rather than just data from a single lender and hence can be considered to have wider applicability than these earlier studies.

By observing the differences in returns between equally-weighted and value-weighted portfolios, Asquith *et al.* (2005) demonstrate that the level of short-selling is more informative as a negative sentiment indicator for smaller capitalization stocks than for larger stocks. Au *et al.* (2007) suggest that a study based on larger capitalization stocks will produce more conservative estimates for the relationship between short-selling and stock returns compared to a study that includes smaller, less liquid stocks. The smallest stocks in the dataset have a market capitalization of approximately £25 million. Thus a limitation of the dataset is that it includes only the larger stocks listed on the London Stock Exchange and excludes the kinds of stocks Asquith *et al* consider contain the most information-driven transactions. On the other hand, this also suggests a degree of conservatism in the findings of this paper.

2.4 Descriptive Statistics

The dataset forms an 'unbalanced panel' dataset in which some cross-sectional units have some of the time periods missing. This form of panel is a result of the number of companies recorded in the Index Explorers database growing over time as smaller capitalization stocks are added. The resulting dataset contains 10,259,946 observations in the overall sample. In Table 1, descriptive statistics are produced for three points in time: the first day of the sample time period for which all the variables existed (September 1st, 2003), the last day of the sample time period (May 31st, 2007) and the mid-point (July 15th, 2005). The mean percentage of market capitalization on loan is a low figure for each of the snapshot dates (less than 3.5 per cent), but is positively skewed. From the Jarque-Bera probabilities, it can be seen that the first five variables are not Normally-distributed.

[INSERT Table 1 about here]

Histograms for each of the six variables are presented in Table 2. For the purpose of visualization the histograms are constructed using the mid-point snapshots. In order to improve the granularity of the histograms, any outliers further than three standard deviations from the mean are removed (this is done only for illustrative purposes with these histograms and does not affect the rest of the study).

[INSERT Table 2 about here]

Tables 3 and 4 present descriptive statistics for the logarithms of the six variables considered earlier.

[INSERT Table 3 about here]

[INSERT Table 4 about here]

An examination of the time series of percentage of market capitalization on loan series for each stock shows that these can be a volatile series. Dividend-paying stocks often experience large increases in shares on loan around divided record dates, indicating a dividend capture effect that is consistent with the known practice of dividend tax arbitrage. Nevertheless, some cross-sections experience a consistently high level through the observed period. During some dates in the sample the maximum value for this series exceeds 100 per cent for some companies, signifying that borrowed shares have been re-lent.

For the first and last snap-shot dates (September 1st, 2003 and May 31st,2007), we construct box-plots for each of the six variables considered above, to provide a visual summary of outliers in the dataset and these are shown in Table 5.

[INSERT Table 5 about]

For each variable considered above, we identify outliers in the study sample using two techniques. First, we observe data points that are more than three standard deviations from the mean for each variable. Secondly, we observe daily changes in each variable that are more than three standard deviations from the mean daily change. Table 6 reports the frequency of these outliers by variable. In studying crowded exits, we are concerned with exceptional situations for short-sellers. As such, 'outliers' in each variable are likely to be important and so are not removed from the dataset.

[INSERT Table 6 about here]

2.5 Asset Pricing Model for Estimating Abnormal Returns

In choosing an asset pricing model for the purposes of calculating abnormal returns, we note that Asquith and Moelbroek (1996) establish that the negative relation between excess returns and short positions is robust to a variety of techniques for calculating excess returns. Dechow *et al.* (2001) measure excess returns by adjusting each firm's return by the equal weighted return for all NYSE and AMEX shares over the same time period. They make no adjustment for risk across firms and cite previous research in this field that has been robust to changes in the asset pricing model used. Asquith *et al.* (2005) and Boehmer *et al.* (2008) use several asset pricing models in calculating abnormal returns for short-sellers and find no significant difference in the results. Cavazos and Savor (2007) apply both benchmark-adjusted returns approach and Fama-French three factors regression to study the relationship between short selling activities and subsequent abnormal returns, and obtain similar results for both. In fact, results in this research area have been uniformly robust to changes in asset pricing model specification. We note this phenomenon, and in this research, we choose to use the CAPM model for its simplicity. This model is also used by Figlewski (1981) and Figlewski & Webb (1993). Abnormal returns are calculated as:

$$AR_{i,t} = R_{i,t} - \left[R_{f,t} + \beta_i\left(R_{m,t} - R_{f,t}\right)\right] \qquad (1)$$

Where $R_{i,t}$ is the return of stock *i* on day *t*, and $R_{f,t}$ is the risk-free rate on day *t*. $R_{m,t}$ is the market return on day *t*, which is calculated from the total return index for the FTSE All Share index. β_i represents the correlation between the returns on stock *i* and the market return premium, which is estimated using CAPM over the period from September 2nd, 2002 to August 31st, 2003, which is a one-year period that precedes the stock lending sample data period. We use 3-month LIBOR as the risk-free interest rate. LIBOR is commonly used as a risk-free proxy. We note that this series is well-behaved during the period of study, but becomes unusually dislocated during the 2007-2008 US and UK banking crisis. In a study that uses UK stock lending data from CREST, Au *et al.* (2007) use weekly one-month LIBOR rates as their measure of the risk-free rate and estimate one-month cumulative abnormal returns relative to FTSE 350 index returns.

3. Methodology

3.1 Definitions of Variables

In this paper, shares on loan are standardized first by the number of shares outstanding and, secondly, by the free float number of shares. Each of these measures serves as a proxy for short interest.

The proportion of market capitalisation on loan (MCOL) of a stock on any given day is calculated as:

$$MCOL_{i,t} = \frac{\text{Shares on loan}_{\text{i,t}}}{\text{Outstanding Shares}_{\text{i,t}}} \qquad (2)$$

This measure represents the proportion of a company *i*'s outstanding shares that are on loan on day *t*. By dividing by outstanding shares, this ensures that the measure of short interest is not dominated by larger firms.

We introduce the proportion of free float on loan (FFOL) as a second measure of short-interest that better reflects the the liquidity of a stock. It is calculated as:

$$FFOL_{i,t} = \frac{\text{Shares on Loan}_{\text{i,t}}}{\text{Size of Free Float}_{\text{i,t}}} \tag{3}$$

The 'size of free float' is the total number of shares in issue that are available to ordinary investors (i.e. excluding shares held by government or long-term family interests).

We also measure the shares on loan relative to the normal trading volume for each firm day. We calculate the 'Days to Cover Ratio' (DCR) as a key factor for identifying crowded positions. This ratio is calculated as:

$$\text{Days to Cover Ratio}_{\text{i,t}} \text{ (DCR)} = \frac{\text{Shares on Loan}_{\text{i,t}}}{\text{Average Daily Trading Volume}_{\text{i,t}}} \tag{4}$$

$\text{Shares on Loan}_{\text{i,t}}$ is the closing number of shares on loan for stock *i* on day *t*.

$\text{Average Daily Trading Volume}_{\text{i,t}}$ is the moving average of the trading volume for stock *i* from days (*t*-61) to (*t*-1). We use 60 days of trading volume as a compromise between the risk of including out-dated information on trading volume and the risk of one or more exceptional days influencing the moving average figure.

3.2 Constructing Portfolios

The primary goal of this paper is to measure the abnormal returns of stocks experiencing crowded exits. A portfolio approach is applied as it allows us to replicate gross and risk-adjusted returns for a potential trading strategy; and it captures certain non-linearities that might characterize the patterns of subsequent returns (Pan and Poteshman, 2006). For each day, we sort the data to construct equal-weighted portfolios containing stocks identified as going through crowded exits. We study the characteristics of the securities included in the crowded exit portfolios, and estimate the abnormal portfolio returns for subsequent time periods.

We use two approaches to select portfolios of stocks. The first approach is a 'simple sort', identifying stocks on each day based on their Days to Cover Ratio (DCR) ranking relative to other stocks. The DCR is a liquidity ratio: the higher the ratio, the more difficult it should be for short-sellers to liquidate their positions without market impact. This simple sort thus creates portfolios that differ by the 'crowdedness of short positions'. The second approach is a 'double sort'. In addition to sorting by DCR, we also divide portfolios according to whether or not each stock is experiencing exceptional short covering.

