Erasmus University
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Master Thesis

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Hedge Funds and Short-Sale Performance

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Submission Date: August 9^{th}, 2019

Abstract

By using a rich dataset of daily short-sale disclosures provided by the European Union, I test the performance of short-sellers from hedge funds over the period November 1 2012 - December 31 2018. I find that short-sellers earn an annualized 4-Factor alpha of -7.23%, which can largely be attributed to unprofitable momentum trading and excessively large short positions. Furthermore, I quantify the performance of short-sellers using a value-added figure and determine that the hedge funds in my dataset create value-added of $-2,375,513,600 per year. Finally, I test the performance of hedge funds in relation to five of their corresponding characteristics: management fees, incentive fees, assets under management, age and rate of return. Majority of the results for these variables are inconsistent, however, I find that incentive fees positively predict hedge funds' short-sale performance.

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1 Introduction

The earliest forms of asset pricing models stem from the Efficient Market Hypothesis (EMH), which argues that security prices incorporate all available information and trade at their fundamental value. According to Fama (1995), an efficient market is one where prices reflect all events that have occurred and events that markets anticipate occurring in the future, which means that prices follow a 'random walk' and cannot be predicted. Considering prices always reflect their fundamental value and are random, the EMH assumes that investors cannot gain a return in excess of the market by searching for additional information. Although the EMH is one of the most documented and accepted theories of asset pricing, an abundance of academic literature has shown that prices do not follow a 'random walk' and that prices systematically deviate from their fundamental value. Systematic price deviations from fundamental values supported by strong economic rational are more commonly referred to as anomalies (Fama & French, 1996). The existence of anomalies has become a focus point of academic literature as it shows that managers can make a return in excess of the market if they successfully exploit these systematic mispricings.

A managers ability to outperform the market is widely accepted as one of the most common skill measure in the investment industry. This is a reflection of a managers skill as it shows they successfully used information not incorporated into prices to generate an excess return above the market. The excess return earned by a manager is more commonly referred to as alpha (Jensen, 1968). To clarify, risk-adjusted return and alpha all have the same meaning and will be used interchangeably throughout this paper. Alpha is defined mathematically using the following equation:

$$\alpha = (R_i - R_f) - [\beta_{i,M}(R_M - R_f)] \tag{1}$$

where R_i is the return of the portfolio, R_f is the risk-free rate, $\beta_{i,M}$ is the beta of the portfolio and R_M is the return of the market. Although alpha is a widely accepted skill measure in the investment industry, it is subject to a major flaw: it does not account for fund size in its measure and, therefore, should not be used to compare funds of different size.

The reason alpha should not be used as a skill measure for funds of different sizes is that there are diseconomies of scale within investment management. Put simply, the larger the assets under management (AUM) of a fund, the more difficult it is for them to earn a higher alpha. This is because managers will have fewer investment opportunities available as AUM increases, which results in them investing more of their AUM in the market portfolio. Of course, this is not beneficial as managers are always working to outperform the market portfolio. The presence of diseconomies of scale in the investment management industry has encouraged researches to find a better skill measure for managers that can be used across funds of varying sizes. One such skill measure, which was recently introduced by Berk & van Binsbergen (2015), is value-added.

Value-added is a quantitative skill measure used to evaluate investment managers and is determined by the product of gross alpha and AUM (Berk & van Binsbergen, 2015). Value-added is regarded as being quantitative because it measures managerial skill using a dollar figure, this being the amount of money a manager extracts from capital markets into their fund. The authors argue that value-added is a better skill measure as it can account for varying fund sizes in its calculation. The effectiveness of value-added compared to alpha can be demonstrated using a simply example. Suppose we have two funds; Fund A and Fund B. The manager of Fund A generates an annualized alpha of 5% on AUM of $1,000,000 while the manager of Fund B generates an annualized alpha of 4% on AUM of $2,000,000. From an alpha perspective, the manager of Fund A is regarded as being more skilled as they earned a higher alpha. However, from a value-added perspective, the manager of Fund B is regarded as being more skilled because they extracted $80,000 ($2,000,000 x 4%) worth of value from capital markets into their fund while the manager of Fund A only extracted $50,000 ($1,000,000 x 5%) worth of value. Alpha does not account for the fact that it is harder for the manager of Fund B to generate a higher alpha as they are managing more money, however, value-added successfully incorporates this into its calculation. A further explanation of value-added and its mathematical determination are provided in Section 4.

The goal of this paper is to use alpha and value-added to measure the skill of a relatively unanalyzed group in the investment community, short-sellers. Short-sellers are typically regarded as intelligent investors considering they are trading against the majority of the market. Despite this assumption, little is known about the actual performance of short-sellers due to a lack of available data. A recent study by Jank & Smajlbegovic (2017) provided the first detailed analysis of short-seller skill from an alpha perspective using a novel data set of daily disclosures provided by the European Union (EU). The authors show that short-sellers generate a positive risk-adjusted return on an annual basis, however, they do not analyze short-sellers from a value-added perspective. Furthermore, I will attempt to identify specific characteristics of firms who over or underperform their peers. Specific characteristics of firms such as age, AUM incentive/management fees and rate of return are those which will be examined in detail. The firms used in my research are limited to hedge funds, which are regarded as the most sophisticated investors and typically engage in short-selling activities in order to generate a profit, as opposed to other investors who may short-sell for hedging purposes.

My research contributes to the academic literature on short-sellers and investor skill in multiple different forms. First, by analyzing short-sellers using value-added, I will assess their skill with a new approach. Second, having data on the alpha and size of each position will allow for an interesting comparison. By comparing the alpha of each short position with the size of the position I will be able to study the effects of performance on short positions of varying sizes. Considering the risks associated with short selling, one could expect to see larger positions earning a higher alpha, as managers will take larger positions on short trades they are more confident about. To the best of my knowledge, this type of comparison has yet to be completed in the academic community. Third, by integrating hedge fund characteristics with performance analysis I will be able directly test whether or not their is a clear and monotonic relationship between the two. Based on prevailing academic literature and the purpose of my research, I have developed three main hypotheses to test:

1. short-sellers generate a positive alpha and extract value from capital markets
2. short-sellers generate a higher alpha on larger short positions
3. hedge funds who are younger, have lower AUM, charge higher management/incentive fees and have a higher rate of return outperform on their short-sales

Based on the results of Jank & Smajlbegovic (2017), I anticipate that the hedge funds in my dataset will generate a positive alpha and that that they will extract value from capital markets. Although there is no academic literature, at least to my knowledge, in relation to short position size and performance, I anticipate that alpha will be higher on larger short positions. If an investor has a high amount of confidence in their trade and the potential outcome of the position, it is logical that they will increase their position size. Given the evidence of hedge fund characteristics and performance, which will be discussed further in Section 2, I expect the firms who are younger and have less AUM will outperform given that they have more flexible investment policy and can focus on more liquid investments. I anticipate that firms who charge higher management and incentive fees will earn a higher return, as they must compensate investors for the excess cost. Finally, it is expected that firms with higher rate of return will generate a superior return on their short-sales as this contributes to them earning a higher rate of return.

The remainder of the paper is structured as follows. Section 2 provides a background on the related literature of short-sellers and investor skill measures and also discusses the EU policy regarding uniform short-sale disclosures. Section 3 describes the data, methods used to collect it and the methods used to create a panel series dataset. Section 4 explains the methodology related to alpha, value-added and hedge fund characteristics and describes the different regression models used in the research. Section 5 analyzes the results and identifies firm specific characteristics related to under or overperformance and section 6 concludes with final remarks.

