# Dissecting Short-Sale Performance:
# Evidence from Large Position Disclosures

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**Abstract**

Short sellers are perceived as informed, sophisticated investors. Yet little is known about their *actual* performance and trading strategies. Using a novel, hand-collected data set of daily position disclosures in Europe, we identify the entry, change, and exit dates of large short-sale positions for a wide cross section of stocks *and* investors. We find that hedge funds, the predominant investor group, generate an annualized Fama and French (1993) risk-adjusted return of about 5.5%, outperforming other investors. Evidence indicates that hedge funds act as arbitrageurs, generating their returns by trading on the mispricing-related factors, e.g. momentum, betting-against-beta, and quality-minus-junk. In the cross section of hedge funds, local, diversified, and active funds outperform their counterparts. On the position level, we document a first-mover advantage. The profitability of short sales also varies significantly with investors' holding period, location, and industry experience.

| *Keywords:* | Short-sale performance, Anomalies, Hedge funds, Fund attributes |
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| *JEL:* | G14, G15, G23 |

# 1 Introduction

Short sellers are generally regarded as informed and sophisticated investors. In theoretical models, rational short sellers take advantage of arbitrage opportunities and cause prices to revert to their fundamentals. In growing limits-to-arbitrage literature, restrictions on short selling are the primary explanations of misvaluation in stocks and return anomalies (e.g., Shleifer and Vishny, 1997; Stambaugh, Yu, and Yuan, 2012).

Primarily due to data restrictions though, empirical studies provide only indirect evidence of short sellers' actual performance and trading. Many studies indicate that aggregate short interest predicts future returns (e.g., Aitken, Frino, McCorry, and Swan, 1998), but individual short positions with observed openings, changes, and closings have not been used yet to measure the actual profitability or trading strategies of short-sales. Moreover, recent research related to the sophistication of institutional investors offers evidence in line with the notion that institutional investors exacerbate capital market anomalies, rather than attenuate them (e.g., DeVault, Sias, and Starks, 2014; Edelen, Ince, and Kadlec, 2015). However, this literature concentrates on long equity holdings and ignores trading in the short leg of anomalies. Studies on short selling also do not provide any link between short-sale profitability and investor characteristics.

To narrow these gaps, we hand-collected recently available data on the large short positions of stocks for all countries in the European Union (EU). This data set is comprehensive, covering large short positions from 0.50% of the company's shares outstanding. The same disclosure rule applies to all investors, irrespective of their location such that, U.S.-based investors account for 63% of our sample. Parsing the 28,442 disclosures in these data, we obtain information about the stock shorted, the magnitude and date of the short position, and its position holder. The disclosure information is very rich compared with that available from other public sources of short-sale information. In particular, our data set allows us to undertake detailed tracking of the evolution of each short position

over time, because position changes crossing every 0.10% threshold must be reported and include the date the position fell below the disclosure threshold.[1]

We construct a large daily panel of investors' short positions in a wide cross section of countries, tracking each investor over time. The sample period runs from November 1, 2012, through December 31, 2014. By identifying the short sellers by name, we enrich the panel with institutional investor characteristics, including locations, investor types, and their portfolio holdings. This new data set further enables us to construct the short position holdings of investors, predominantly hedge funds, and study their performance.[2] Moreover, we use three potential misvaluation-related anomalies and test whether hedge funds act on mispricing. Finally, we explore the cross section of positions and relate the profitability of short-sales to a list of investor and position characteristics.

We find that hedge funds, as a whole, generate an annualized Fama and French (1993) risk-adjusted return of 5.46% to 7.53%, outperforming all other investors. Using different weighting schemes and levels of analysis, we find that the performance of short-sales can be explained by hedge funds trading on well-known factors associated with mispricing. Notably, the performance can be explained by hedge funds trading on momentum, betting-against-beta, and, to some extent, the quality-minus-junk factor. Looking more closely at the cross section of hedge funds, we find that almost all hedge funds (87.4%) have a positive exposure on betting-against-beta. Momentum trading, in contrast, is predominantly driven by hedge funds with a large portion of short investments. To ensure that the results are not driven by non-completed positions (and therefore, non-realized returns), we also run our analysis on short-sales that enter *and* exit our data set within our sample period. The performance of these positions is at least 5% per year higher, compared with our original results, irrespective of the return adjustment.

In a second step, we link the short-sale positions to hedge fund characteristics. In the cross section of hedge funds, active, large, and local funds outperform their counterparts. Looking at each position individually, we document a first-mover advantage for investors

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[1] Further information on the disclosure regulation requirements can be found in Section 2.

[2] By performance, we refer to short-sale performance, unless stated otherwise.

that initiate a short position in a stock. We also find strong, robust evidence of inferior performance for short-term positions. In addition to the local proximity advantage documented at the fund level, we find that this effect occurs *within* funds. That is, local positions of the same fund outperform distant positions. Accounting for factor trading, we find that investors' industry experience, as proxied by their holdings in the long portfolio, is positively associated with performance. That is, industry experience appears particularly important for stock-picking skills.

Our study contributes to existing literature in several ways. A large stream of literature discusses whether and how short sellers are informed. Several empirical studies show that the amount of short selling predicts negative future stock returns (e.g., Senchack and Starks, 1993; Aitken, Frino, McCorry, and Swan, 1998; Boehmer, Jones, and Zhang, 2008; Diether, Lee, and Werner, 2009), which would suggest that short sellers are informed. Yet this predictability is not always consistent. For example, Boehmer, Jones, and Zhang (2008) find that large short-sale orders are extremely profitable on the NYSE, but Diether, Lee, and Werner (2009) document that only small short-sale trades are predictive of future returns on the NASDAQ. Moreover, most findings are based on aggregate measures, long-short portfolios, or event studies using initiations of short positions. To our knowledge, no prior study has used actual short positions of (informed) investors to analyze whether short sellers turn a profit between opening and closing their positions.[3] Using long-short portfolios and event studies with the initiation of a short position as the event date does not necessarily indicate positive performance of short sellers. Even today, there is no conclusive evidence about whether investors realize profits from opening, changing, or closing their positions. Moreover, Boehmer, Duong, and Huszár (2015) show that the price impact of covering short positions is significant and even stronger than the potential impact of opening short positions. Heterogeneity in short-sale profitability also remains an important, unanswered question, mostly because data limitations constrain our understanding of short sellers' trading strategies. We add to short-selling literature in three ways. First, we follow