Simple Sorts

For each day, we rank all stocks by DCR. We then construct three portfolios containing the 99th, 95th, and 90th percentile of stocks by DCR. These higher percentiles represent the most 'crowded' short positions. A prerequisite of a crowded exit is that the stock should have a high level of short interest relative to its liquidity, and this simple sort captures that condition.

Double Sorts

We carry out simultaneous sorts, creating portfolios based on a ranking of stocks by DCR and also whether or not they meet the test of showing an 'exceptional' decrease in shares on loan. A condition for a crowded exit is that it will lead to a significant reduction in short positions as covering takings place. Using the above we sort stocks into independent quintiles twice, first we sort stocks into 99th, 95th, and 90th percentiles based on their DCR, and then by ranking by exceptional changes in short interest on the previous day. We define the resultant portfolios as portfolios of stocks experiencing crowded exits: these portfolios include stocks with high DCRs and also exceptional decreases in short interest on the previous day.

To define an exceptional reduction in short interest level, we use two criteria. First, we filter the data to include only stocks with decreasing shares on loan. See equation (5) below:

Change in shares on loan (t) = shares on loan (t) – shares on loan (t-1) (5)

A negative number indicates that short-sellers are covering their positions on day t. Only publicly-traded stocks are generally loaned and so it important in any study of liquidity problems to consider each firm's free-float rather than total shares outstanding. We use the proportion of free float on loan in defining an exceptional decrease in short interest level. We first calculate the change in the free float on loan (CFFL) from day t-1 to day t. The average change across all stocks for day t is defined as the cross sectional mean on day t, according to the equation below:

$$\text{Average market change } (CFFL_{m,t}) = \frac{\sum_{i=1}^{n} CFFL_{i,t}}{n} \tag{6}$$

Where n is the total number of stocks in the universe on day t. We adjust the daily change in free float on loan for stock i ($CFFL_{i,t}$) for the market average change, and obtain the adjusted daily change in free float on loan relative to the market average change, as shown in the equation below:

$$\text{Relative daily change for stock } i \ (RCFFL_{i,t}) = \frac{CFFL_{i,t}}{CFFL_{m,t}} \tag{7}$$

Next, we test whether or not each $RCFFL_{i,t}$ is 'exceptional'. For each firm day, we calculate $RCFFL_{i,t}$ for each day from day (t-21) to day (t-1) and measure the mean and standard deviation of this series. If $RCFFL_{i,t}$ exceeds ± 2 standard deviations, we determine this to be an 'exceptional' change. If this exceptional change is accompanied by fewer shares on loan and a lower CFFL, it is defined as an exceptional decrease in the level of short interest.

Using this technique and having already undertaken a simple sort, we proceed to separate each of the DCR groups into two smaller portfolios: a 'Crowded Exit Portfolio' (where each stock experiences an exceptional decrease in short interest) and a 'Not Crowded Exit Portfolio' (the stocks do not experience an exceptional decrease in short interest).

We study the characteristics of securities found in the 'Crowded Exit Portfolios' and compare to those for the 'Not Crowded Exit Portfolios'. These characteristics include the short interest ratios defined in Section 3.1; and liquidity factors (daily trading volume and percentage of outstanding shares that are free floating). We also measure fundamental factors, including market capitalization, market-to-book, volatility of returns, and past returns. The 'past return' is the raw return for a portfolio of stocks over the previous 20 trading days.

3.3 Abnormal Returns around Crowded Exits

Portfolio abnormal returns are estimated from the CAPM model, as described in Section 2.5. We calculate equal-weighted portfolio abnormal returns for each portfolio resulting from a sort. In measuring abnormal returns following crowded exits, for each portfolio we skip one day and hold the portfolios over *N* trading days. We start the holding period on day (*t+2*) to reduce the risk that stock prices are disproportionately at either bid or ask (to address the 'bid-ask bounce problem'). We calculate Cumulative Abnormal Returns (CAR) over a series of holding periods (1, 5, 10, 20 and 60 days) to investigate the aggregate losses to short-sellers who cannot or do not cover their positions.

The daily abnormal return on portfolio *p*, $AR_{p,t}$, is given by:

$$AR_{p,t} = \frac{1}{I}\sum_{i=1}^{I} AR_{i,t} \tag{8}$$

$AR_{i,t}$ is the abnormal return for the i^{th} stock assigned to portfolio *p* based on the daily ranking of DCR. *I* is the number of stocks contained in the portfolio.

We skip one day to avoid the bid-ask bounce problem and estimate the abnormal return from day (*t+2*). We establish the window for one day [*t+2, t+3*], 5 days [*t+2, t+6*], 10 days [*t+2, t+11*], 20 days [$t+2$, $t+21$], and 60 days [$t+2$, $t+61$]. The Cumulative Abnormal Return (CAR) is estimated based on the above windows.

Cumulative abnormal returns for periods of up to 60 days are estimated for each day, and thus there is a problem of 'overlapping' data to address. Estimates based on overlapping periods could capture autocorrelation and heteroscedasticity in a firm's excess returns, thus biasing the results. Senchack and Starks (1993) use monthly data and apply an event window covering 15 days before and after short interest announcement date to avoid the overlapping problem. Angel et al. (2003) study stocks returns by partitioning their study sample into non-overlapping four-day sub-samples. However, we are using daily data to obtain greater granularity in studying liquidity problems, and such techniques would not be suitable for this study. Since we rank by DCR daily and hold portfolios for the subsequent *N* days, we need to adjust for unknown autocorrelation and heteroskedasticity in returns. The Newey-West (1987) Heterockedasticity Autocorrelation Covariance (HAC) Matrix Estimator is widely used for such adjustment. Diether *et al.* (2007) sort stocks into quintiles based on the percentage of daily trading volume due to short selling, and study the day ($t+2$) to day ($t+5$) holding period. They use the Newey-West (1987) approach with lag 5 to adjust for autocorrelation over the overlapping holding period. However, Petersen (2006) notes that, although the Newey-West HAC matrix estimator is more efficient, its weighting scheme is not as optimal as clustered White (1980) standard errors. Also, if there is a requirement to adjust for autocorrelation, the test is mis-specified. To solve this problem whilst making full use of the daily data, we undertake a calendar-time approach to calculate average daily returns. This approach is used by Mitchell and Stafford (2000) and Boehmer *et al.* (2008) to address the overlap problem.

4. Results

Table 7 shows summary statistics for the entire sample period (September 1st, 2003 to May 31st, 2007) and for three 'snapshots': the sample beginning date (September 1st, 2003), the sample mid-date (July 15th, 2005), and the sample end date (May 31st, 2007). Panel A presents statistics for variables related to stock lending. Panel B presents statistics for stock characteristics. In Panel A, by comparing the mean to the median and the upper percentiles for shares on loan, it is clear that the distribution of shares on loan is highly skewed. Likewise, the Days to Cover Ratio (DCR) distribution is also skewed. Whereas Cavazos and Savor (2007) find increasing short interest for NASDAQ stocks between 1988 and 2001, there is no obvious increasing trend in short interest for London Stock Exchange stocks during the period 2003 to 2007.

[INSERT Table 7 about here]

4.1 Simple Sorts

In the simple sort, each day stocks are ranked according to DCR and portfolios containing the 99th, 95th and 90th percentile of stocks by DCR are constructed. The portfolio characteristics resulting from these simple sorts are shown in Table 8:

[INSERT Table 8 about here]

Panel A reports the variables related to short interest. Unsurprisingly, the higher DCR percentiles have higher short-interest. Panel B presents statistics associated with liquidity factors: As expected, liquidity is generally poorer in portfolios with higher DCRs. A high DCR thus typically results from the combination of high short interest and poor liquidity. Panel C presents statistics for other portfolio characteristics, including market capitalization, stock return volatility, book-to-market ratio and past returns. Boehmer *et al.* (2008) find that high shorting tends to occur in small stocks. In addition, small stocks are expected to have lower trading volume and poorer liquidity. Considering these two features, we expect the higher DCR percentiles to be dominated by smaller stocks. Panel C reveals that the higher DCR portfolios exhibit a lower mean market capitalization than that for the whole sample. In fact, mean market capitalization declines monotonically with the higher DCR portfolios. The mean portfolio book-to-market ratio rises with DCR ratio and each of the higher DCR portfolios has above average book to market ratio. Based on medians, however, no clear relationship exists. This suggests that a small number of 'value' stocks dominate the mean figures. Boehmer *et al.* (2008) point out that although short-sellers are able to identify over-valued stocks, high levels of short-selling are neither necessarily nor sufficiently related to a low book-to-market ratio. Financial distress risk is likely to be present with extreme value stocks. There is no apparent relationship between volatility and DCR, or between past returns and DCR.