2 Literature and Policy Review

2.1 Review of EU Policy on Short-Sale Disclosures

On November 1, 2012 the European Union put into effect Article 9 of Regulation (EU) No 236/2012. This new regulatory act requires a uniform short-sale position disclosure for any firm or individual shorting a stock in the EU, regardless of their country of origin. For example, if a Canadian investment firm is shorting a company based in the United Kingdom (UK) then the Canadian company is required to report their position on a daily basis to the UK authorities. It is then the responsibility of the UK authorities to maintain and report this data to the EU, at which point the EU will make it available to the public. This uniform disclosure rule takes effect when the size of the short position exceeds 0.50% of the outstanding shares of the company. Furthermore, the disclosure must be updated every time the size of the short position increase by 0.10% above the threshold of 0.50% (0.60%, 0.70%, 0.80%, etc). The firm is required to disclose the following details in relation to their short position: the name of their investment firm, name of the company they are shorting, International Securities Identification Number (ISIN), magnitude of the short position (% of shares outstanding) and position date. The aforementioned disclosure information is standardized and required across all EU countries. The goal of this regulation is to increase the transparency of short selling in the EU, which helps to avoid issues such as 'naked short selling'. Therefore, firms who take on the role of market maker are excluded from this regulation as they only take positions to increase liquidity and help regulate financial markets.

2.2 Investor Skill Measures

Gross and net alpha are regarded as common skill measures to assess the performance of investment managers, however, the resulting literature on the topic has provided consistently differing conclusions. In terms of analyzing the aggregate performance of mutual funds, there are a few seminal papers that provide evidence of under and overperformance. Carhart (1997) uses net alpha to show that mutual fund managers are neither skilled nor informed and that their outperformance can be attributed to the fact that they luckily hold large positions in last years winning stocks, which is not persistent in the long-run. Fama & French (2010) show that net returns for investors are minimal, but after adding back fund expenses there is evidence of superior and inferior performance on a gross basis. Kosowski et al. (2006) use bootstrap simulations to test the extreme tails of the nonnormal return distribution and find that some funds do have superior stock picking abilities and generate a high enough return to cover costs, thus leading to a positive net alpha. These are just a few examples of the heterogeneous results relating to managerial skill in the investment community on an aggregate level. The fact that results are so inconsistent sheds light on the fact that alpha, on a gross or net basis, does not truly reflect investor skill. This is one of the key motivations for the research completed by Berk & van Binsbergen (2015); not only do they show why alpha incorrectly measures skill, they explain why their approach, value-added, perfectly measures skill in all situations.

The authors argue that net alpha measures the abnormal return earned by investors and reflects the competitiveness and rationality of capital markets, not the skill of the manager. This logic stems from the work of Berk & Green (2004), who argue that if investors compete with one another for positive present value investment opportunities, all non-zero net alpha opportunities will be competed away. Therefore, the presence of a positive net alpha does not necessarily imply investor skill, but rather that capital markets are not competitive in the cross-section and that investors are not supplying enough capital to compete away the abnormal return. With a low supply of capital, managers choose to actively manage all their AUM and do not index anything. This is because they have sufficient scale to manage this amount of money and choose to do so as they can only earn a fee for what they actively manage. To understand why gross alpha does not proxy for skill, it is important to understand the link between gross and net alpha. Gross alpha is simply net alpha plus the management fee:

$$\alpha_i^g = \alpha_i^n + f_i = f_i \tag{2}$$

where α_i^g is gross alpha, α_i^n represents net alpha and f_i is the fee managers charge. Therefore, in a situation in which net alpha is always equal to zero, this implies that gross alpha is equal to the management fee (Berk & van Binsbergen, 2015). Considering managers choose the fee they want to charge, it cannot be a skill measure as it is a choice variable. Managers will only choose to actively manage the funds in which they can generate a gross alpha (management fee) on, so any AUM in addition to this will be indexed by the manager. Considering AUM varies greatly across firms, gross alpha will only work as a skill measure if all funds are managing the same amount of money; only then can a comparison be made as all managers will have chosen to actively manage the same amount of money.

The fact that managers will only invest the portion of AUM that they can successfully earn a fee on implies that firms with larger AUM will earn a lower gross alpha, as they must invest a large portion in the market portfolio. This provides clear and direct evidence that investment firms are affected by diseconomies of scale. Not only does this concept make sense logically, it has also been empirically documented in other research. Pástor et al. (2015) find that diseconomies of scale exist at an industry-level and a firm-level, which contributes to the deteriorating performance of a fund over its lifetime. The benefit of the value-added measure is that it eliminates the problem of diseconomies of scale by interacting gross alpha with AUM, therefore allowing comparison between funds of different sizes. Furthermore, it allows for a quantitative measure as skill is measured in terms of dollars, not return. Using value-added, Berk & van Binsbergen (2015) were able to find consistent performance in the cross-section of mutual funds that remains persistent for a 10-year period.

2.3 Hedge Fund Aggregate Performance

Although the majority of academic literature on aggregate performance of investment firms focuses on mutual funds due to availability of data, there is significant coverage specifically related to the performance of hedge funds compared to mutual funds. Agarwal, Boyson, & Naik (2009) examine the performance of hedge funds, traditional mutual funds and hedged mutual funds, which is a mutual fund that employs a hedge fund like strategy but does not have the incentive structure as a hedge fund and is subject to the same regulatory requirements as a mutual fund. The authors find that hedged mutual funds outperform traditional mutual funds due to the use of a more dynamic investment policy, but underperform hedge funds as they are subject to regulation and lack strong managerial inventive structures. Stulz (2007) finds similar results and shows that the hedge fund industry has grown rapidly as a result of their outperformance compared to mutual funds, which is a result of hedge funds pursuing complex investment strategies not available to mutual funds. Based on the findings of these two papers, it appears the flexibility in investment policy enjoyed by hedge funds appears to contribute to their outperformance. Eling & Faust (2010) examine the performance of hedge funds and mutual funds in emerging markets where hedge funds use of short-selling and derivatives is limited due to regulation. Regardless of this disadvantage, the authors find that some hedge funds still produce a significant alpha and that mutual funds do not outperform their benchmark, indicating the hedge funds continue to outperform in an unfavourable environment. When compared to mutual funds, it appears that hedge funds are the better investment vehicle and are growing in popularity. Further evidence of this is shown by hedge funds massive increase in AUM, increasing from $39 billion in 1990 to $2.97 trillion in 2015 (Agarwal et al., 2015).

Specifically looking at hedge funds, Liang (2001) studies hedge fund performance over the period of 1990-1999 and finds that hedge funds underperformed the S&P 500 by 4.6% on average over the sample period, however, they also exhibited roughly half the standard deviation of the S&P 500, showing that they were effective at diversifying against systematic risk. Ackermann et al. (1999) finds similar results in relation to hedge funds underperforming standard market indices over the period 1988-1995, however, the authors also find contradicting results as they show hedge funds had much higher volatility than the indices over this period. They also document that hedge funds outperformed mutual funds in this period, but also had higher volatility. Agarwal & Naik (2000) examine the persistence of hedge fund performance by using multi-period models and find that maximum persistence only exists on a quarterly level, indicating that it is short lived. Amin & Kat (2003) show that hedge funds, as a stand alone investment, do not offer any superior risk-return tradeoff to investors. However, hedge funds can have an attractive risk-return payoff if they are mixed in a portfolio with the S&P 500, due to the fact that hedge funds have low correlation with the equity market. Finally, in recently conducted research releated to hedge funds and short selling, Agarwal et al. (2018) study the performance of hedge funds Unobserved Performance (UP), which is the difference between the reported risk-adjusted return of the portfolio and the hypothetical portfolio return derived from disclosed equity holdings. Based on this measure, the UP should proxy for the performance of hedge funds derivative usage, shorting activity and undisclosed holdings. The authors discover that firms with high UP outperform firms with low UP, implying that hedge funds engaging in more shorting activities could contribute to their outperformance. In general, the literature on aggregate hedge fund performance indicates that hedge funds typically outperform mutual funds, but do not necessarily always outperform the market portfolio.