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[3]Another strand of literature uses important corporate events to isolate the sources of informed trading (Christophe, Ferri, and Angel, 2004; Engelberg, Reed, and Ringgenberg, 2012).

the investors individually, starting when they enter a large position and until they exit their large position, and we calculate their actual performance by accounting for changes in their positions. Second, we strive to understand the extent to which short sellers trade on mispricing and what strategies they follow as a group. With these efforts, we add to extant literature by proposing a positive impact of short sellers on market efficiency (e.g., Bris, Goetzmann, and Zhu, 2007; Saffi and Sigurdsson, 2011; Boehmer and Wu, 2013). Third, we distinguish among different investors and link their short-sale performance to their characteristics.

A recent strand of literature examines trading on so-called "capital market anomalies" by institutional investors. In a surprising finding, Edelen, Ince, and Kadlec (2015) show that institutional investors, who are perceived as informed traders on the financial markets, are on the wrong side of the anomalies. In other words, they exacerbate return anomalies by buying overpriced stocks and selling underpriced stocks. This article, and all other studies of institutional investor trading, can only observe the long equity holdings. Thus, these studies are not able to test whether institutional investors actually trade on the short leg of these anomalies. To our knowledge, no study uses actual short positions to test whether institutional investors, particularly hedge funds, act on mispricing by trading on prominent misvaluation factors. Our findings provide evidence of this phenomenon and are in line with Akbas, Armstrong, Sorescu, and Subrahmanyam (2015), who look at aggregate flows to mutual and hedge funds. That is, they find that flows to mutual funds appear negatively related to cross-sectional mispricing, which is in line with the findings of Edelen, Ince, and Kadlec (2015), and they also show that hedge fund flows appear to attenuate aggregate mispricing.

Our study also contributes to literature on hedge funds. Several studies seek to understand the performance and trading strategies of hedge funds by using self-reported aggregate returns and fund characteristics (e.g., Fung and Hsieh, 1997; Fung, Hsieh, Naik, and Ramadorai, 2008; Agarwal and Naik, 2000). However, return data from commercial databases suffers from several biases, including the survivorship, backfilling, smoothing,

and self-reporting bias (see Agarwal, Fos, and Jiang, 2013; Joenväärä, Kosowski, and Tolonen, 2014). Moreover, the large set of investment opportunities for hedge funds makes the task of linking the reported returns to equity holdings and certain trading strategies very difficult. Some studies employ quarterly *long* equity holdings data from 13-F filings to overcome these issues (e.g., Brunnermeier and Nagel, 2004). However, prior literature has not analyzed the hedge fund performance in short sales, but instead focuses only on the overall or long performance of hedge funds. With this study, we examine the short-selling performance of hedge funds and we link the performance heterogeneity to several investor characteristics.

By using a newly established database of short position disclosures, our study also relates to very recent publications on the effect of short-sale disclosures on financial stability and price efficiency (Duong, Huszár, and Yamada, 2015; Jones, Reed, and Waller, 2015). Using these rich data, we explore the performance and trading of short sellers, which is somewhat related to Boehmer, Duong, and Huszár's (2015) work. However, whereas they explore the effect of covering shorts on performance using similar data from Japan, we seek to understand the performance of short sellers, from the moment they enter until they exit their positions, such that we analyze both time-series and cross-sectional determinants.

The remainder of this article is structured as follows: Section 2 provides a history and overview of the EU transparency regulation and describes the data set. Section 3 analyzes the performance of short sellers using different aggregation levels and weighting schemes. Section 4 explores the cross-sectional determinants of short-sale profits on both the investor and position level. Section 5 concludes.

## 2 Data and descriptive statistics

### 2.1 Background on the short-selling disclosure rules in the EU

On November 1, 2012, the European Union adopted, in accordance with Article 9 of Regulation (EU) No 236/2012, a uniform short position disclosure requirement.[4] One of the main goals of the new regulation was to increase the transparency of short positions held by investors in EU securities. For all stocks traded on European exchanges, significant net short positions in shares must be disclosed to the public when they cross the threshold of 0.50% of shares outstanding. The short position also must be reported when crossing every 0.10% threshold above 0.50%, such as 0.60%, 0.70%, 0.80%, and so forth. The disclosure is obligatory, irrespective of the investors' origin, and it applies to nearly all stocks traded within the EU. The disclosures are standardized across all European countries and contain the date of the short position and the disclosure, the International Securities Identification Number (ISIN), and name of the shorted stock, as well as the magnitude of the position reported as a percentage of shares outstanding, and the name of the investor.[5] In the following, we provide an example of typical short-sale positions in our data set.

Figure 1 illustrates a course of disclosures of net short positions for the stock of *Belgacom*, a Belgian telecommunication company. On February 6, 2013, the net short position of *AKO Capital LLP* exceeded the threshold of 0.50%, with an initial value of 0.62%. Thereafter, *AKO Capital LLP* continued to increase its short position: On February 22, 2013, the position crossed the 0.70% threshold with a value of 0.71%, and then on March 5, 2013, it crossed the 0.80% threshold with a value of 0.86%, and so forth. The maximum reported net short position of *AKO Capital LLP* reached 1.30% on September 3, 2013. Finally, the net short position fell under the 0.50% disclosure threshold on August

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[4]The regulation applies to all market participants except market makers. Market-making activities relate to liquidity provision rather than informed trading. Because our aim is to capture the informed short positions of investors, we actually profit from this exemption. Moreover, the European Securities and Markets Authority (ESMA) requires notifications for short positions created by not only trading shares, but also trading outside of trading venues and net short positions created by the use of derivatives, such as options, futures, and index-related instruments.