Table 9 presents the abnormal returns and cumulative abnormal returns associated with higher DCR portfolios.

[INSERT Table 9 about here]

Table 9 reveals positive abnormal returns for each of the higher DCR portfolios over each time period considered. Statistical significance is generally stronger over the longer holding periods; and for the 90th and 95th percentiles compared to the 99th percentile. This latter effect is due to the lower volatility of abnormal returns in the 90th and 95th percentile portfolios, such that statistical significance can be established at a lower abnormal return.

4.2 Double Sorts

Table 10 shows portfolio characteristics for the higher percentile DCR portfolios, separated into crowded exit portfolios and all portfolios. This allows for a comparison between the characteristics of stocks experiencing crowded exits, and all stocks that belong to higher percentile DCR portfolios.

[INSERT Table 10 about here]

In Panel B, it can be seen that mean and median turnover by shares is dramatically lower for the ‘Crowded Exits’ portfolios compared to the ‘All’ portfolios, suggesting that lower trading volume is an important factor in explaining crowded exits. Panel C reveals that the Book-to-Market ratio is lower for ‘Crowded Exits’ portfolios than for ‘All’ portfolios.

We examine each of the stocks appearing in the ‘Crowded Exits’ portfolios to identify if there are Regulatory News Service releases around the time of the crowded exit. In approximately half the cases, there are regulatory news announcements in the period beginning 7 days before the start of exceptional short covering. This suggests that publicly-released, company-specific news could be the catalyst for a crowded exit in some, but not all, cases. Stocks typically stay in the crowded exit portfolio for a limited number of days (a mean of 3.35 days for the 99th percentile portfolios, 3.55 days for the 95th percentile portfolios and 4.45 days for the 90th percentile portfolios).

For the crowded exit portfolios, we calculate equal-weighted portfolio returns using the calendar-time approach over holding periods of 1, 5, 10, 20, and 60 trading days. As before, we skip one day to counter the bid-ask bounce problem. This approach is repeated every day. We expect stocks experiencing crowded exits to show higher positive AR and CARs than stocks that do not experience crowded exits. Results are shown in Table 11:

[INSERT Table 11 about here]

For each percentile, the 'Crowded Exits' column reports the AR and CARs for portfolios of stocks that have high Days to Cover Ratios but that also show exceptional decreases in short interest – each of these stocks is said to experience a 'crowded exit'. The 'Difference' column shows the difference between stocks experiencing crowded exits and those that do not, within each percentile group. 'Crowded Exit' portfolios have positive AR and CARs, most of which are statistically significant. Comparing to the simple sorts, these AR and CARs are also all higher. For example, the highest CAR is observed in the 99th percentile over the holding period of 60 trading days, with 18.93 per cent, which is statistically significant at the 5 per cent level, while the CAR(+60) for the 99th percentile based on a simple sort is only 2.03 per cent, significant at the 10 per cent level. The mean CAR(+60) for the 99th percentile Crowded Exit portfolios, at 18.93 per cent, is also economically significant. This indicates potentially large losses for short-sellers during crowded exits. Noting from Table 10 that the 99th percentile has an average DCR of over 147 days, it is unsurprising that such stocks could remain crowded after 60 days. Although the positive CARs are not statistically significant over shorter periods, they are all statistically significant over periods of 10 days or greater.

The results are consistent with the hypothesis that crowded exits represent a risk to short-sellers. For longer holding periods, results are both statistically and economically significant. The greatest CARs are in the highest DCR portfolios. As a robustness check, we consider stocks that have high Days to Cover Ratios and that also exhibit a decrease in shares on loan over a 5 day period (as opposed to exhibiting an 'exceptional' decrease in shares on loan as defined in Section 3.2). We find that the abnormal returns for each category are generally no longer positive, and that none is statistically significantly different from zero. This reveals that it is the exceptional nature of short-covering associated with crowded exits that leads to losses for short-sellers.

4.3 Adjustment for Arbitrage

Not all short-sales are motivated by negative opinions on a stock. For example, short-sellers might short stocks to conduct convertible bond arbitrage and so take advantage of relative mispricing between a stock and a convertible bond issued by the same company. Where a short-seller is arbitrage-motivated, they will be partially hedged against movements in the stock price. The presence of such arbitrageurs could thus obfuscate our results and weaken the power of the tests. We use Thomson One Banker to identify those firms with outstanding convertible bonds. We then re-estimate abnormal returns and CARs for the Double Sorts, separating firms with convertible bonds from those without. Cavazos and Savor (2007) separate firms with convertible securities outstanding in excess of USD10 million, from those firms below this threshold. In this study, we separate firms with any convertible bonds in issue from those without convertible bonds, to completely remove any obfuscation due to convertible bond arbitrage. Approximately one fifth of stocks in the panel have convertibles in issue. Table 12 shows the results from our double sorts, adjusted for arbitrage-motivated short-selling.

[INSERT Table 12 about here]

We expect greater CARs for the non-convertible portfolios compared to the convertible portfolios, as short positions in the non-convertible portfolios are not hedged by long positions in convertible bonds. In all cases we find greater ARs and CARs for the non-convertible portfolios, as expected. For the arbitrage-motivated ‘Convertible’ portfolios, all but one of the AR and CARs are insignificant at any level. This is consistent with the findings of Diether *et al* (2007) and Cavazos and Savor (2007) on arbitrage-motivated short-selling.

5. Conclusions

It is rational for investors to take account of published evidence on stock market anomalies. In particular, a number of quantitative analysts incorporate empirical evidence on stock market anomalies into their investment processes, in their search for out-performance. Lev and Nissim (2004) study short-selling and the ‘accrual anomaly’ and find that in recent years institutions have altered their portfolio positions more actively in response to accrual disclosures, suggesting that the publication of academic research influences investor behaviour. There exists a substantial body of literature showing that heavily shorted stocks perform poorly. Furthermore, Cohen *et al.* (2007) show empirically that increasing borrowing demand for a stock is followed by poor performance. These studies suggest a potential trading strategy for short-sellers: identify heavily shorted stocks (or stocks with increasing borrowing demand) and build short positions in those stocks. This is an imitation strategy, similar to those described by Fligstein (1996, 2001), White (1981, 2001) and Mackenzie (2006). However, the act of imitation changes the market dynamics and can lead to unexpected consequences. With imitation, short-positions become more crowded, and the risk of ‘crowded exits’ increases. This could lead to examples of ‘counter-performativity’, as described by MacKenzie (2006), whereby the widespread and plentiful practice of short-selling, as assumed in economic models such as Arbitrage Pricing Theory, leads not always to a more efficient market, but to an increasing number of occasions on which stock prices move temporarily away from fair value.

Crowded exits are a liquidity problem unique to short-sellers. They have yet to be examined in the literature, and this study fills this gap. Crowded exits arise in stocks where short-sellers hold large positions relative to normal trading volume, and when a catalyst prompts short-sellers to rapidly and simultaneously cover their positions. Catalysts include, but are not limited to, public news releases by companies. We find that crowded exits are associated with losses to short-sellers that are economically and statistically significant. We show that stocks with higher short interest, smaller sizes and poorer liquidity are more likely to have crowded exits. We conclude that the risk of a crowded exit represents an indirect constraint on short-selling stocks.

This research makes a contribution to the literature by furthering our knowledge of indirect short-sale constraints. It also makes a practical contribution, as our findings suggest sensible steps that short-sellers can take to mitigate crowded exit risk. First, short-sellers should be risk-aware when short-selling smaller, less liquid stocks with high days-to-cover ratios. Second, given the prolonged nature of crowded exits, short-sellers should cover their short positions immediately upon observing exceptional levels of covering by other shorts-sellers in crowded positions. However, such short-covering will in itself exacerbate the crowded exit effect for others.