2.4 Hedge Fund Characteristics and Performance

In terms of the skill of investment managers on a non-aggregate firm level, there is a large body of evidence showing that firms who possess certain characteristics outperform their peers. Possibly one of the most examined firm characteristics is size. Chen et al. (2004) document an inverse relation between the size of a fund and its performance, both before and after fees, and indicate that the existence of this relationship is twofold. One explanation is that bigger funds have to invest more in small and illiquid stocks, indicating that they are adversely affected by liquidity. The second argument is that as fund size increases, funds with multiple managers experience organizational diseconomies, which damages their performance. In relation to liquidity, Yan (2008) finds similar results and shows that the inverse relation between size and performance increases as funds hold less liquid portfolios. Specifically in relation to hedge funds, Boyson (2008) finds that younger and smaller hedge funds significantly outperform older and larger hedge funds by 9.6% per year. Furthermore, he documents that hedge funds who recently performed well outperform firms who recently performed poorly by 3.9% annually. Aggarwal & Jorion (2010) find similar results to this and show that younger hedge fund managers and emerging funds tend to outperform older managers and funds. The authors cite a desire to establish their reputation and build AUM as the main result for this outperformance and also state it could be a result of agile trading in the market. Therefore, investors looking to invest in hedge funds should look for emerging funds who are younger, smaller and who have had recent strong performance.

Another important relationship to examine is the performance of hedge funds and the fees that the managers earn. If hedge funds pay higher fees to their managers, this cost will be passed on to the investors and they will pay higher fees to the fund. Edwards & Caglayan (2001) find that hedge funds who pay their managers higher performance fees experience higher excess returns, indicating that manager skill does have an impact on the performance of a hedge fund. Agarwal, Daniel, & Naik (2009) document similar results and show that greater managerial incentives, based on multiple different incentive measures, correlate with superior returns. The authors go one step further and also document a relationship between a higher degree of managerial discretion, measured by longer managerial lockup, notice and redemption periods, and greater performance. Restrictions like this can help managers invest in arbitrage opportunities subject to noise trader risk and also make it so they do not have to worry about performance based arbitrage issues, such as an investor withdrawing funds at an inopportune moment (Agarwal et al., 2015). A common finding on managerial incentives and hedge fund performance is that managers who have high-water mark provisions in their contract, meaning they only earn incentives if they outperform the previous maximum share value, are highly related to firms who outperform (Agarwal, Daniel, & Naik, 2009; Liang, 1999). In general, it appears that funds who pay higher performance fees to their managers are rewarded by superior returns, indicating there is a relation between manager skill and manager compensation.

There are several other interesting, potentially less documented, findings related to hedge fund characteristics and performance. Li et al. (2011) find that fund managers who attended undergraduate schools with above average SAT scores generate higher returns, take on less risk and receive higher capital inflows, indicating that educational training has an effective on managerial ability. In relation to hedge fund performance and location, Teo (2009) examines Asia-focused hedge funds and finds that funds with domestic offices in the geographical area where they are investing, or fund managers who speak the local language, outperform there distant counterparts by 3.72% annually. Considering some of the previous literature relating to hedge funds being used as a diversification tool from the stock market (Amin & Kat, 2003), Titman & Tiu (2010) explore the relationship between exposure to systematic risk factors and performance. The authors find that firms with lower R^2 produce higher Sharpe ratios, information ratios and alphas. Finally, Siegmann et al. (2017) study the existence of a first mover advantage in hedge fund performance and discover that funds who enter first into an specific investment or asset classes will outperform those who join later. In short, it seems evident that there is a plethora of firm specific characteristics that can contribute to hedge fund outperformance.

2.5 Short-Sale Performance

Due to lack of available data, little literature is available in relation to the direct performance of short-sellers. One of the first insights into the direct performance of short-sellers was provided by Jank & Smajlbegovic (2017), who use daily disclosure data of short positions in EU stocks and find that short-sellers generate an annual alpha of 5.5%. Despite the lack of literature available on direct performance, there is an abundance of research done in relation to the types of trades short-sellers enter and whether or not they are informed traders. Desai et al. (2006) explore the relationship between short sellers and earnings restatements and find that they take positions several months in advance in firms who be restate earnings, indicating that they trade on information related to accruals. In relation to short-selling and news announcements, Engelberg et al. (2012) find that the empirically documented relation between short-sales and negative returns is twice as large on news days and four times as large on negative news days, showing that short-sellers who are skilled at processing information use public news to develop trading opportunities. Christophe et al. (2010) find that short-sellers take positions in stocks days before they are downgraded by analysts and that the level of shorting before the downgrading is significantly related to the reduction of the share price from the downgrade.

In light of the fact that growth firms underperform relative to value, Dechow et al. (2001) discover that short-sellers trade on this information and take positions in stocks that are priced high relative to their earnings and fundamental value. In a recent research project, Gargano et al. (2019) examine the performance of short-sellers in a large cross-section of US equities. The authors find that, on average, short-sellers experience losses consistent with a positive equity risk premium, however, there is a wide dispersion of profits and losses within a stock, indicating that timing and level of informativeness effect the performance and short-sellers. They also show that short-sellers generate profits on stocks that are most heavily shorted, which supports existing evidence that high short interest in a stock predicts negative returns. It appears that the consensus of the academic community is that short-sellers are intelligent and informed investors who successfully use different types of information to trade to their advantage.

3 Data

3.1 Short-Sale Disclosures

I start by collecting all short-sale disclosures from the United Kingdom (UK), Germany and France for the period November 1, 2012 to December 31, 2018.[1] I choose these three countries

[1] A list of links to the individual national websites can be found at: https://www.esma.europa.eu/databases-library/esma-library

as they are three of the largest economies in the EU and have enough disclosures between them to allow for a rich dataset. The disclosures are uniform across the three countries and include the Position Holder, Share Issuer, ISIN, Net Short Position (%) and Position Date. Considering certain firms report positions under slightly different names because of different office locations, I standardize all company names to the name that appears most often in my dataset so their performance can be grouped together. Next, I delete any disclosures from my dataset that are not reported by hedge funds. This is because hedge funds are typically regarded as the most informed investors and using only hedge funds allows for direct comparisons between firms. It would not be accurate to compare the short-selling activities of hedge funds to the short-selling activities of mutual funds or pension funds. In order to remove firms who are not hedge funds, I download a list of all hedge funds that exist in the Lipper Hedge Fund Data Base (TASS) and compare them to the firms who have reported short-positions in my dataset. For the firms in my dataset that do not appear in TASS, I manually research them on Bloomberg to see if they operate as a hedge fund to account for the fact that they may not exist in TASS. I only keep these firms if Bloomberg has classified them specifically as "Hedge Fund" and do not include them if Bloomberg classifies them as "Investment Manager" or "Investment Adviser". Doing so leaves me with 210 different hedge funds with reported short-positions.

Finally, in order to achieve the most accurate dataset possible, I take two steps to clean the disclosures. First, I delete any short disclosures who's initial value was above the 0.50% threshold as they are assumed to have begun before November 1st 2012. Considering I cannot accurately estimate the size of these positions before this date, due to unavailable data, I believe it is more accurate to delete them. Second, I delete those still open at the end of my sample period. A short position is classified as open if its last reported value for Net Short Position is above the 0.50% threshold. Therefore, all the short disclosures in my dataset have a final reported value for Net Short Position equal to or less than 0.50%. This method is preferred, as opposed to keeping open positions, as the return on positions that are still open cannot be accurately relied upon. There is no way to determine if these positions will close at a profit or a loss, so it is better to disclude them. Using only closed positions will ensure that the computed alpha of short-sellers is accurate and reliable, which is essential when calculating value-added. Considering value added is the product of AUM and gross alpha, the accuracy of its calculation depends on the accuracy of the calculated alpha. After deleting all open positions, there is a total of 2,695 short-positions remaining in my dataset across 665 different ISIN's. For convenience purposes, Table 1 in the Appendix displays a summary of the data statistics.