[5]Figure A.1 in the Appendix provides an example of a disclosure from the institution *Marshall Wace LLP* on its short position in the French company *Air France-KLM*.

6, 2014, with a value of 0.49%, which was also the final value reported. A position above the 0.50% reporting threshold is denoted as a significant short position (SSP). We refer to the period from the entry on February 6, 2013, to the exit on August 6, 2014, to be a SSP episode. Following *AKO Capital LLP*, a second investor, *Marshall Wace LLP*, disclosed an SSP on March 8, 2013. Subsequently, *Pennant Capital Management LLC* and *Luxor Capital Group LP* both reported SSPs. This example nicely displays the advantages of our data set: It provides detailed information on the position holder, the shorted stock, and most importantly, the entry, change, and exit of significant short positions.

## 2.2 Data sources and descriptive statistics

We hand-collected 28,442 public disclosures from the websites of the National Competent Authorities (NCA) for all 28 EU member states during the sample period, that is, from November 1, 2012, the beginning of the disclosure rule, until December 31, 2014. We find SSPs for 13 developed (Austria, Belgium, Denmark, Finland, France, Germany, Ireland, Italy, Netherlands, Portugal, Spain, Sweden, and United Kingdom) and 2 emerging (Hungary and Poland) markets.[6]

The way NCAs present disclosures to the public is surprisingly heterogeneous. Some authorities, such as the British FCA and the German BaFin, provide easily accessible files with short position data. However, in cases for which the textual data were too cumbersome to hand-collect, we employed Perl algorithms to parse through the short-sale disclosures and identify all relevant position information.[7] Then, we enriched the SSP data by merging them with three further databases: (1) *Thomson Reuters Datastream*,

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[6]For the remaining EU countries (Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Latvia, Lithuania, Luxembourg, Malta, Romania, Slovakia, and Slovenia), there were no SSP disclosures during the sample period or, in the case of Greece, there was only one, which we did not include in our sample, because its duration is less than 2 days. Table A.1 in Appendix A provides further details related to the summary statistics of the SSPs by country.

[7]At the end of October 2014, the authorities of Spain (CNMV) and Portugal (CMVM) did not report the date when investors fell below the 0.50% threshold for archived positions in their databases, despite the EU regulation requirements. After we contacted both authorities, the Spanish CNMV adjusted its filing system and updated the list of disclosures with the missing dates. The Portuguese CMVM database, however, did not contain exit dates for closed positions by the time of our analysis. However, the authority staff were kind enough to provide us with the dates in a textual file. This file is available on request.

which is the source for stock-level price and return data, and to which we applied several commonly used data filters to ensure the quality of the data (see Ince and Porter, 2006); (2) *FactSet Ownership*, formerly known as *LionShares*, which provides institutional investors' characteristics, including ownership information for equities that is not limited to the United States (13-F filings) but rather spans worldwide; and (3) *Markit*, which supplies information on stock borrowing costs. Finally, as in Figure 1, for each trading day, investor, and stock, we assign the magnitude of the short position from the last filing and update the value whenever we observe a new disclosure. Further information on the sample construction is provided in Appendix B.

Figure 2 shows both the number of SSPs in stocks and their market value over time. On average, there are about 750 open short positions on any given day. The summary statistics in Table 1, Panel A, provide further details about SSP episodes. The average short position as a percentage of shares is 0.75. Moreover, we find that if one investor has an open short position, it is quite common for there to be additional investors with open short positions. This case of multiple investors occurs in 69% of the observations, resulting in an average number of investors per stock of around 3. The distribution of the duration of the holding period is heavily skewed, with an average of approximately 93 days and a median of 37 days.[8]

Using the borrowing fee buckets provided by *Markit*, we observe that SSPs mainly occur in stocks that are cheapest to borrow. *Markit* categorizes stocks in 6 fee buckets, ranging from 0 to 5, on the basis of their borrowing fee. Around 46% of SSPs occur in the stocks that are cheapest to borrow. Serving as a point of reference, the overall percentage of stocks within the lowest fee bucket in the *Markit* stock universe is merely 28%.[9]

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[8]In comparison, Jones, Reed, and Waller (2015) report an average holding period of 51 days after excluding positions that were still open at the end of their sample period. The large difference in durations can be explained by the left and right censoring of the open SSPs. For example, the average duration will be underestimated if SSPs are still open and the sample period is very short. If we consider the sample period of Jones, Reed, and Waller (2015), which ends in December 2013, and exclude all opened positions, we obtain an average duration of 66 days. Further differences might be explained by Jones, Reed, and Waller's (2015) consideration of other disclosure regimes, with a lower reporting threshold, before November 1, 2012.

[9]Figure A.2 in the Appendix provides the full details of the distribution of borrowing fee buckets in the overall sample and the sample of stocks with SSPs.

In terms of the types of investors that enter into large short positions, Table 2 shows the distribution of the 358 investors with SSPs in our sample. The entity that reports the disclosures and *Factset* data is the institution, not the particular fund or portfolio. *FactSet* provides information on the investor type, which helps us categorize the investors. For our analysis, it is very important to distinguish between informed (e.g., hedge funds) and uninformed investors, who might use short positions to hedge their risk exposure and do not necessarily trade on negative information. Hedge funds make up the vast majority of investor types in our sample at 63.1%, and 67.9% indicated days with open SSPs. Other investor types, such as *other investment advisors*, *mutual funds*, or *brokers*, play minor roles.[10] We even identify three individual investors with SSPs, though their effect is negligible. In terms of the market value of the short positions, hedge funds constitute the dominant investor group, with a share of 78.0%, and all remaining investor groups are in single-digit percentages.[11]

For adjusting the raw returns, we use the European daily risk factors and anomalies from Andrea Frazzini's data library, provided through AQR's website.[12] The factors we consider are the market excess return (MKTRF), small-minus-big (SMB), high-minus-low (HML), winner-minus-loser (WML), betting-against-beta (BAB), and quality-minus-junk (QMJ) (see Fama and French, 1992, 1993, 1996; Jegadeesh and Titman, 1993; Carhart, 1997; Frazzini and Pedersen, 2014; Asness, Frazzini, and Pedersen, 2014). With the exception of the size factor, SMB, these factors all have been shown to be priced in Europe.