References

Ackert, L.F., and Athanassakos, G., 2005. The relationship between short interest and stock returns in the Canadian market. *Journal of Banking and Finance,* 29(7): 1729-1749

Aitken, M.J., Frino, A., McCorry, M.S. and Swan, P.L., 1998. Short sales are almost instantaneously bad news: evidence from the Australian Stock Exchange', *Journal of Finance*, 53(6): 2205-2223

Angel, J.J., Christophe, S.E., and Ferri, M.G., 2003. A close look at short selling on NASDAQ. *Financial Analysts Journal* 59(6): 66-74.

Asquith, P., and Moelbroek, L., 1996. An empirical investigation of short interest, Working paper, *Harvard University*

Asquith, Paul, Pathak, Parag A. and Ritter, Jay R., 2005. Short interest, institutional ownership and stock returns, *Journal of Financial Economics*, 78: 243-276

Au, Andrea S., Doukas, John A. and Onayev, Zhan, 2007. Daily short interest, idiosyncratic risk, and stock returns. Working Paper (November, 2007).

Biais, B., Bisiere, C., Decamps, J., 1999. Short sales constraints, liquidity and price discovery: An empirical analysis on the Paris Bourse. *European Financial Management,* 5: 395-409

Boehmer, Ekkehart, Jones, Charle M., Zhang, Xiaoyan, 2008. Which shorts are informed? *Journal of Finance*, 63(2): 491-527

Christoffersen, Susan E. Kerr, Geczy, Christopher C. and Musto, David K., 2005. Crossborder dividend taxation and the preference of taxable and non-taxable investors: evidence from Canada. *Journal of Financial Economics*, 78: 121-144

Christoffersen, Susan E. Kerr, Geczy, Christopher C., Musto, David K. And Reed, Adam V., 2007. vote trading and information aggregation, *Journal of Finance* 62: 2897-2929

Christophe, Stephen E., Ferri, Michael G. and Angel, James J., 2005. Short-selling prior to earnings announcements, *Journal of Finance*, 59: 1845-1875

Christoffersen, S., Geczy, C., Musto, D., & Reed, A., 2001. The market for legal ownership of equities, Working paper, McGill University and University of Pennsylvania

Cohen, Lauren, Diether, Karl B. and Malloy, Christopher J., 2007, Supply and demand shifts in the shorting market, *Journal of Finance*, 62(5): 2061-2096.

D'Avolio, G., 2002. The market for borrowing stock, *Journal of Financial Economics,* 66: 271-306

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

Diether, K.B., Lee K.H., and Werner, I.M., 2008. Short-sale strategies and return predictability, *Review of Financial Studies*, October 2008

Diether, K.B., Malloy, J., and Scherbina, A., 2002. Differences of opinion and the cross-section of stock returns, *Journal of Finance*, 57: 2113-2141

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

Figlewski, S., 1981. The informational effects of restrictions on short sales: some empirical evidence, *Journal of Financial and Quantitative Analysis*, 16: 463-476.

Figlewski, Stephen and Webb, Gwendolyn P., 1993. Options, short sales, and market completeness, *Journal of Finance*, 48: 761-777.

Fligstein, Neil, 1996. Markets as politics: a political-cultural approach to market institutions, *American Sociological Review*, 61: 656-673.

Fligstein, Neil, 2001. *The Architecture of Markets*. Princeton University Press, Princeton, New Jersey

Friedman, D., 1991. Evolutionary games in economics, *Econometrica* 59(3): 637-666

Gamboa-Cavazos, M, and Savor, P., 2007. Holding on to your shorts: when do short-sellers retreat? *Harvard University* Working Paper.

Geczy, Christopher C., Musto, David K., and Reed, Adam V., 2002. Stocks are special too: an analysis of the equity lending market, *Journal of Financial Economics*, 66: 241-269.

Gopalan, M., 2003, Short constraints, difference of opinion and stock returns. Working paper, *Duke University*

Lev, Baruch Itamar and Nissim, Doron, 2004. The persistence of the accruals anomaly, available at SSRN: http://ssrn.com/abstract=546108

MacKenzie, Donald A., 2006. An *Engine, Not A Camera: How Financial Models Shape Markets*, MIT Press, Cambridge, MA, USA

Mitchell, M., and Stafford, E., 2000. Managerial decisions and long-term stock price performance, *Journal of Business*, 73: 287-329

Nagel ,Stefan, 2005. Short-sales, institutional investors and the cross-section of stock returns. *Journal of Financial Economics*, 78(2): 277-309

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

Ofek, Eli, Richardson, Matthew and Whitelaw, Robert F. 2004. Limited Arbitrage and short sale restrictions: evidence from the options market, *Journal of Financial Economics*, 74: 305-342

Pan, J., and Poteshman, A., 2006. The information in option volume for future stock prices, , *Review of Financial Studies*, 19(3):871-908

Poitras G., 2002. Short sales restrictions, dilution and the pricing of rights issues on the Singapore stock Exchange. *Pacific-Basin Finance Journal* 10: 141-162.

Saffi, Pedro.A.C. and Sigurdsson, Kari., 2007. Price efficiency and short-selling, Working Paper, *London Business School* (accessed 10/12/2007).

Senchack, A.J., and Starks, L.T., 1993. Short-sale restrictions and market reaction to short-interest announcements, *Journal of Financial and Quantitative Analysis*, 28(2): 177-194

White, Harrison C., 1981. Where do markets come from? *American Journal of Sociology*, 87: 517-547

White, Harrison C., 2001. *Markets from Networks*. Princeton University Press, Princeton, New Jersey

Table 1: Descriptive Statistics for the Raw Dataset

Descriptive statistics are provided for three points in time: the first day of the sample time period (September 1st, 2003), the mid-point (July 15th, 2005) of the sample time period and the final day of the sample time period (May 31st, 2007). The descriptive statistics are parameters that measure central tendency, dispersion, minimum/maximum values, number of observations, skewness, kurtosis and Jarque-Bera statistics for stock price, market capitalization, percentage of market capitalization on loan, shares on loan, book value per share* and free float number of shares (%).

		Price (GBp)	Market Cap (mill GBP)	Market Cap on Loan (%)	Shares on Loan (mill)	Book Value per Share (GBP)	Free float number of shares (%)
01/09/2003	Mean	348.9678	2190.933	2.426836	28.13055	1.523835	56.71614
	Median	217.75	311	1.62	5.5	1.1105	57
	Maximum	20500	95755	15.63	1078.8	186.318	100
	Minimum	2.35	47	0.15	0.1	-422.447	9
	Std. Dev.	985.9779	8613.22	2.50429	79.08176	18.8214	17.15801
	Skewness	16.55132	8.035531	2.482568	9.250658	-16.40918	-0.182926
	Kurtosis	317.4105	75.15189	10.31674	116.0577	421.1521	2.843907
	Jarque-Bera	2440439	112015.6	895.895	150383.2	4662099	3.757554
	Probability	0.00	0.00	0.00	0.00	0.00	0.152777
	Observations	586	492	275	275	636	570
15/07/2005	Mean	423.317	2503.904	3.48463	32.44019	2.511012	78.57348
	Median	266	381	2.35	8.5	1.261	82
	Maximum	23650	130630	19.32	866.1	221.26	100
	Minimum	5.85	51	0.32	0.2	-76.755	11
	Std. Dev.	1030.296	9924.584	3.137033	75.87327	10.13917	17.03667
	Skewness	18.55561	8.7192	1.647085	6.389255	15.77574	-0.921704
	Kurtosis	409.2458	91.73508	5.882677	57.78028	348.8487	3.510788
	Jarque-Bera	4416875	184346	248.2996	41002.37	3256384	95.44044
	Probability	0.00	0.00	0.00	0.00	0.00	0.00
	Observations	637	541	311	311	648	626
31/05/2007	Mean	610.4427	3034.235	3.037874	25.2274	3.314581	74.67109
	Median	399	463	1.78	3.00	1.467	77
	Maximum	26725.01	109377	29.33	3793.2	264.7	100
	Minimum	5.85	20	0.01	0.00	-2.855	18
	Std. Dev.	1203.783	10065.52	3.60918	154.0299	13.12218	17.355
	Skewness	15.83103	6.728114	2.623158	22.11777	17.33452	-0.648486
	Kurtosis	330.5056	57.06653	12.92178	538.0428	337.5389	2.958836
	Jarque-Bera	3071946	82650.91	3506.041	8022336	2229372	47.56819
	Probability	0.00	0.00	0.00	0.00	0.00	0.00
	Observations	681	639	668	668	473	678

** For the BV variable the snapshots presented are for the BV shifted.*

Table 2: Histograms for the Raw Dataset

Histograms for six variables (stock price, market capitalization, percentage of market capitalization on loan, shares on loan, book value per share and free float number of shares (in per cent)) are constructed. For the purpose of visualization the histograms are produced using the mid-date snapshot (July 15th, 2005). In order to improve the granularity of the histograms, outliers of greater than three standard deviations from the mean are removed (this is done for the illustrative purposes only).