3.2 Stock-Level Data and Firm Characteristics

I collect all stock-level data from Datastream, the database most commonly used for daily securities information, by using the list of ISIN's accompanying the short-sale disclosures. After the initial download, I notice that a number of ISIN's have no data, as ISIN's can change over time. In order to correct for this, I look up the ISIN's with missing data in Bloomberg in order to locate their updated ISIN. Next, I download the stock data with the new list of updated ISIN's and integrate this into my original list. In terms of daily stock-level data, I retrieve the Total Return Index (TRI) and Market Value (MV) for all stocks in my dataset. Considering that my list of hedge funds consists of hedge funds from around the globe, I download all stock-level data in USD in order to standardize returns. TRI is needed in order to calculate the holding period return of each security and MV is needed in order to calculate the dollar amount of each short-position. Having the daily MV of each firm, combined with the daily Net Short Position expresses as a percentage, provides the necessary information to calculate daily position sizes. In order to calculate the holding period return of each stock, I use the change in the TRI as expressed by the following formula:

$$R_{i,t} = \frac{TRI_{i,t} - TRI_{i,t-1}}{TRI_{i,t-1}} \tag{3}$$

In order to reduce the effect of spurious outlier return data, I set any daily return figure $R_{i,t}$ to missing if it is greater then 100% or less than -100%. Next, I subtract the risk-free rate in order to convert the returns to excess returns. I use the following formula to convert the excess returns and alpha figures discussed in the results section from daily to annually:

$$AnnualReturn = [(1 + DailyReturn)^{250} - 1] * 100 \tag{4}$$

where it is assumed that there are 250 trading days in the year and the equation is multiplied by 100 to express the result as a percentage.

Finally, I enrich my dataset with characteristics on the individual hedge funds, which are retrieved from Thomson Reuters Lipper TASS database. Specifically, I retrieve information on funds Assets Under Management (AUM), Inception Date, Management Fee, Incentive Fee and Rate of Return. Inception date is the variables used in order to determine the age of the hedge fund. Considering not all the firms in my dataset exist in TASS, my sample size is reduced to 83 hedge funds for the sorted portfolios analysis. Although a large number of hedge funds are eliminated from the dataset for the sorted portfolio analysis, there still remains a large number of short positions and ISIN's. When using only the 83 remaining hedge funds there are still 1451 short positions and 530 ISIN's.

4 Methodology

4.1 Alpha

In order to investigate the performance of short-sellers, I employ a timing approach that takes advantage of the daily disclosures provided by my short-sale disclosure dataset. Specifically, my investment strategy shorts a stock every time an investor reports a disclosure above the 0.50% threshold and continues to short this stock until the disclosure falls below the 0.50% threshold. This investment strategy begins shorting the stock the day the disclosure is made and stops shorting it the last reported day of the disclosure. An example of the investment strategy can be seen in Figure 1 in the Appendix. For this investment strategy I construct a short-value-weighted (SVW) portfolio return, where the investment in each stock is weighted on the past market capitalization of each short position. I believe the SVW portfolio is the best method as it most closely resembles the actual performance of short-sellers.

After forming SVW portfolios, I run a time-series regression of the excess returns from each portfolio i on a standard set of pricing factors, which converts the raw returns into risk-adjusted returns. The regression analysis is represented by the following equation:

$$-(R_{i,t} - R_{f,t}) = \alpha_i + \bar{\mathbf{X}}'\boldsymbol{\beta_i} + \epsilon_{i,t} \tag{5}$$

where $R_{i,t}$ represents the return of the portfolio and $R_{f,t}$ is the risk-free rate. The excess returns are multiplied by -1 as a negative portfolio return translates into a positive gain for a short-sale. $\bar{X}'$ is a vector containing common pricing factors (MKTRF, SMB, HML, WML, QMJ, BAB)[2] and will change across the different models under analysis. In addition, α_i is the portion of the excess return unexplained by the pricing factors used in the vector, β_i represents the exposure of the excess portfolio returns to these factors and $\epsilon_{i,t}$ is the random error component.

In order to fully validate the strength of this model, it is important to explain the motivation for choosing the aforementioned pricing factors. MKTRF represents the Capital Asset Pricing Model (CAPM) and measures the exposure of the excess returns to systematic risk in the market. This factor stems from the early work of Markowitz (1952), who introduced Modern Portfolio Theory, and was solidified as the standard for asset pricing theory in the seminal research completed by Sharpe (1964). Examining whether short-sellers are positively or negatively exposed to systematic market risk will provide valuable insight into their investment behaviour. SMB and HML were introduced by Fama & French (1993), which they combined

[2] I use the daily European pricing factors provided by AQR Capital Management as my dataset consists of European stocks. The daily European pricing factors provided by AQR are expressed in USD, which is ideal as I have also expressed my returns in USD. The following is a link to the AQR Data Library where the factors were obtained: `https://www.aqr.com/Insights/Datasets`

with MKTRF in order to create there famous 3-Factor model, a standard approach used in asset pricing research to convert raw excess returns into risk-adjusted returns. SMB is a factor expressing the outperformance of small-cap firms relative to large-cap firms and HML is a factor conveying the outperformance of firms with high B/M ratios relative to firms with low B/M ratios.

The remaining three factors (WML, QMJ, BAB) are relevant to include as they are the three strongest candidates for mispricing related factors. Considering hedge funds and short-sellers are regarded as intelligent investors, it is necessary to examine whether they trade on these mispricings. WML refers to the momentum anomaly, most noticeably documented by Jegadeesh & Titman (1993). The authors find that stocks that have performed well in the past will continue to perform well in the future, therefore allowing for a rather simple predictability in future returns. Including this pricing factor will allow me to examine whether or not short-sellers exploit this reliable predictability. QMJ was discovered by Asness et al. (2014) and states that quality stocks outperform junk stocks. Quality (junk) stocks are defined as those with high (low) profitability, growing (declining) profitability and high (low) safety scores. Finally, BAB refers to the the anomaly that high-beta stocks have their prices bid-up by constrained investors, which subsequently leads to them having lower returns then low-beta stocks. BAB was discovered by Frazzini & Pedersen (2014) and is a key factor to include as it directly contradicts the standard CAPM; including both in my regression analysis will allow for a direct comparison between the two.

4.2 Value-Added

To quantify the performance of short-sellers I calculate their value-added, which is defined as the dollar value of what the short-sellers add to their fund over their benchmark (Berk & van Binsbergen, 2015). Put simply, it is the product of gross alpha and the size of their short position. Considering I have data on the size and gross alpha of each short position in my dataset, it is possible to use this skill measure. Value-added is considered to be a quantitative measure as it measures skill using an amount, in this case dollars, as opposed to gross alpha which measures skill using a percentage figure. The calculation of realized value-added between time periods $t-1$ and t is expressed as follows:

$$V_{it} = q_{i,t-1}(R_{it}^g - R_{it}^b) \tag{6}$$

where $q_{i,t-1}$ is the value of short position i at time period $t-1$ and $(R_{it}^g - R_{it}^b)$ is the benchmark adjusted realized gross return of short position i at time period t. This formula gives the value-added for one short position and needs to be furthered to capture the value-added of an entire collection of short positions.

For a collection of short positions that exist for T_i periods the value-added is equal to the total value-added of all short positions divided by the number of periods:

$$\hat{S}_i = \sum_{t=1}^{T_i} \frac{V_{it}}{T_i} \tag{7}$$

considering my dataset consists daily disclosures, this represents the value-added from short positions per day. For convenience purposes, value-added will be converted into a yearly measure when analyzing results. Finally, to determine the average value-added per short position per day, an estimate of the mean is given by:

$$\bar{S} = \frac{1}{N} \sum_{i=1}^{N} \hat{S}_i \tag{8}$$

where N is the number of short positions in my dataset. The breakdown of these formulas mirror those presented by Berk & van Binsbergen (2015), however, in their paper $q_{i,t-1}$ represents AUM and N represents number of mutual funds.