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[10]In addition to relying on the *Factset* categorization of investors, we follow the procedure of Brunnermeier and Nagel (2004) and search for each *other investment adviser* (as defined by *Factset*) to determine if it has filed registration documents (Form ADV) with the SEC. Then we reviewed the filings and checked whether (1) at least 50% of the registered firm's clients are "other pooled investment vehicles (e.g., hedge funds)" or "high net worth individuals," and (2) the institution charges performance-based fees. If both requirements are fulfilled, the investor is re-categorized as a hedge fund.

[11]Of 359 investors 27 remained uncategorized, such that a name was provided through their SSP filing with the national competent authorities, but there was no record found with *Factset*. For further details on the sample construction, see Appendix B.

[12]We obtain the risk-free rate, MKTRF, SMB, HML, WML, and QMJ through www.aqr.com/library/data-sets/quality-minus-junk-factors-daily/data and the BAB factor through www.aqr.com/library/data-sets/betting-against-beta-equity-factors-daily/data.

# 3   Performance of the average short sale

This section investigates the average performance of short sales in our sample. Specifically, we conduct analyses on three different aggregation levels. First, we evaluate how short sellers perform as a group. Second, we focus on the investor level and look at cross-sectional performance and trading characteristics. Third, we investigate the more detailed, position level and explore whether short sellers turn a profit from entry to exit.

## 3.1   Calendar time portfolio approach

To determine the average performance of short sales, we first apply a calendar time portfolio approach. In this setting, we exploit the rich information provided by short-sale disclosures, namely, information about the duration of SSP and the magnitude of short sales, such that we can very closely simulate the actual behavior of short sellers.

Our investment strategy shorts a stock whenever an investor discloses an SSP over the disclosure threshold of 0.50%. The investment strategy continues to short the stock until the investor's SSP again falls under 0.50%, thereby exploiting the information provided by the duration of SSPs. We adopt a conservative timing convention, by assuming that investors trade at the end of each day. Using our previous example, *AKO Capital LLP* reported to having entered an SSP on February 6, 2013, and exited the SSP on August 6, 2014. The investment strategy in this example therefore would considers returns from February 7, 2013 (one trading day later), until August 6, 2014 (the day the position falls below 0.50%). This approach is conservative in two ways: First, we omit the potential price impact of building up the short position when entering, which would work in favor of the performance. Second, we include the price impact from covering the short position, which works against the profitability of the investment strategy (Boehmer, Duong, and Huszár, 2015).

For the first investment strategy, we form an equal-weighted (EW) portfolio return of all open SSPs on each day in our sample period. We also form two additional portfolios

that reflect the average performance of SSPs more closely: a value-weighted (VW) portfolio that uses the previous day's market capitalization of each stock as the portfolio weight, and a short-position-weighted (SPW) portfolio, which uses the past market capitalization of each short position as the portfolio weight. To mitigate the spurious effects of outliers, we winsorize net short positions above the 99th percentile, which corresponds to short positions greater than 3% of shares outstanding. Among the three investment strategies, the SPW portfolio is the one that most closely emulates the investment performance of the actual investors, because it also accounts for the portfolio adjustment that the investor undertakes. Finally, to avoid capturing non-informed short-selling strategies of certain investors, we devote our attention to the arguably most sophisticated investors, the hedge funds. In a second step, we exploit this heterogeneity in our data set and compare the short-sale performance of hedge funds against other investors.

After forming equal-, value-, and short position-weighted portfolios, we run for each portfolio $i$ a time-series regression of excess returns on different factors:

$$- (R_{i,t} - R_{f,t}) = \alpha_i + \mathbf{f_t}'\boldsymbol{\beta}_i + \varepsilon_{i,t}, \tag{1}$$

where $R_{i,t}$ is the return of the portfolio, $R_{f,t}$ is the risk-free rate, and $\mathbf{f}$ is a vector of pricing factors [MKTRF SMB HML WML BAB QMJ]. In addition, $\boldsymbol{\beta}_i$ measures the factor exposures, and $\alpha_i$ represents the excess return unexplained by these factors. Because stocks are shorted, we multiply excess returns by $-1$. As a consequence, a positive $\alpha$ signifies outperfomance of the investment strategy. We use the factors MKTRF, SMB, and HML, motivated by Fama and French (1993). Their seminal paper established this model as the benchmark for risk-adjusting excess returns in asset pricing and investments. However, over the past few years, researchers have found a "zoo of new factors" (Cochrane, 2011). Some of these anomalies disappear after publication (McLean and Pontiff, 2015), but a large number of the predictive variables remain significant, with persistent predictive power. Moreover, Stambaugh, Yu, and Yuan (2012) show that profitability of the strategies

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is mainly driven by overpriced stocks in the short leg. Because short sellers are perceived as sophisticated investors, it seems natural to test whether they trade on these anomalies. Therefore, we use three candidates of mispricing-related factors to conduct this test: winner-minus-loser (WML), betting-against-beta (BAB), and quality-minus-junk (QMJ).