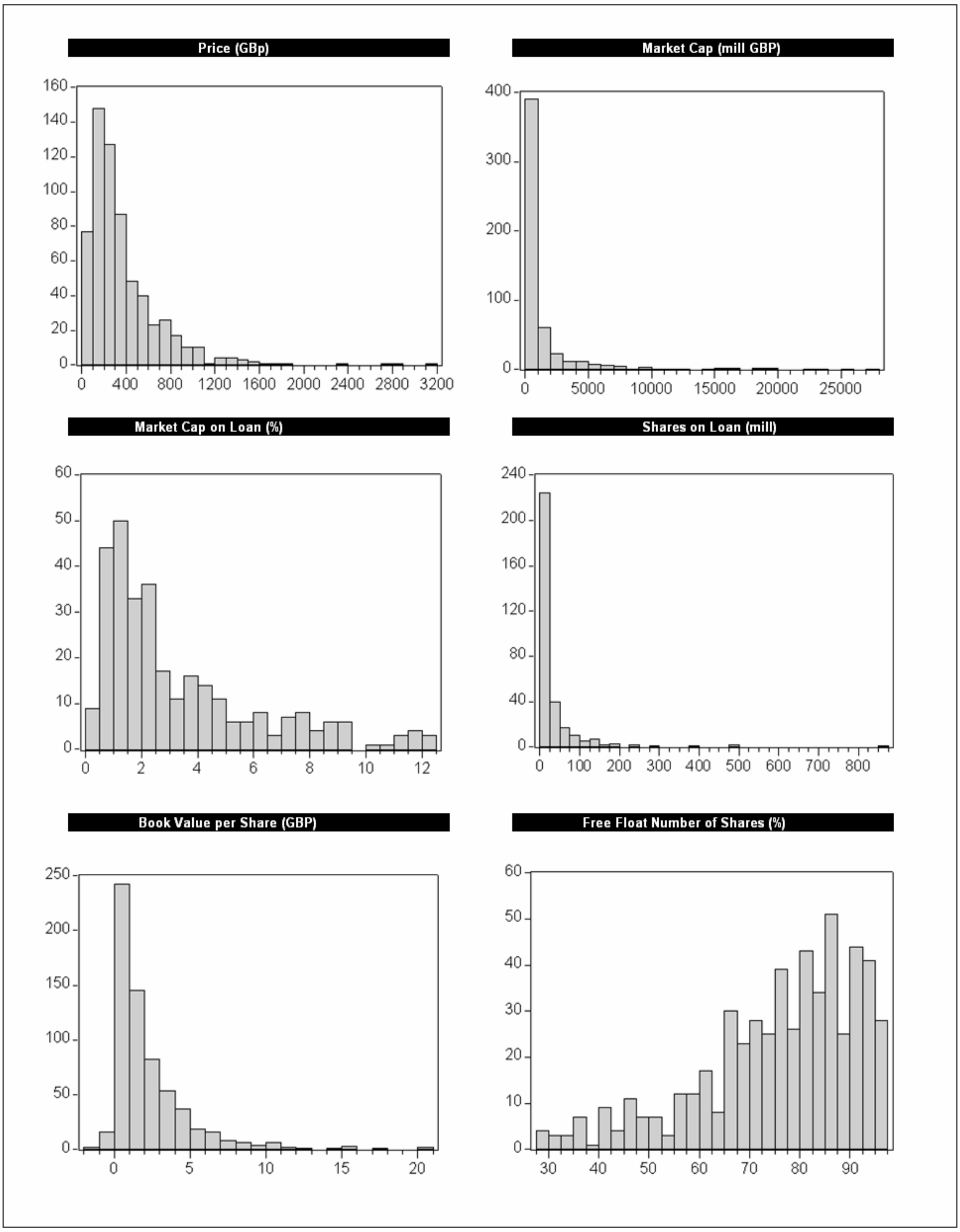

Table 3: Descriptive Statistics for the Logarithmic Dataset

Descriptive statistics are provided for three points in time: the first day of the sample time period (September 1st, 2003), the mid-point (July 15th, 2005) of the sample time period and the final day of the sample time period (May 31st, 2007). The descriptive statistics are parameters that measure central tendency, dispersion, minimum/maximum values, number of observations, skewness, kurtosis and Jarque-Bera statistics for six variables: stock price, market capitalization, percentage of market capitalization on loan, shares on loan, book value per share* and free float number of shares (%).

		Price (GBp)	Market Cap (mill GBP)	Market Cap on Loan (%)	Shares on Loan (mill)	Book Value per Share (GBP)	Free float number of shares (%)
01/09/2003	Mean	5.316258	6.046764	0.487787	1.834715	0.058888	3.981826
	Median	5.383342	5.739793	0.482426	1.704748	0.188966	4.043051
	Maximum	9.92818	11.46955	2.749192	6.983604	5.227455	4.60517
	Minimum	0.854415	3.850147	-1.89712	-2.302585	-5.521461	2.197225
	Std. Dev.	0.968889	1.50577	0.894732	1.773594	1.258237	0.359823
	Skewness	-0.272131	0.993897	0.055387	0.180727	-0.629466	-1.253193
	Kurtosis	5.221265	3.76551	2.824535	2.377743	5.023834	5.077885
	Jarque-Bera	127.7051	93.01533	0.493385	5.93E+00	142.2571	251.7399
	Probability	0.00	0.00	0.78	0.05	0.00	0.00
	Observations	586	492	275	275	601	570
15/07/2005	Mean	5.567265	6.24073	0.880144	2.194331	0.252293	4.333748
	Median	5.583496	5.9428	0.854415	2.140066	0.293037	4.406719
	Maximum	10.07112	11.78012	2.961141	6.764	5.399338	4.60517
	Minimum	1.766442	3.931826	-1.139434	-1.609438	-4.710531	2.397895
	Std. Dev.	0.930843	1.460353	0.873153	1.655141	1.204421	0.266321
	Skewness	-0.215372	1.047292	0.055395	0.071518	-0.387375	-1.963846
	Kurtosis	4.853598	3.923735	2.261525	2.446984	4.299419	9.156942
	Jarque-Bera	96.11709	118.1313	7.225814	4.23E+00	59.12548	1391.147
	Probability	0.00	0.00	0.03	0.12	0.00	0.00
	Observations	637	541	311	311	620	626
31/05/2007	Mean	5.899454	6.474853	0.415943	1.239666	0.420813	4.279769
	Median	5.988961	6.137727	0.576613	1.193923	0.439221	4.343805
	Maximum	10.19336	11.60256	3.378611	8.240965	5.578597	4.60517
	Minimum	1.766442	2.995732	-4.60517	-2.302585	-3.963316	2.890372
	Std. Dev.	1.01162	1.495919	1.345159	2.045757	1.20275	0.275389
	Skewness	-0.276713	0.932306	-0.619932	0.144035	-0.147303	-1.485895
	Kurtosis	4.001597	3.59038	3.190487	2.387284	4.254811	5.865685
	Jarque-Bera	37.15639	101.8494	43.7971	1.22E+01	31.15017	481.4841
	Probability	0.00	0.00	0.00	0.00	0.00	0.00
	Observations	681	639	668	638	450	678

** For the BV variable the snapshots presented are for the BV shifted.*

Table 4: Histograms for the Logarithmic Dataset

Histograms for six variables (stock price, market capitalization, percentage of market capitalization on loan, shares on loan, book value per share and free float number of shares (per cent)) are constructed. For the purpose of visualization the histograms are produced using the mid-date snapshot (July 15th, 2005). In order to improve the granularity of the histograms, outliers of greater than three standard deviations from the mean are removed (this is done for the illustrative purposes only).