4.3 Sorted Portfolios

To test for the outperformance of firms containing certain characteristics, a single-sorted portfolios method will be utilized where daily quintiles are formed based on the different hedge fund characteristics. In order to measure the performance across characteristics, I regress the excess returns of each daily quintile on the same set of pricing factors discussed in Section 4.1. In all tables relating to portfolio sorts in the Appendix, Panel A represents CAPM alpha (MKTRF), Panel B represents Fama & French 3-Factor Model (MKTRF, SMB, HML), Panel C represents 4-Factor Model (MKTRF, SMB, HML, WML) and Panel D represents the 6-Factor Model (MKTRF, SMB, HML, WML, BAB, QMJ). Specifically, I will perform single-sorted portfolios on five different firm characteristics: age, AUM, management fees, incentive fees and rate of return. For age, the highest (lowest) quintile represents the oldest (youngest) hedge funds. In regards to AUM, the highest (lowest) quintile corresponds to the hedge funds with the highest (lowest) AUM. For management and incentive fees, the highest (lowest) quintile represents the hedge funds who charge the highest (lowest) management and incentive fees. Finally, the highest (lowest) quintile corresponds to funds with the highest (lowest) rate of return. As previously mentioned, I form daily quintiles (5 different portfolios) for the different hedge fund characteristics, however, a slightly different approach is taken for incentive fees. Due to the fact that the data for incentive fees is heavily skewed to the high and low ends, I make only two daily portfolios for this variable. The lack of variety in the incentive data makes it not possible to create five daily portfolios, therefore, I choose to create two as the data allows for this and doing so will still provide clear evidence in relation to the performance of firms charging high and low incentive fees. Next, for each characteristic, I determine the performance of each quintile and check for a monotonic relationship. If a monotonic relationship exists, this is evidence that the characteristic under scrutiny has an impact on performance. Besides specific characteristics of hedge funds, I will also perform a sorted portfolios analysis on “short-value”, which is the dollar value of each short position. The goal of this is to determine if the larger short positions are generating a higher alpha than the smaller short positions. Similar to hedge fund characteristics, the highest (lowest) decile will represent the portfolio of the largest (smallest) short positions. To test for the effect of size on performance, I decide to sort on short-value as opposed to NSP as short-value expresses size in terms of a dollar amount whereas NSP expresses size in terms of percentage. Using NSP would not be a true reflection of the size of a short position as it does not account for the fact that firms with varying amounts of market capitalization’s are being shorted; measuring short positions using a dollar figure (short-value) eliminates this issue.

4.4 Fama-MacBeth Analysis

As a follow-up and robustness check to the sorted portfolios, I will also perform a regression analysis along the lines of Fama & MacBeth (1973) to test whether hedge fund characteristics can predict hedge fund performance. With daily excess returns of various hedge fund short positions as the dependent variable, the regression analysis can be expressed using the following equation:

$$EXRET_{i,t} = \alpha_t + \beta_t MNGMT_{i,t} + \beta_t INC_{i,t} + \beta_t AUM_{i,t} + \beta_t AGE_{i,t} + \beta_t ROR_{i,t} + \epsilon_{i,t} \quad (9)$$

where MNGMT denotes management fee, INC represents incentive fees, AUM indicates assets under management, AGE denotes age and ROR represents rate of return, all of which pertain to hedge fund i at time period t. The goal of this analysis is to obtain the time-series average of each estimated regression coefficient for each hedge fund characteristics under scrutiny. Based on the resulting time-series regression coefficients it will be possible to tell whether or not a characteristic positively or negatively predicts hedge fund performance. It is anticipated that the results will support the findings from the sorted portfolio analysis. In this analysis six different models will be used. Models 1-5 will use each of the aforementioned five hedge fund characteristics in a singular model whereas model 6 will incorporate all five characteristics at once in order to test whether the results remain significant when controlling for other variables, which is one of the main benefits of this type of analysis.

5 Results

5.1 Alpha

This section discusses the results of the short-sale strategy by analyzing the factor loadings and alpha's of the different models. A summary of the results can be found in Table 2 in the Appendix. In regards to factor loadings, the null hypothesis is that the factor loading will equal 0. The only exception to this is that the null hypothesis for MKTRF will equal -1. In an analysis of factor loadings consisting of long positions the null hypothesis is always that MKTRF will equal 1, so it is therefore the opposite in an analysis of short-sale performance. The t-statistics for factor loadings and alphas are computed with Newey & West (1986) standard errors in order to mitigate the effects of autocorrelation. In this analysis excess short-sale returns are regressed on pricing factors across four different models. Model 1 uses MKTRF, Model 2 is the Fama-French 3-Factor model, Model 3 is the Carhart 4-Factor model and Model 4 is the Carhart 4-Factor model with the inclusion of BAB and QMJ.

One of the most interesting and consistent results is that the factor loading on MKTRF is consistently less then -1 in all models as it fluctuates between -1.136 and -1.192. This indicates that short-sellers systematically deviate from the market portfolio as they are exposed to greater risk. The fact that short-sellers are exposed to greater risk than the market portfolio is reinforced by the positive and significant factor loading on BAB on model 4. A positive portfolio tilt toward BAB, as revealed by the factor loading of 0.196 and corresponding t-stat of 8.06, indicates that investors are either buying low-beta stocks or shorting high-beta stocks. The factor loadings from MKTRF and BAB together reveal that the investors in my group are shorting high-beta stocks. Two other results that remain persistent across all models are the negative and significant factor loadings on SMB and HML. A negative factor loading on SMB implies that the investors are shorting small-cap stocks, which is surprising as small-cap stocks tend to experience higher returns. The same logic applies to a negative HML factor loading. This coefficient insinuates that the investors are shorting stocks with a high B/M ratio, which is unexpected as these stocks outperform there low B/M ratio counterparts. Similar results also appear with respect to the factor loading on QMJ. A negative and significant factor loading on QMJ implies that the investors in my dataset are shorting stocks that are of high quality, which is unexpected as high quality stocks tend to experience positive returns. Finally, the factor loading on WML is consistently positive, significant at the 1% level and the largest of all in the regression analysis. This positive exposure to momentum trading shows that the investors in my dataset are shorting "losing stocks", which are stocks that have experienced negative returns in the recent months.

The CAPM (Model 1) alpha resulting from the regression analysis is -2.89% indicating that short-sales which take more risk than the standard market portfolio will not lead to any out-performance. When extending the CAPM to a 3 Factor model with the inclusion of SMB and HML, the alpha slightly improves and becomes -2.65%. Despite this, both the CAPM and 3 Factor alpha are statistically insignificant and cannot be accurately relied upon. The most interesting result in regards to alpha occurs in Model 3 with the inclusion of the momentum factor. When the WML factor is added to the model the alpha becomes -7.23% with a corresponding t-statistic of -2.80. This result suggests that trading on momentum is driving the underperformance of short-sellers in my dataset. Although there are a lot of studies supporting the profitable trading of momentum strategies (Jegadeesh & Titman, 1993; Novy-Marx, 2012) it is important to recognize the debate about the performance of momentum over time. For example, Bhattacharya et al. (2017) study the profitability of momentum strategies form 1965-2012 and find that momentum profits have become insignificant from the late 1990's onward. My results support there findings and indicate that the short side of momentum trading has continued to be unprofitable from 2012 onward. Finally, after extending the model again with the inclusion of BAB and QMJ, the alpha remains significant and negative (-7.06%). Although there is slight improvement, the lack of change between Model 3 and Model 4 indicates that the inclusion of these two additional factors does little to improve the analysis or the overall performance of short-sellers.

5.2 Value-Added

In order to analyze short-sellers from a value-added perspective it is necessary to first calculate the excess return $R^g_{it} - R^b_{it}$, which requires choosing the appropriate benchmark return R^b_{it}. Choosing an appropriate benchmark can be a challenging process as the investments in the benchmark portfolio need to be as similar as possible to the investments in the portfolio under analysis. For example, if studying the performance of a mutual fund who invests only in large-cap equities it would be logical to select the S&P 500 as this is the most comparable universe of stocks. Considering a detailed analysis of the stocks comprising my dataset are outside the scope of my research, I simply select the market portfolio as my benchmark. Although an indication of the type of stocks being traded on by short-sellers is given from the factor loadings in Table 2, a completely accurate benchmark cannot be determined from this, so choosing the market portfolio appears to be the best option. I use the returns from the pricing factor MKTRF previously discussed in Section 4.1 as the market portfolio.

A summary of the results from the value-added calculations can be found in Table 3. Over the period November 1st 2012-December 31st 2018 the total value-added, V_{it}, from the hedge funds in my dataset is $-14,633,163,776, showing that hedge funds actually destroy value on their short positions. On an annual basis, $\hat{S}_i$, this translates into value-added of \$-2,375,513,600 per year. Considering there are 210 hedge funds in my dataset, this means that the average value-added per hedge fund on an annual basis is \$-11,311,970. The mean value-added per short position per day, $\bar{S}$, is \$-22,481, however, there is a large standard deviation of \$1,499,294, indicating that there are short positions that are generating positive and large value-added. The overall losses experiences by short-sellers and wide spread dispersion of profits and losses across short positions, as indicated by the mean and standard deviation, are consistent with the findings of Gargano et al. (2019) who find similar results in a large cross-section of US equities.