Arguably, the most prominent anomaly associated with mispricing is the WML strategy, also known as the momentum effect (Jegadeesh and Titman, 1993). Due to the slow convergence of the stock price to the fundamental value, past returns positively predict the cross section of future returns. If short sellers exploit this simple predictability, the short-sale portfolio should relate positively to the momentum factor. A second candidate is the betting-against-beta factor, proposed by Frazzini and Pedersen (2014). In their model, constrained investors bid up high-beta stocks, which results in a relatively low alpha for these stocks. Consequently, unconstrained investors should "bet against beta" by underweighting or short-selling high beta stocks to profit from mispricing. To test whether hedge funds, probably the most unconstrained investors in the market, actually bet against beta in the short leg, we augment the factor model by Frazzini and Pedersen's (2014) BAB factor. The third mispricing factor we consider is the high- and low-quality anomaly. Asness, Frazzini, and Pedersen (2014) show that investing in high-quality stocks and shorting low-quality stocks earns a positive and significant risk-adjusted return. Their result is consistent with the notion that quality stocks are relatively underpriced and "junk" stocks are overpriced. Therefore, we also consider the quality-minus-junk (QMJ) factor as a misvaluation factor in our estimations.

Table 3 provides the time-series regression results for the factor loadings and alphas. We estimate standard errors following Newey and West (1987), with the lag length selected according to the optimal lag-selection algorithm proposed by Newey and West (1994). For the three different weighting schemes (EW, VW, and SPW) we consider four different asset pricing models: Columns 1 to 3 show the results of the Capital Asset Pricing Model (CAPM), Columns 4 to 6 refer to the Fama and French (1993) three-factor model, Columns 7 to 9 display the Carhart (1997) four-factor model, and Columns 10 to 12 indicate

the Carhart (1997) model adjusted for the betting-against-beta and quality-minus-junk factors, which we refer to as the six-factor model.

Panel A of Table 3 displays the calendar time portfolio approach results for hedge funds, our main investor group of interest. Hedge funds' short positions generate an economically large and statistically significant three-factor alpha, ranging from 2.11 to 2.88 bp per day. Assuming 250 trading days per year, this value translates to an annualized return of 5.40% to 7.47%. When using the CAPM, hedge funds consistently yield a positive and sizable alpha (4.45% to 5.01% p.a.), though it is only partly significant. Looking at the factor betas, we see that the short portfolio of hedge funds has a negative exposure to HML and a market beta below $-1$. A market beta of exactly $-1$ would indicate that the short portfolio does not systematically differ from the market. A market beta of below $-1$, instead, indicates that the short portfolio contains high-beta stocks. We test whether the market beta is statistically significant below $-1$, which is the case for all specifications at all conventional significance levels (see the t-values under MKTRF). In other words, hedge funds predominantly short high-beta stocks. This finding is in line with the model predictions of Frazzini and Pedersen (2014), who show that constrained agents overweight high-beta assets, producing a flatter security market line. Consequently, unconstrained arbitrageurs exploit this investor behavior and short-sell high-beta assets (and buy low-beta assets). Our performance analysis on the short leg reveals strong empirical evidence in favor of this proposition. Later, we directly test whether hedge funds bet against beta by using Frazzini and Pedersen's (2014) BAB factor.

In addition to their tendency to sell high-beta stocks, our sample of short sellers are growth investors, going short in value stocks. This finding is very robust and suggests that the short sellers in our sample hedge against the HML risk factor. Similar results arise with regards to the SMB loadings. Although these results might suggest that hedge funds' short positions are on the "wrong side" of profitable trading strategies (Edelen, Ince, and Kadlec, 2015), we acknowledge the longstanding debate about whether the value and size factors capture mispricing, risk, or both. To determine whether hedge funds act

as arbitrageurs and exploit mispricing using short sales, we extend the Fama and French (1993) model gradually with three additional factors that are predominantly associated with mispricing in literature.

We include the first anomaly candidate, the momentum factor (WML), in Columns 7 to 9, similar to Carhart (1997). The shorting portfolio has a significant positive exposure to WML, in particular for the economically more meaningful VW and SPW portfolios. The inclusion of WML results in a substantial reduction in alpha, by more than half for the VW and SPW portfolios. Thus, much of the outperformance of hedge funds' short positions can be attributed to them trading on the momentum anomaly. This result regarding the momentum trading of short sellers is of vast importance. Previous literature on momentum trading of institutions had to rely on quarterly changes in long equity holdings due to data limitations (e.g., Nofsinger and Sias, 1999; Grinblatt, Titman, and Wermers, 1995; Falkenstein, 1996; Gompers and Metrick, 2001; Bennett, Sias, and Starks, 2003; Sias, 2007; Baltzer, Jank, and Smajlbegovic, 2015). With information only on the long positions, it is unclear whether a decrease in ownership of past loser stocks represents momentum trading or is mechanically driven, for example, by institutional settings such as stop-loss orders (Lakonishok, Shleifer, and Vishny, 1992). The positive momentum loading on the short leg, in contrast, represents strong evidence that hedge funds take advantage of overpricing among loser stocks.

We next include the BAB and QMJ factors in the Carhart (1997) model. Columns 10 to 12 of Table 3 show the loadings and alphas of the resulting six-factor model. The short-sale portfolio has a large and statistically significant BAB loading across all different weighting schemes, corroborating Frazzini and Pedersen's (2014) hypothesis that unconstrained investors bet against high beta stocks. This finding is also consistent with the previous result that the market beta exposure is considerably below -1. Trading on QMJ, in comparison with the other mispricing factors, is weaker. Even though the QMJ factor yields a positive factor exposure for all three portfolios, it is significantly different from zero only for the EW and VW portfolios. Overall, our findings related to the short-sale

trading strategies of hedge funds are in line with Frazzini, Kabiller, and Pedersen's (2013) results, showing that the two factors, BAB and QMJ, explain a large portion of Warren Buffett's "mystical" performance over the years. Our findings add to this evidence and suggest that even hedge funds, as a whole, trade on these factors in the short leg.

In essence, WML, BAB, and QMJ explain the large three-factor alpha of short-sales; controlling for these factors makes the alpha negative and statistically insignificant, ranging between -0.90 and -0.47 bp per day. To estimate how much of this reduction can be attributed to the different factors, we calculate a three-factor alpha based on coefficient estimates from Column 12. Then we calculate the contribution of the WML, BAB, and QMJ factors to explain the three-factor alpha. This alpha difference attributes 58.9% to WML, 29.3% to BAB, and 11.9% to QMJ. In essence, our result supports the notion that sophisticated investors as a whole generate their alpha by so-called "exotic betas" (Cochrane, 2011) or factor trading rather than by stock-picking abilities.