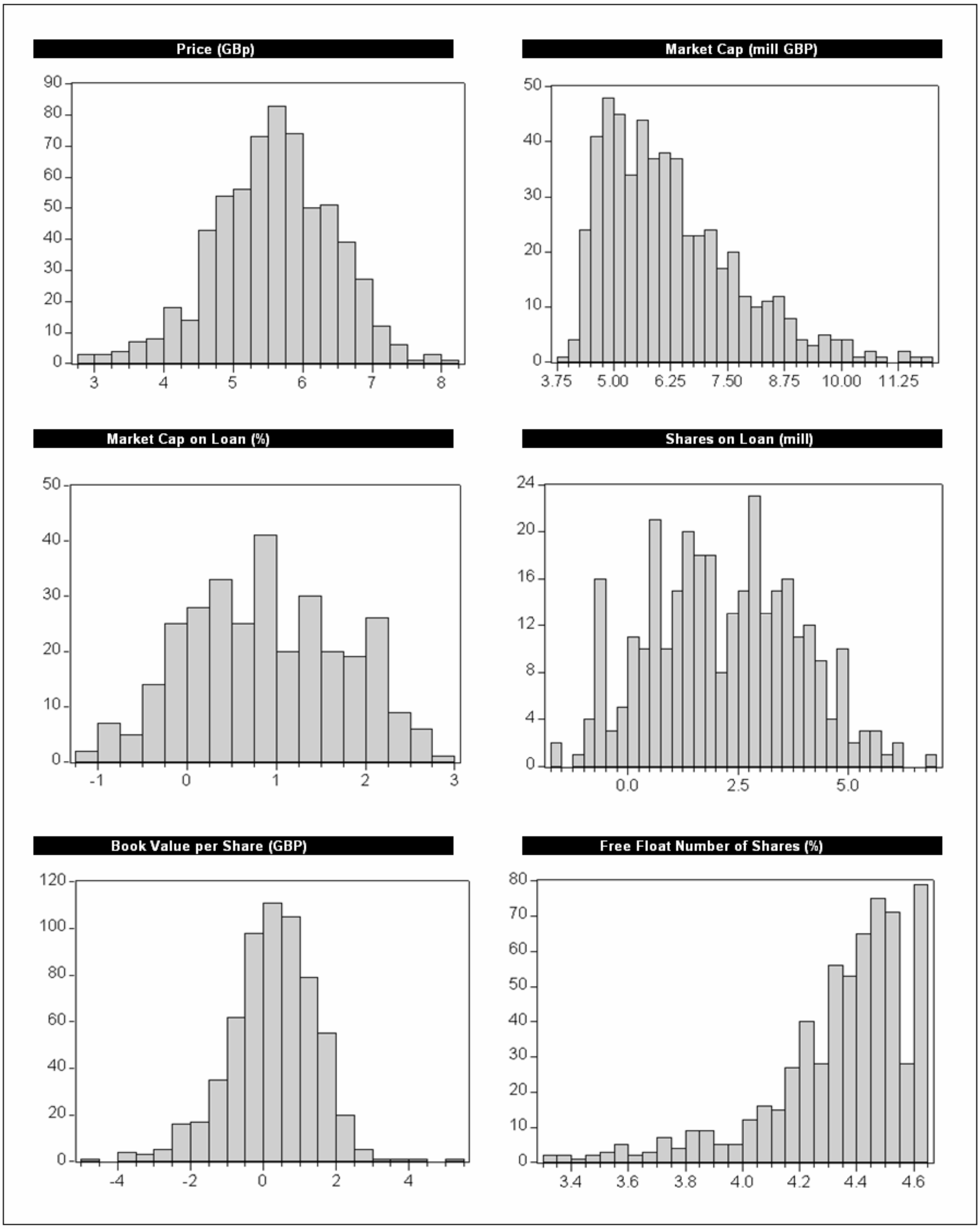

Table 5: Box-plots

Box-plots are constructed for each of the six variables in the dataset for the first (September 1st, 2003) and for the last (May 31st, 2007) snap-shot dates. They intend to provide a visual summary of the outliers in the dataset. For most of the variables there are more outliers in the last snapshot of data than in the first one, which is consistent with the notion of a growing panel.

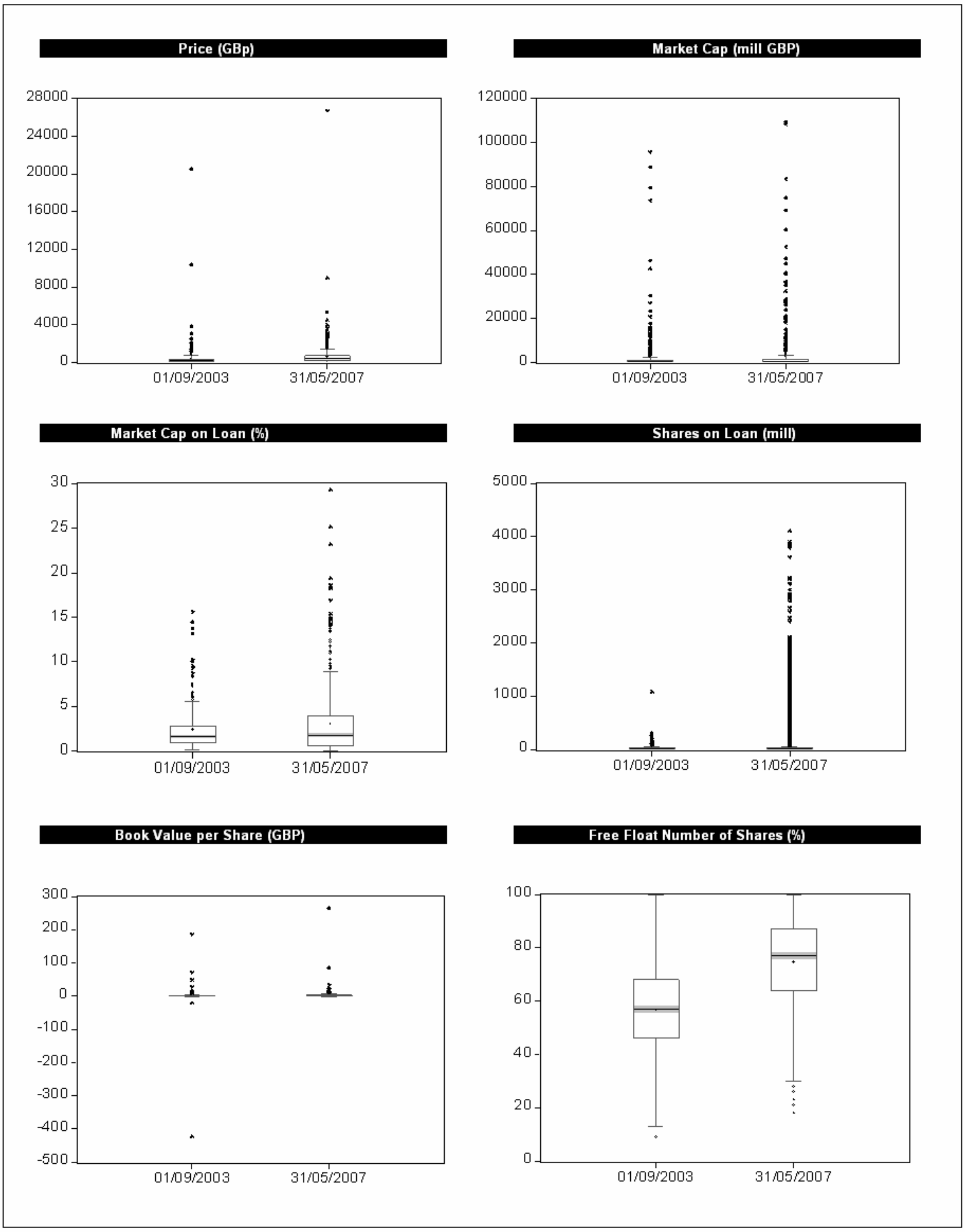

Table 6: Outliers

The top panel of the table shows for each of the six variables the number of observations greater than three standard deviations from the mean as well as its equivalent presented as a percentage of the total number of observations. The bottom panel of the table presents the number of occasions (and its percentage equivalent) each variable has changed in one day by more than three standard deviations from the mean daily change. Both measures aim to capture ‘exceptional’ data points.