5.3 Sorted Portfolios

This section discusses the results associated with the sorted portfolios technique. First, results related to position size and performance are analyzed followed by results related to hedge fund characteristics and performance.

5.3.1 Position Size

Considering there is a large standard deviation in the mean of value-added it is important to analyze which short positions are creating value and which short positions are destroying value. Based on this, I form daily quintiles of excess returns sorted on short-value and regress them on different pricing factors. The results of this analysis can be found in Table 4. It is expected that the larger short positions (quintile 5) will generate a higher alpha as investors will take bigger positions when they are more confident about the expected return. Contrary to expectations, the opposite result is found across all models. In all panels, quintile 5 has the lowest alpha, indicating that it is actually the largest short positions that are driving the underperformance of short-sellers. Although there is not a perfectly monotonic relationship across deciles, it is evident based on the extreme quintiles in all panels that position size impacts the returns. There is a 5-1 return differential ranging from -3.05% (Panel A) to -5.66% (Panel C) and all of the return differences are statistically significant. Furthermore, it can be inferred from the results in Panel C, which includes the WML pricing factor, that trading on momentum is driving the underperformance of short-sellers in my dataset, especially on the largest short positions in quintile 5. These results support the findings previously discussed in Section 5.1.

5.3.2 Hedge Fund Characteristics

This section discusses the results of the sorted portfolios analysis based on the hedge fund characteristics, the results of which can be found in Tables 5-9 in the Appendix. Beginning with Table 5, Management Fees, a relationship between performance and management fees begins to exist in Panel C and Panel D. The hedge funds who charge the lowest management fees, quintile 1, are underperforming the hedge funds who charge the highest fees, that being quintile 5. Focusing on Panel C, quintile 1 generates a 4-factor alpha of -2.41% whereas quintile 5 generates a 4-factor alpha of -1.34%, both of which are significant at the 5% level. This annualized return difference of 1.07%, which can be found in the 5-1 column, indicates that hedge funds charging more for their services are providing a better return than hedge funds charging less for their services, however, these results are not statistically significant. Similar results are found in Panel D when using a 6-factor model. These findings are consistent with those of Edwards & Caglayan (2001) who also find a positive relationship between management fees and performance. With regard to Incentive Fees in Table 6, a very interesting relationship is found. The Hedge Funds in Portfolio 1 charging low incentive fees are greatly underperforming the Hedge Funds in Portfolio 2, who are charging the high incentive fees. The 2-1 return differential ranges from 3.89% in the CAPM model to 6.78% in the 6-Factor model. Furthermore, all of the results in the return differentials are statistically significant. These results support the findings of Agarwal, Daniel, & Naik (2009) who document a positive relationship between incentive fees and hedge fund performance.

Moving towards Table 7, which discusses AUM, there appears to be a positive relationship between AUM and performance, which is against expectations resulting from prevailing literature previously discussed. Focusing on Panel D, the hedge funds with the lowest AUM, quintile 1, have an annualized 6-factor alpha of -4.99% whereas the hedge funds with the highest AUM, quintile 5, have an annualized 6-factor alpha of -3.50%. When focusing on these two extreme deciles one could conclude that hedge funds with higher AUM have better performance compared to hedge funds with lower AUM based on the annualized return difference of 1.94%. Regardless of the existence of this return differential in the extreme quintiles, the results should be approached with caution as there is not a perfectly positive and monotonic relationship and the return differential is not statistically significant in any panel. Considering the positive relationship found between AUM and returns, it appears that these findings contradict Chen et al. (2004) and Yan (2008) who discover an inverse relationship between fund size and performance.

Next, with respect to Table 8, which presents the results for Age, it is expected that the firms in quintile 1 who are younger will outperform. Contrary to expectations, it is actually the older firms in quintile 5 who consistently outperform in all panels. In Panel A quintile 1 generates a CAPM alpha of -1.66% while quintile 5 earns a CAPM alpha of -0.62%, leading to a 5-1 return differential of 1.05%, however, these results are not statistically significant. The outperformance of quintile 5 remains moving from Panel A to Panel D, however, the return differential is greatly reduced and does not become significant. Overall, it does appear that age positively predicts returns, contradicting previous findings by Boyson (2008) and Aggarwal &

Jorion (2010). Finally, with respect to Table 9, which discusses the results for rate of return, it can be concluded that there is no relationship between the rate of return of hedge funds and their short-sale performance. When moving across quintiles the results are inconsistent and and it is clear that there is no monotonic relationship. Furthermore, the 5-1 return differentials across all panels are not statistically different than zero.

5.4 Fama-MacBeth Analysis

To determine whether or not hedge fund characteristics can predict hedge fund performance I use Fama & MacBeth (1973) regressions, the results of which can be found in Table 10. Beginning with Model 1, which uses management fee as the explanatory variable, the resulting regression coefficient is -0.072, indicating that management fees negatively predict hedge fund performance. This result is inconsistent with the findings from the portfolio sorts, however, both the 5-1 return differentials from the portfolio sorts and resulting regression coefficient from this analysis are statistically insignificant. Moving towards Model 2, which uses incentive fee as the explanatory variable, the regression coefficient is 1.122 with a corresponding t-statistic of 1.83. This result supports the findings from the portfolio sorts and reinforces the fact that incentive fees positively predict hedge fund performance. Model 3, which uses the natural logarithm of AUM as the explanatory variable, has a regression coefficient of -0.102 and is not statistically significant. These results are not in line with the findings from the sorted portfolios analysis, however, the results from both analyses are not statistically significant. In regards to model 4, which uses the natural logarithm of age as the explanatory variable, there is a large and positive regression coefficient of 3.287, indicating that age positively predicts hedge fund performance. This supports the findings from the sorted portfolio analysis, however, neither the 5-1 return differential from the portfolio sorts nor the regression coefficient from this analysis are statistically significant, so the results need to be analyzed with caution. Finally, there is a regression coefficient of -2.642 and corresponding t-statistics of -1.83 in model 5, which uses rate of return as the explanatory variable. This result suggests that rate of return actually negatively predicts hedge funds' performance on their short-sales. This contradicts the findings from the portfolio sorts, however, the 5-1 return differential in the portfolio sorts was not statistically significant whereas the regression coefficient from this result is, therefore adding validity to the result from this analysis as opposed to the sorted portfolios.

The far most right column, model 6, presents the results which include all hedge fund characteristics in one regression. This model is of the most importance as it will show whether or not the results from models 1-5 are robust when controlling for other firm characteristics. Upon controlling for the effects of other characteristics, nearly all the regression coefficients become not statistically different then zero, indicating that these characteristics cannot predict hedge fund performance. The only exception to this is the regression coefficient for incentive fee, which increases to 1.950 and becomes statistically significant at the 1% level (t-statistics of 3.76). The fact that the coefficient increases and becomes more significant indicates that incentive fees can positively predict hedge fund performance and is robust when controlling for other common hedge fund characteristics. This result further supports the strong empirical results found in the sorted portfolio analysis resulting from the 5-1 return differential. In summary, it is evident from the portfolio sorts and Fama-Macbeth regressions that incentive fees are the only variable that can reliably predict hedge fund performance. In regards to the other four variables, it cannot be stated with confidence whether or not they predict hedge fund performance due to the inconsistent and statistically insignificant results.