In the next step, we turn to the question of how presumably less informed investors perform. On the one hand, we might expect that hedge funds, representing the most sophisticated market participants, generate higher returns than other investors. However, prior literature does not confirm the superior skill of hedge fund managers. For example, Griffin and Xu (2009) find that hedge funds do not significantly outperform mutual funds using long equity holdings. Panel B of Table 3 reports the same analysis for the group of non-hedge fund investors. Panel C directly compares the alpha differences between hedge funds and other investors. In general, the performance of other investors is considerably worse than that of hedge funds; in particular, other investors' VW and SPW portfolios, which are economically speaking the most meaningful, yield a negative alpha that is statistically significant at the 5% and 10% level for the six-factor model (Columns 11 and 12). Panel C shows that hedge funds have a higher alpha than other investors across all specifications. Again, the difference is largest for the economically meaningful VW and SPW specifications, for which it is statistically significant in 5 of 8 cases. The difference

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in the alphas mainly can be attributed to trading on momentum. Because of the superior performance of hedge funds, we focus solely on this investor group hereafter.

In summary, the calendar time portfolio approach shows that hedge funds yield a significant Fama and French (1993) risk-adjusted return and thereby outperform other investors in their shorting activity. Moreover, the economically large Fama and French (1993) alpha of the average hedge fund can be attributed to exploiting the momentum and the betting-against-beta anomaly.

## 3.2  Variation of the entry or exit date

The findings in the previous section of a significantly positive Fama and French (1993) alpha are based on very detailed disclosures about the *significant* short positions of different investors. Consequently, we do not observe exactly what happens below the threshold of 0.50% of the company's shares outstanding, nor can we measure the performance of short sellers for non-disclosed positions. Therefore, to address the representativeness and generalizability of the performance results, we analyze a series of pseudo-investment strategies.

For each episode of all SSPs, we alter the entry date, holding the exit date constant, then the exit date, holding the entry date constant.[13] Specifically, we form an investment strategy that entered one day earlier and compare its performance against the benchmark. We repeat this exercise for hypothetical entry days that are up to 20 days earlier and 20 days later. For the variation of the exit date, we proceed accordingly. To make the results comparable, we only consider short position episodes with a duration of at least 20 trading days. Again, we do not observe the trading behavior of investors below the disclosure threshold. However, if we extend the holding period by earlier entries and later exits of SSP episodes, we can look at the potential performance of the short sellers if they have a short positions below the threshold, before or after the original episode. If the

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[13]In this exercise, we resort to the VW investment strategy as the benchmark, instead of the SPW strategy, because there is no information about the magnitude of the short position available for these pseudo-investment strategies. Moreover, the previous performance analysis shows a very similar performance trend across the VW and SPW portfolios.

adjustment of the entry and exit date leads to significant negative differences of returns between the pseudo episodes and the actual episodes, our first performance results *could* be upward biased. However, if we find that the return difference is zero or even positive, we are very confident that the results with the actual SSPs are representative or even downward biased.

In this analysis, we also strive to understand the role of the potential price impact of position openings and closings for the performance of investors. As mentioned previously, we use a very conservative imitation investment strategy, assuming that all trades take place at the end of each trading day. As a result, we omit the price impact when building up the position, which would work in favor of performance. However, we include the potential price impact from covering the short position, which works to the disadvantage of performance. By moving the entry and exit date one day earlier, we observe the effect if we had constructed our portfolio in a non-conservative way, by including the returns for the entire entry and excluding the return of the exit date.

Figure 3 shows the difference in performance, measured by the three-factor Fama and French (1993) alpha, if the entry and exit dates were modified. The shaded areas between -1 and 0 indicate the uncertainty about whether investors opened or closed the position at the end of the day $(t = 0)$, which is the conservative assumption of the original investment strategy, or at the beginning of the day $(t = -1)$.

Figure 3(a) shows the effect on performance if investors had entered their short position earlier or later. If investors had entered one day earlier (or at the beginning of the disclosure date) at $t = -1$, their outperformance would be 0.20 bp per day higher, which is also statistically significant, as seen from the 95% confidence intervals. This effect is either associated with a forward-looking bias or the price effect due to opening/increasing the short position. More importantly, we find that if the investors were short in the stock before we observe the disclosure, they would generate higher profits compared with the original findings. A later entry instead has no significant effect on performance, as can be seen from the right-hand side of Figure 3(a). The difference in alpha values is not

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statistically different from zero at any point during the 20 days period after the closing date.

Figure 3(b) shows the effect on performance if investors had exited their short position earlier or later. If investors had exited one day earlier, their performance would have been around 0.27 bp per day higher. This difference is significant at the 10% significance level. The difference in alpha in the days shortly before the actual exit potentially indicates price pressure effects caused by covering the short position (Boehmer, Duong, and Huszár, 2015). A longer holding period would not decrease performance, as can be seen from the alpha difference to the right of the exit date, which is essentially zero. This finding suggests that even if the short seller did not completely close its position after falling below the disclosure threshold and kept the position for a longer period, the profits generated in the SSP episode would not significantly decline.