		Price (GBp)	*Market Cap (mill GBP)*	*Market Cap on Loan (%)*	*Shares on Loan (mill)*	*Book Value per Share (GBP)*	*Free float number of shares (%)*
> or < than	***Number of observations***	3443	942	3469	3849	21496	1300
($\mu \pm 3\sigma$)	***% of sample***	0.3386%	0.17%	0.83%	0.9150%	2.2378%	0.1608%
> or < than	***Number of observations***	810	1167	3834	6929	NA*	8207
($i_{-1} \pm 3\sigma$)	***% of sample***	0.0797%	0.21%	0.92%	1.6472%	NA*	1.0151%

****the information is not applicable as BV changes once a year***

Table 7: Summary Statistics

Panel A reports summary statistics for different short selling measures. Shares on Loan is the number of shares borrowed over the period (01 Sep 2003 to 31 May 2007), which we use as the proxy of number of shares shorted. Market Cap on Loan is the number of shares on loan divided by market cap over the sample period. Free Float on Loan is the number of shares on loan divided by the size of free float, which indicates the relationship short selling activities and stock liquidity. DCR (Days to Cover Ratio) is the number of shares on loan divided by average daily trading volume, which indicates how long it takes short sellers to cover their short positions. Panel B shows the summary statistics of stock characteristics. Market Cap is used to measure the size of firm, and B/M refers to lagged book to market as defined in Fama French (1993). Trading Volume is the number of shares traded in the market per day. Free Float shows the percentage of outstanding shares which are not closely held. Each panel reports statistics for the entire sample period and also snapshots for the beginning date (01 Sep 2003), the middle date (15 Jul 2005), and the final date (31 May 2007).

Panel A: Short Selling Summary Statistics

		Shares on loan (millions)	Market Cap on loan (%)	Free float on loan (%)	DCR (days)
01 Sep 2003-31 May 2007	mean	23.39	2.90	4.68	7.88
	median	4.40	1.84	2.70	4.48
	Std.Dev	74.99	3.07	5.68	29.29
01 Sep 2003 (Snapshot 1)	mean	28.84	2.43	4.57	6.74
	median	5.50	1.64	2.79	3.51
	Std.Dev	81.60	2.43	5.18	19.01
15 Jul 2005 (Snapshot 2)	mean	33.38	3.55	4.55	7.94
	median	9.90	2.41	2.69	5.02
	Std.Dev	77.58	3.18	4.39	15.65
31 May 2007 (Snapshot 3)	mean	33.27	3.37	4.42	8.42
	median	4.35	2.18	2.53	4.30
	Std.Dev	191.39	3.66	5.49	28.49

Panel B: Stock Characteristics Summary Statistics

		Market Cap (millions)	Daily Trading Volume (millions)	B M	Free Float (%)
01 Sep 2003-31 May 2007	mean	2293.70	3.24	0.67	66.54
	median	370.00	0.31	0.50	69.00
	Std.Dev	8485.05	15.74	1.51	21.64
01 Sep 2003 (Snapshot 1)	mean	1571.23	4.95	0.89	56.95
	median	272.00	1.19	0.65	57.00
	Std.Dev	7165.67	11.56	3.36	14.69
15 Jul 2005 (Snapshot 2)	mean	2495.48	6.14	0.69	82.07
	median	383.50	1.75	0.53	85.00
	Std.Dev	10011.37	12.76	1.19	15.66
31 May 2007 (Snapshot 3)	mean	2700.54	4.71	0.48	74.99
	median	459.50	0.84	0.36	78.00
	Std.Dev	7817.87	10.96	0.37	17.68

Table 8: Portfolios based on Simple Sorts

This table reports the characteristics of portfolios sorted daily by Days to Cover Ratio (DCR) over the period 01 September 2003 to 31 May 2007. DCR is calculated as shares on loan divided by average daily trading volume. The first column shows variables for the entire sample, the following three columns show the 99th, 95th, and 90th percentiles by DCR respectively. Past Return is calculated as the raw percentage return of each portfolio over the previous 20 trading days.

		All	99th Percentile DCR>19.4	95th Percentile DCR>12.4	90th Percentile DCR>8.11
Panel A. Short Interest					
DCR (days)	Mean	7.88	147.26	52.87	34.71
	Median	4.48	62.68	25.76	19.36
	Std. Dev.	29.29	224.63	119.21	86.97
Shares on Loan (in millions)	Mean	23.39	25.90	26.31	33.17
	Median	4.40	14.10	7.80	9.40
	Std. Dev.	74.99	63.48	58.36	67.72
Mkt Cap on Loan (%)	Mean	2.90	5.60	6.22	6.20
	Median	1.84	3.54	4.66	4.90
	Std. Dev.	3.07	4.19	4.39	4.52
Free Float on Loan(%)	Mean	4.68	9.82	10.77	10.66
	Median	2.70	6.75	7.76	7.93
	Std. Dev.	5.68	7.93	9.05	9.04
Panel B. Stock Liquidity					
Turnover by shares (in millions)	Mean	3.24	0.45	1.21	1.94
	Median	0.31	0.10	0.16	0.26
	Std. Dev.	15.74	2.10	3.82	5.35
Free Float (%)	Mean	66.54	65.34	66.07	66.64
	Median	69.00	65.00	68.00	69.00
	Std. Dev.	21.64	21.64	20.00	20.42
Panel C. Other Stock Characteristics					
Volatility	Mean	0.24	0.25	0.24	0.25
	Median	0.22	0.22	0.22	0.23
	Std. Dev.	0.14	0.14	0.12	0.12
Mkt Cap (in millions)	Mean	2294	697	983	1574
	Median	370	444	443	499
	Std. Dev.	8485	3740	2980	5093
Book to Market ratio	Mean	0.67	6.21	1.86	1.21
	Median	0.48	0.47	0.55	0.49
	Std. Dev.	37.91	15.36	7.68	5.52
Past Return (%)	Mean	1.93	2.23	1.41	1.49
	Median	1.60	1.67	1.34	1.36
	Std. Dev.	8.37	8.72	7.81	7.60

Table 9: Abnormal Returns and Cumulative Abnormal Returns based on Simple Sorts (%)

The Table reports abnormal returns and cumulative abnormal returns (CAR) for higher-percentile DCR portfolios from 01 Sep 2003 to 31 May 2007. Stocks are sorted into 99th, 95th, and 90th percentiles based on their Days to Cover Ratio (DCR). Portfolios are re-balanced daily. By skipping one day to avoid concerns about bid-ask bounce, daily abnormal returns, cumulative abnormal returns and t-statistics are calculated using a calendar-time approach with a holding period of 1, 5, 10, 20, and 60 trading days. All returns are quoted as percentages.

		99th Percentile	95th Percentile	90th Percentile
AR(+1)	Mean	0.034	0.020	0.027
	t-Stat	1.345	1.720 *	2.429
CAR(+5)	Mean	0.127	0.127	0.116
	t-Stat	1.188	2.710 ***	2.951 ***
CAR(+10)	Mean	0.291	0.307	0.263
	t-Stat	1.032	3.250 ***	3.423 ***
CAR(+20)	Mean	0.348	0.562	0.622
	t-Stat	1.742 *	2.989 ***	4.265 ***
CAR(+60)	Mean	2.027	1.203	1.463
	t-Stat	1.682 *	1.970 **	3.419 ***

Note: * indicates significance at 10% level, ** indicates significance at 5% level, and *** indicates significance at 1% level.

Table 10: Portfolios based on Double Sorts

This table reports the characteristics of portfolios sorted according to both Days to Cover Ratio (DCR) and exceptional decreases in the percentage of free float on loan over the period 01 September 2003 to 31 May 2007. DCR is calculated as shares on loan divided by average daily trading volume. Exceptional decreases in free float on loan are identified as described in the Methodology section. For each percentile, the column 'All' shows variables for all stocks in that percentile group based on a simple sort; the Crowded Exits column reports portfolios which have a high DCR combined with exceptional falls in short interest, as defined in the Methodology section. Past Return is calculated as the raw percentage return of each portfolio over the previous 20 trading days.