6 Conclusion

In this research project I use a rich dataset of daily short-sale disclosures provide by the EU in order to test the performance of short-sellers from hedge funds and to identify firm specific characteristics of hedge funds that relate to performance. I use short-sales that were disclosed between the period November 1 2012 - December 31 2018 provided by three countries: United Kingdom, Germany and France. I find that short-sellers underperform the market and earn an annualized 4-Factor alpha of -7.23%. The underperformance of short-sellers can be largely attributed to unprofitable trading on momentum strategies and excessively large short positions. Furthermore, I quantify the performance of short-sellers using a value-added metric and determine that the hedge funds in my dataset create value-added of $-2,375,513,600 per year. Despite this negative value added, the mean value-added per hedge fund per day in my dataset is $-22,481 with a standard deviation of 1,499,294, indicating that there are short positions in my dataset which are highly profitable. Based on portfolio sorts of short-value, the dollar value of each short position, it is evident that it is the largest short positions which are destroying value. Finally, I look at the performance of hedge funds and their corresponding characteristics by examining management fees, incentive fees, AUM, age and rate of return. The majority of the results related to these variables are inconclusive, however, I find very strong results related to incentive fees. Using portfolio sorts and regression analysis, I find that incentive fees positively and significantly predict hedge fund performance and that these results are robust when controlling for other firm characteristics.

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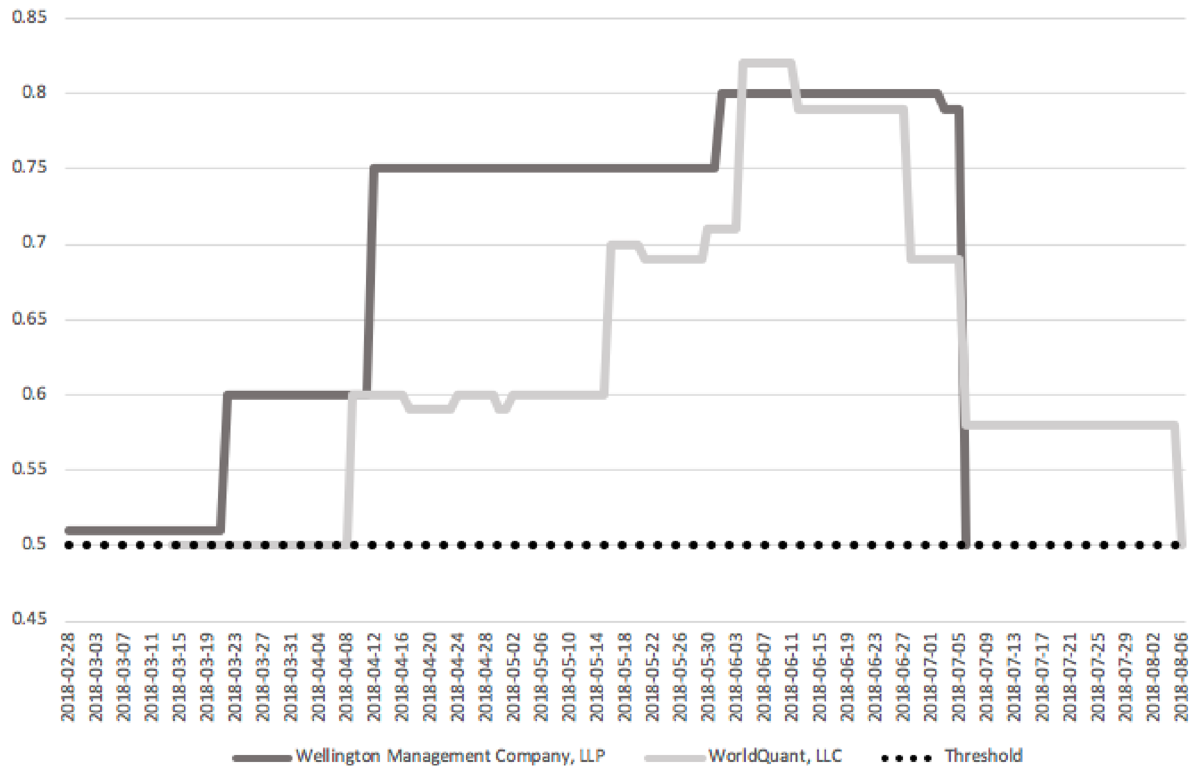
A Tables and Figures

Table 1: Summary Statistics

Variable	N
Firms (Total)	210
Firms (Sorted Potrfolios)	83
Short Positions (Total)	2695
Short Positons (Sorted Portfolios)	1451
ISIN's (Total)	665
ISIN's (Sorted Portfolios)	530

This table displays the summary statistics of the key variables discussed in Section 3. Variables followed by "Total" in parentheses indicate summary statistics for variables in Section 4.1 and Section 4.2 while variables followed "Sorted Portfolios" in parentheses indicate summary statistics fro variables in Section 4.3.

Figure 1: Example of Investment Strategy



This figure provides an example of the short-sale investment strategy discussed in Section 4. The stock being shorted is Dunelm Group PLC (ISIN:GB00B1CKQ739). The black dashed line represents the 0.50% threshold where investors are required to disclose their position and the solid dark and light grey lines represents the size of the two investment firms positions. The vertical axis is Net Short Position expressed as a %.

Table 2: Short-Sale Performance

Short-Value Weighted	**(1)**	**(2)**	**(3)**	**(4)**
MKTRF	-1.142***	-1.160***	-1.136***	-1.192***
	(-5.75)	(-6.25)	(-4.89)	(-6.43)
SMB		-0.147***	-0.136***	-0.300***
		(-4.33)	(-4.24)	(-7.96)
HML		-0.371***	-0.168***	-0.340***
		(-10.13)	(-4.47)	(-7.02)
WML			0.391***	0.409***
			(14.09)	(14.77)
BAB				0.196***
				(8.06)
QMJ				-0.271***
				(-4.93)
α	-2.89	-2.65	-7.23***	-7.06***
	(-1.01)	(-0.96)	(-2.80)	(-2.76)
Adj R^2	81.41	82.55	84.39	84.96

This table displays the performance of the short-sale strategy described in Section 4. The table reports factor loadings, alphas and the Coefficient of Determination (R^2) for each model. Factor loadings and alphas are reported with t-statistics computed using Newey-West standard errors below in parentheses. The excess short-sale returns are regressed on different pricing factors depending on the model. *, **, *** represent significance at the 10%, 5% and 1% levels, respectively. All alphas reported have been annualized.

Table 3: Value-Added Statistics

Value-Added	Amount ($)
Total	-14,633,163,776
Annual	-2,375,513,600
Per Hedge Fund	-11,311,970
Mean	-22,481
Standard Deviation	1,499,294

This table displays the value-added statistics, expressed in USD, from the short-sales discussed in Section 5.2.

Table 4: Portfolio Sorts Based on Short-Value

Short-Value	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(5-1)**
Panel A: CAPM						
Constant	-0.49	1.96	0.73	-0.38	-3.54*	-3.05**
t-stat	(-0.86)	(0.52)	(0.74)	(-0.05)	(-1.79)	(-2.01)
Panel B: 3-Factor						
Constant	-0.40	0.31	0.53	1.84	-3.79**	-3.39**
t-stat	(-0.70)	(0.87)	(1.10)	(0.25)	(-1.99)	(-2.26)
Panel C: 4-Factor						
Constant	-0.84	-1.23	-1.82	-0.92	-6.50***	-5.66***
t-stat	(-1.46)	(-0.35)	(-0.39)	(-1.31)	(-3.55)	(-3.73)
Panel D: 6-Factor						
Constant	-0.90	-1.91	-0.26	-0.92	-6.29***	-5.39***
t-stat	(-1.57)	(-0.54)	(-0.56)	(-1.31)	(-3.43)	(-3.61)

This table displays the alphas (constants) of five daily short-value-weighted (SVW) portfolios sorted on the Short-Value of each short position, expressed as a percentage. All alphas have been annualized and the t-statistics in the parentheses have been computed with Newey-West standard errors. *, **, *** represent significance at the 10%, 5% and 1% levels, respectively. Panel A represents CAPM alphas, Panel B represents 3-Factor alphas, Panel C represents 4-Factor alphas and Panel D represents 6-Factor alphas, all of which were described in Section 4.1.