Overall, from conducting this exercise, we achieve two important findings. First, assuming that the short sellers open (keep) their positions before (after) the observed SSP episodes, the strong performance of short sellers that we identified in Section 3.1 does not decrease. If anything, the returns would even increase if we were to assume open short positions before observing the initial disclosure. Second, Figure 3 shows that the potential price impact of building up and covering the short position is substantial. Taken together, the performance difference on the day of entry and the day of exit amounts to 0.47 bp. Relating this figure to the conservative lower bound performance of 2.29 bp per day (Table 3, Panel A, Column 5), we see that the upper bound is approximately 20% higher.[14]

### 3.3 Short-sale performance of hedge funds

Hedge funds as a group generate, on average, a positive and significant risk-adjusted return. We therefore address the question of how short-sale performance and trading strategies

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[14]The results for the six-factor model are very similar, as shown in Figure A.3 in the Appendix. We also repeat the analysis of Table 3 using the timing convention, such that trades occur at the beginning of each day. Performance increases for all specifications, as can be seen from Table A.3 in the Appendix.

vary in the cross section of the hedge fund. In particular, we aim to determine how many of the hedge funds in our sample generate a positive alpha and whether the trading on mispricing phenomenon is pervasive across the majority of funds or driven by only a small number of investors. To investigate these questions, we consider a hedge fund as the entity of interest and construct short portfolios using the SPW approach. Thus we can estimate the factor exposure and alpha for each fund. For running the factor time-series regression, we require at least half a year of data, or 125 trading days.

Table 4 shows the results for the fund-level performance. The first column shows the equal-weighted cross-sectional average of factor loadings and alphas. Focusing on the alphas, we see that the average hedge fund generates a substantial alpha when considering the CAPM, Fama and French (1993) three-factor model, and even the Carhart (1997) four-factor model, ranging from 2.17 bp to 4.26 bp. However, as previously observed, once QMJ and BAB are included as factors, the alpha shrinks to 1.62 bp and is not statistically different from zero.

Columns 2 to 8 provide the summary statistics pertaining hedge funds' shorting performance and factor exposures, revealing a large cross-sectional variation. Column 2 shows the percentage of hedge funds with a positive alpha. Whereas the majority of hedge funds achieve outperformance when we apply the CAPM, three-factor, or four-factor model (Panel A to C), only a minority do so when we include BAB and QMJ as factors (Panel D). Regarding factor loadings, Column 2 provides the percentage of funds with a positive SMB, HML, WML, BAB, and QML loading and the percentage of funds with a market factor exposure (MKTRF) above -1. The latter figure reveals that only a small minority of hedge funds have a market factor loading above -1, indicating that the vast majority of funds short high beta stocks. The notion that hedge funds are betting against beta is corroborated by the majority of funds that trade on the BAB factor: Up to 87.4% of funds have a positive BAB loading.

Finally, Column 9 shows the aggregate SPW performance of funds. In this test, the average performance of each hedge fund is calculated by weighting the returns with the

market capitalization of its short positions. The performance results are very much in line with the previous findings: The CAPM and three-factor model yield significant alphas, but the outperformance disappears if the factors associated with mispricing (WML, BAB, and QMJ) are included. Although the results of Table 3 show that a large portion of alpha can be explained by WML, surprisingly, only half of the hedge funds trades on the momentum factor. Comparing the equal-weighted WML loadings of 0.00 and 0.08 against the short-position-weighted WML loadings of 0.14 and 0.20 (Panel C and D, respectively), we determine that hedge funds with high shorting activity trade on the momentum anomaly.

## 3.4    Performance of short-sale positions

In the following section, we use a "bottom-up" approach to determine the risk-adjusted performance of SSPs. That is, we first estimate alphas and betas for each stock, using a rolling window approach, and subsequently aggregate the values by applying different weighting schemes. The advantage of this estimation procedure is that it accounts for time-varying betas, whereas the approach in Section 3.1 and 3.3 assume constant betas. Moreover, estimating alphas at the position-stock-day level allows us to analyze each SSP episode separately.

Specifically, we estimate betas for each stock using a rolling regression window of 200 trading days. To mitigate the spurious effect of outliers in the beta estimates, we winsorize factor loadings at the 1% and 99% level. Then, the daily alpha of a stock is calculated as the difference between the realized excess return and the predicted excess return, using beta loadings estimated over the previous 200 days. We again form portfolios if an SSP is active, applying the timing convention of trades taking place at the end of each day.

Table 5 shows the results of this exercise. Columns 1, 2, and 3 provide the equal-, value- and short position-weighted returns for the entire sample, where Panels A through D again reflect the different factor models. The results of the overall sample are remarkably similar to the findings presented in Sections 3.1 and 3.3: The Fama and French (1993) model

produces significant alphas, as does the CAPM for the VW and SPW approaches. This outperformance diminishes if the factors associated with mispricing (WML, BAB, and QMJ) are included. The average factor loadings also are in line with the previous results.

The position-stock-time level estimation of risk-adjusted performance enables us to investigate whether the short position was profitable, from entry to exit the position. For example, when an investor shorts a stock to profit from mispricing, prices might first move in the opposite direction before converging to the fundamental value. In this case, open short positions do not show realized profits. Therefore, in the following, we condition only on completed positions (Columns 4 to 6). The performance of all *closed* positions is consistently higher than that of all positions, in particular for the economically meaningful VW and SPW. Completed positions generate significant and sizable four-factor and six-factor alphas of up to 3.56 and 2.19 bp per day, which translates into an annualized return of 9.38% and 5.67%, respectively.

## 4   The cross section of short-sale performance

In this latter part of the paper, we utilize the rich heterogeneity in our data set to analyze the cross section of short sales. Because we identify the investors, we can match the returns of short positions with the investors' and position-specific characteristics. We focus our cross sectional analyses on a sample of hedge funds that covers nearly 80% of the market capitalization of our short-sale data set. As previously mentioned and supported by our findings, this group of investors is perceived as informed, so we have a strong interest in understanding their outperformance, relative to the performance of other short sellers. Moreover, using a sample of hedge funds ensures that heterogeneity in the explanatory variables and characteristics is not driven by differences in the institutional background.[15]

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[15]First, mutual funds, pension funds, and hedge funds are all subject to different regulations. Second, these investor types serve clients with very different investment targets. Third, some explanatory variables (e.g., size, turnover) are not comparable across different investor groups.