First Sort (By DCR)		**99th Percentile**		**95th Percentile**		**90th Percentile**	
Second Sort (By Exceptional Change)		**All**	**Crowded Exits**	**All**	**Crowded Exits**	**All**	**Crowded Exits**
Panel A. Short Interest							
DCR (days)	Mean	147.26	91.43	52.87	36.55	34.71	25.76
	Median	62.68	57.30	25.76	24.56	19.36	18.58
	Std. Dev.	224.63	94.80	119.21	48.08	86.97	34.74
Shares on Loan	Mean	25.90	27.70	26.31	33.41	33.17	45.37
(in millions)	Median	14.10	18.90	7.80	15.70	9.40	16.60
	Std. Dev.	63.48	24.54	58.36	57.53	67.72	84.69
Mkt Cap on Loan (%)	Mean	5.60	4.51	6.22	6.73	6.20	6.73
	Median	3.54	2.98	4.66	5.90	4.90	5.90
	Std. Dev.	4.19	3.87	4.39	4.58	4.52	4.53
Free Float on Loan(%)	Mean	9.82	7.89	10.77	12.02	10.66	12.11
	Median	6.75	3.63	7.76	9.91	7.93	9.90
	Std. Dev.	7.93	7.48	9.05	9.74	9.04	9.73
Panel B. Stock Liquidity							
Turnover by shares	Mean	454.9	0.4	1206.1	1.7	1936.7	3.0
(in millions)	Median	103.2	0.1	161.9	0.3	260.7	0.5
	Std. Dev.	2096	899	3823	3908	5346	8116
Free Float (%)	Mean	65.34	67.21	66.07	64.56	66.64	64.64
	Median	65.00	71.00	68.00	66.00	69.00	67.00
	Std. Dev.	21.64	23.05	20.00	20.82	20.42	21.22
Panel C. Other Stock Characteristics							
Volatility	Mean	0.25	0.27	0.24	0.25	0.25	0.25
	Median	0.22	0.21	0.22	0.22	0.23	0.23
	Std. Dev.	0.14	0.19	0.12	0.14	0.12	0.12
Mkt Cap	Mean	696.8	642.7	982.8	1257.5	1573.8	1953.6
	Median	444.0	497.0	443.0	503.0	499.0	587.0
	Std. Dev.	3740	692	2980	2224	5093	6234
B/M	Mean	6.21	0.11	1.86	0.49	1.21	0.49
	Median	0.47	0.15	0.55	0.46	0.49	0.43
	Std. Dev.	15.36	0.86	7.68	0.59	5.52	0.51
Past Return	Mean	0.022	0.02	0.014	0.02	0.015	0.02
	Median	0.017	0.02	0.013	0.02	0.014	0.02
	Std. Dev.	0.087	0.08	0.078	0.07	0.076	0.07

Table 11: Abnormal Returns and Cumulative Abnormal Returns based on Double Sorts (in %)

The Table reports mean abnormal returns and cumulative abnormal returns (CAR) for crowded exit portfolios from 01 Sep 2003 to 31 May 2007. For each day, stocks are first sorted into 99th, 95th, and 90th percentiles based on their Days to Cover Ratio (DCR). Within each percentile, stocks showing exceptional decreases in short interest (as defined int he Methodology section) are studied - these stocks are said to experience a 'crowded exit'. For each percentile, the first column reports the abnormal returns for stocks experiencing a crowded exit. The second column reports the difference in mean returns between portfolios of stocks experiencing crowded exits and those that do not experience crowded exits. By skipping one day to avoid concerns about bid-ask bounce, daily abnormal returns, cumulative abnormal returns and t-statistics are calculated using a calendar-time approach with a holding period of 1, 5, 10, 20, and 60 trading days. All numbers are quoted as percentages.

		99th Percentile		**95th Percentile**		**90th Percentile**	
		Crowded Exits	**Difference**	**Crowded Exits**	**Difference**	**Crowded Exits**	**Difference**
AR(+1)	Mean	0.518	0.233	0.158	0.026	0.151	0.105
	t-Stat	0.915	0.641	2.161 **	0.256	1.332	1.512 *
CAR(+5)	Mean	1.833	0.647	0.404	-0.050	0.402	0.320
	t-Stat	0.862	0.523	1.409	-0.133	0.873	1.157
CAR(+10)	Mean	4.916	4.125	1.005	1.065	1.051	0.986
	t-Stat	2.191 **	1.949 **	2.344 **	0.834	1.773 *	1.611 *
CAR(+20)	Mean	5.254	5.858	3.403	1.869	3.610	1.986
	t-Stat	1.831 *	1.506 *	4.413 ***	1.426 *	2.994 ***	2.012 **
CAR(+60)	Mean	18.930	14.446	5.033	3.022	6.370	3.640
	t-Stat	2.065 **	1.298 *	1.964 **	0.758	1.703 *	1.324 *

Note: * indicates significance at 10% level, ** indicates significance at 5% level, and *** indicates significance at 1%

Table 12: Double Sort Results Adjusted For Arbitrage

The Table reports mean abnormal returns and cumulative abnormal returns (CAR) for crowded exit portfolios from 01 Sep 2003 to 31 May 2007. First, stocks that are experiencing crowded exits are identified based on double sorts. Any company with a convertible bond in its capital structure is identified as being exposed to arbitrage-motivated short-selling. Crowded exit stocks are then seperated into 'non-convertible' portfolios and 'convertible' portfolios. By skipping one day to avoid concerns about bid-ask bounce, daily abnormal returns, cumulative abnormal returns and t-statistics are calculated using a calendar-time approach with a holding period of 1, 5, 10, 20, and 60 trading days. All numbers are quoted as percentages.

		99th Percentile		95th Percentile		90th Percentile	
		non-convertible	convertible	non-convertible	convertible	non-convertible	convertible
AR(+1)	Mean	0.728	-0.451	0.190	0.040	0.167	0.076
	t-Stat	1.117	-1.408	1.295	0.332	1.895 *	1.079
CAR(+5)	Mean	2.350	-0.545	0.494	0.142	0.466	0.108
	t-Stat	0.096	-0.476	0.825	0.285	1.443	0.194
CAR(+10)	Mean	6.106	-0.559	1.327	0.338	1.095	0.721
	t-Stat	2.279 **	-0.319	1.815 *	0.286	2.120 *	1.054
CAR(+20)	Mean	8.083	-7.759	3.763	3.173	3.569	3.197
	t-Stat	2.235 **	-1.831	2.571 **	1.570	3.974 ***	1.920 *
CAR(+60)	Mean	26.981	-18.103	8.312	0.815	5.514	3.526
	t-Stat	2.508 **	-1.423	1.949 *	0.105	1.967 *	0.594

Note: * indicates significant at the 10% level, ** indicates significant at the 5% level, and *** indicates significant at the 1% lev

Table 13: Double Sort Results Adjusted for Arbitrage and News Announcements

The Table reports mean abnormal returns and cumulative abnormal returns (CAR) for crowded exit portfolios from 01 Sep 2003 to 31 May 2007. Based on the double sort results after adjusting for convertibles (see Table 6), companies without convertibles in each percentile group are further seperated into 'With News' portfolios and 'Without News' portfolios. Any regulatory news announcement within 5 trading days prior to the event day is identified. By skipping one day to avoid concerns about bid-ask bounce, daily abnormal returns, cumulative abnormal returns and t-statistics are calculated using a calendar-time approach with a holding period of 1, 5, 10, 20, and 60 trading days. All numbers are quoted as percentages.

		99th Percentile		**95th Percentile**		**90th Percentile**	
		Non-Convertible	**Non-Convertible Without News**	**Non-Convertible With News**	**Non-Convertible Without News**	**Non-Convertible With News**	**Non-Convertible**
AR(+1)	Mean	0.184	0.473	0.356	0.057	0.216	0.097
	t-Stat	0.839	0.839	2.341 **	0.383	1.942 *	1.092
CAR(+5)	Mean	0.623	1.270	0.814	0.140	0.713	0.220
	t-Stat	0.575	0.821	1.341	0.259	1.687 *	0.684
CAR(+10)	Mean	4.007	5.083	1.716	1.151	1.562	1.072
	t-Stat	1.510	1.884 *	1.467	1.249	1.867 *	1.491
CAR(+20)	Mean	2.955	9.927	4.886	3.137	4.040	3.471
	t-Stat	1.077	2.056 **	2.321 **	1.699 *	2.658 ***	3.034 ***
CAR(+60)	Mean	3.462	35.572	15.460	4.700	8.766	3.849
	t-Stat	0.467	2.514 **	2.370 **	0.855	1.807 *	1.120

Note: * indicates significant at the 10% level, ** indicates significant at the 5% level, and *** indicates significant at the 1% level.