Table 5: Portfolio Sorts Based on Management Fee

Management Fee	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(5-1)**
Panel A: CAPM						
Constant	-0.82	-1.94	-0.53	0.97	-0.91	-0.09
t-stat	(-0.67)	(-1.18)	(-0.50)	(0.81)	(-1.44)	(-0.40)
Panel B: 3-Factor						
Constant	-0.73	-1.73	-0.68	1.32	-0.95	-0.22
t-stat	(-0.61)	(-1.07)	(-0.65)	1.12	(-1.50)	(-0.26)
Panel C: 4-Factor						
Constant	-2.41**	-3.42**	-1.42	0.74	-1.34**	1.07
t-stat	(-2.06)	(-2.14)	(-1.37)	(0.62)	(-2.12)	(1.55)
Panel D: 6-Factor						
Constant	-2.35**	-3.70**	-1.20	1.18	-1.32**	1.03
t-stat	(-2.04)	(-2.30)	(-1.15)	(1.00)	(-2.09)	(1.58)

This table displays the alphas (constants) of five daily short-value-weighted (SVW) portfolios sorted on Management Fee, expressed as a percentage. All alphas have been annualized and the t-statistics in the parentheses have been computed with Newey-West standard errors. *, **, *** represent significance at the 10%, 5% and 1% levels, respectively. Panel A represents CAPM alphas, Panel B represents 3-Factor alphas, Panel C represents 4-Factor alphas and Panel D represents 6-Factor alphas, all of which were described in Section 4.1.

Table 6: Portfolio Sorts Based on Incentive Fee

Incentive Fee	**(1)**	**(2)**	**(2-1)**
Panel A: CAPM			
Constant	-3.27	0.62	3.89**
t-stat	(-1.45)	(0.75)	(2.07)
Panel B: 3-Factor			
Constant	-3.24	0.72	3.96**
t-stat	(-1.46)	(0.88)	(2.15)
Panel C: 4-Factor			
Constant	-6.39***	-0.02	6.37***
t-stat	(-3.01)	(-0.03)	(3.52)
Panel D: 6-Factor			
Constant	-6.60***	0.18	6.78***
t-stat	(-3.10)	(0.23)	(3.73)

This table displays the alphas (constants) of two daily short-value-weighted (SVW) portfolios sorted on Incentive Fee, expressed as a percentage. All alphas have been annualized and the t-statistics in the parentheses have been computed with Newey-West standard errors. *, **, *** represent significance at the 10%, 5% and 1% levels, respectively. Panel A represents CAPM alphas, Panel B represents 3-Factor alphas, Panel C represents 4-Factor alphas and Panel D represents 6-Factor alphas, all of which were described in Section 4.1.

Table 7: Portfolio Sorts Based on AUM

AUM	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(5-1)**
Panel A: CAPM						
Constant	-1.11*	-0.31	-0.01	-0.83	-0.55	0.56
t-stat	(-1.70)	(-0.41)	(-0.02)	(-0.65)	(-0.51)	(0.35)
Panel B: 3-Factor						
Constant	-0.97	-0.19	0.13	-0.92	-0.68	0.29
t-stat	(-1.03)	(-0.25)	(0.17)	(-0.73)	(-0.63)	(0.14)
Panel C: 4-Factor						
Constant	-1.78*	-0.89	-0.61	-2.41**	-1.35	0.43
t-stat	(-1.91)	(-1.18)	(-0.81)	(-1.97)	(-1.26)	(0.25)
Panel D: 6-Factor						
Constant	-4.99**	-2.01	-1.29	-6.14**	-3.05	1.94
t-stat	(-2.13)	(-1.06)	(-0.68)	(-1.99)	(-1.14)	(0.50)

This table displays the alphas (constants) of five daily short-value-weighted (SVW) portfolios sorted on AUM, expressed as a percentage. All alphas have been annualized and the t-statistics in the parentheses have been computed with Newey-West standard errors. *, **, *** represent significance at the 10%, 5% and 1% levels, respectively. Panel A represents CAPM alphas, Panel B represents 3-Factor alphas, Panel C represents 4-Factor alphas and Panel D represents 6-Factor alphas, all of which were described in Section 4.1.

Table 8: Portfolio Sorts Based on Age

Age	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(5-1)**
Panel A: CAPM						
Constant	-1.66	-0.61	0.01	-0.83	-0.62	1.04
t-stat	(-1.49)	(-0.68)	(0.02)	(-0.77)	(-0.46)	(0.47)
Panel B: 3-Factor						
Constant	-1.50	-0.43	0.04	-0.82	-0.83	0.67
t-stat	(-1.36)	(-0.48)	(0.04)	(-0.77)	(-0.64)	(0.21)
Panel C: 4-Factor						
Constant	-2.53**	-1.61*	-1.27	-1.24	-2.23*	0.30
t-stat	(-2.32)	(-1.87)	(-1.43)	(-1.16)	(-1.75)	(0.04)
Panel D: 6-Factor						
Constant	-2.52**	-1.60*	-1.41	-1.27	-2.13*	0.39
t-stat	(-2.30)	(-1.87)	(-1.60)	(-1.17)	(1.67)	(0.09)

This table displays the alphas (constants) of five daily short-value-weighted (SVW) portfolios sorted on Age, expressed as a percentage. All alphas have been annualized and the t-statistics in the parentheses have been computed with Newey-West standard errors. *, **, *** represent significance at the 10%, 5% and 1% levels, respectively. Panel A represents CAPM alphas, Panel B represents 3-Factor alphas, Panel C represents 4-Factor alphas and Panel D represents 6-Factor alphas, all of which were described in Section 4.1.

Table 9: Portfolio Sorts Based on Rate of Return

Rate of Return	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(5-1)**
Panel A: CAPM						
Constant	-1.34	0.90	-1.31*	-0.66	-0.93	0.41
t-stat	(-1.29)	(1.08)	(-1.86)	(-0.64)	(-1.11)	(0.38)
Panel B: 3-Factor						
Constant	-1.23	0.97	-1.25*	-0.67	-0.93	0.30
t-stat	(-1.19)	(1.17)	(-1.81)	(-0.69)	(-1.13)	(0.28)
Panel C: 4-Factor						
Constant	-2.34**	-0.02	-2.04***	-1.24	-1.87**	0.47
t-stat	(-2.29)	(-0.03)	(-3.00)	(-1.28)	(-2.29)	(0.41)
Panel D: 6-Factor						
Constant	-2.44**	0.22	-2.11***	-1.00	-2.21***	0.23
t-stat	(-2.37)	(0.27)	(-3.10)	(-1.03)	(-2.69)	(0.18)

This table displays the alphas (constants) of five daily short-value-weighted (SVW) portfolios sorted on Age, expressed as a percentage. All alphas have been annualized and the t-statistics in the parentheses have been computed with Newey-West standard errors. *, **, *** represent significance at the 10%, 5% and 1% levels, respectively. Panel A represents CAPM alphas, Panel B represents 3-Factor alphas, Panel C represents 4-Factor alphas and Panel D represents 6-Factor alphas, all of which were described in Section 4.1.

Table 10: Fama-MacBeth Analysis

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
MNGMT	-0.072					0.062
	(-0.77)					(0.08)
INC		1.122*				1.950***
		(1.83)				(3.76)
ln (AUM)			-0.102			-0.379
			(-0.69)			(-0.50)
ln (AGE)				3.287		-0.086
				(1.31)		(-0.12)
ROR					-2.642*	0.176
					(-1.83)	(0.36)
Constant	-0.87	-2.47	-1.00	18.51	-2.54	-3.59
	(-0.13)	(-0.38)	(-0.15)	(1.14)	(-0.38)	(-0.51)
Avg. R^2	0.020	0.019	0.019	0.021	0.019	0.060
Nobs	402,474	402,474	402,474	402,474	402,474	402,474

This table displays the standardized coefficient estimates of a panel regression of hedge funds' excess returns from short-sales on their characteristics using Fama-MacBeth regressions. Models 1-5 regress excess returns on one dependent variable per model and Model 6 regresses excess returns on all five variables at once. The t-statistics in the parentheses have been computed with Newey-West standard errors and *, **, *** represent significance at the 10%, 5% and 1% levels, respectively. All the reported Constants have been annualized. Further information about this analysis is provided in Section 4.4.