## 4.1 The cross section of hedge funds

The average hedge fund generates a positive Fama and French (1993) risk-adjusted return, yet we observe strong variance in short-sale performance. We now turn to the cross section of hedge funds to determine whether certain fund characteristics can explain the heterogeneity in returns. Our approach is similar to that in Section 3.3, such that we form a portfolio of shorted stocks for each day and hedge fund. Then, we adjust the time-series of portfolios by the Fama and French (1993) and the six-factor model for each hedge fund, respectively. This panel of fund-day risk-adjusted returns then is merged with a list of potential determinants at the investor level.

To estimate the effects of our explanatory variables, we use a linear regression model, similar to the generalization of the calendar time portfolio approach by Hoechle, Schmid, and Zimmermann (2012) with Driscoll and Kraay (1998) standard errors. These standard errors are robust to general forms of both the cross-sectional and temporal dependence of regression disturbances. The advantage of this approach is that it allows for the inclusion of multiple explanatory variables instead of relying on sorting exercises, and perhaps even more important, it ensures valid statistical inference. We also control for time-specific, unobservable effects by including week-fixed effects.[16] All explanatory variables (excluding dummy variables) are standardized with a mean of 0 and a standard deviation of 1. To ensure that our results are not affected by the noisy, short-term appearances of some hedge funds, we require hedge funds to have data available for at least half a year (125 trading days) before they may be included in our analysis.

For the choice of explanatory variables, we rely on previous studies that employ fund characteristics and quarterly holdings to explain funds' portfolio performance (e.g., Ferreira, Keswani, Miguel, and Ramos, 2013). However, our analysis is the first to focus on the short-sale performance of hedge funds. All explanatory variables are lagged by at least

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[16]We conduct Fama and MacBeth (1973) regressions as well, with the results being provided in the Appendix, in Table A.4.

one quarter. In the following, we discuss each of our explanatory variables and the results of our regressions.

**Turnover:** More active funds charge higher fees and cause higher trading costs. A natural question, of great importance to both academics and practitioners, is whether a higher volume of trading is guided by skill. Moreover, do more active managers outperform less active ones? Prior literature on institutional investors provides mixed evidence at best. One vein of studies on mutual fund performance suggest a negative turnover-performance relation (e.g., Elton, Gruber, Das, and Hlavka, 1993; Carhart, 1997). The evidence for hedge funds is rather scarce, and findings obtained from mutual funds are not necessarily applicable. The hedge fund industry generally attracts talented traders, and compensation is strongly performance based. Institutional and incentive scheme differences between these two industries accordingly may lead to different results. For example, being fast and active in the hedge fund industry may be of particular importance for finding and cultivating new investment opportunities. This effect may be greater for risky investments such as short selling.

To test the relation between activity and performance, we calculate the standard turnover measure from the quarterly holdings in the long equity portfolio (see Brunnermeier and Nagel, 2004). We define turnover as the ratio between the minimum of the absolute values of buys and sells of a hedge fund in a given quarter and the total stock holdings. This definition ensures that we only capture turnover that is unrelated to fund inflows or outflows. Moreover, we require at least three years of data and calculate our activity proxy (if available) by a five-year rolling window. In Columns 2 and 5 of Table 6, we observe that turnover relates positively to future short-selling performance when employing both return adjustment models. However, the effect is not statistically significant at any conventional level.

One explanation for this weak result might be that the turnover-performance relation is non-linear, and as such, the link is driven by the tails of the distribution. To test this

alternative hypothesis, we employ a dummy variable that equals 1 if the hedge fund is in the upper quartile of the turnover cross section of funds. In line with this idea, we find in Columns 3 and 6 that the effect of turnover on future performance is economically and statistically very strong and has a positive sign. As a result, hedge funds in the highest turnover quartile outperform, ceteris paribus, all other funds by more than 5.60 bp per day (4.54 bp per day) in the three-factor model (six-factor) model. The result from Column 1, which indicates that the average performance of hedge funds is 3.72 bp per day with a standard error of 1.21 for the Fama and French (1993) model, puts the magnitude of the turnover effect nicely into perspective.

**Size:** Vast literature tries to answer the question of whether the size of mutual funds (e.g., Chen, Hong, Huang, and Kubik, 2004) and hedge funds (e.g., Teo, 2009) relates to managers' skill and performance. The prevalent results of these studies are consistent with the notion of diseconomies of scale. Namely, when funds grow in size, it becomes more difficult to find new and lucrative investment opportunities (Berk and Green, 2004). Meanwhile, small funds can focus on smaller and fewer profitable investments. Another channel through which size negatively affects performance is the liquidity constraint hypothesis proposed by Chen, Hong, Huang, and Kubik (2004). They suggest that high volume trades of large funds attract the attention of other investors and therefore heighten the price impact and worsen the performance. However, larger funds have several advantages. They can spread their fixed costs over a larger asset base and profit from sharing resources. Also, higher trading volume and larger positions represent a bargaining tool that they can use to negotiate lower spreads and brokerage commissions (Brennan and Hughes, 1991). The size of a fund also may serve as a proxy for collateral, which is of considerable importance for short sales. Overvalued stocks do not necessarily revert back immediately to their fundamental values in the presence of noise-trader risk (Shleifer and Vishny, 1997). Short-term deviations in the stock price even may worsen performance, forcing the manager to provide additional collateral or even close the short position.

Consequently, larger funds are less sensitive to such deviations, in that they simply deposit additional securities and do not need to cover short-sale positions that result in losses. This potential channel would imply a positive size-performance relation for short sales.

To proxy for the size of the fund, we employ the funds' market capitalization of the quarterly holdings obtained from *Factset*. In Columns 2 and 3, we find a positive relation between size and future short-sale performance. A one standard deviation increase in the long portfolio size is associated with an increase of around 2 bp per day using Fama and French (1993) adjusted returns. Yet this relationship dissipates when we employ the additional factors in Columns 5 and 6. This finding suggests that larger funds generate, on average, higher risk-adjusted returns by trading on misvaluation factors rather than stock picking.

**Age:** Similar to the case of fund size, the direction of the age effect on fund performance is ambiguous. On the one hand, age can serve as a proxy for the longevity and experience of the fund (manager), which is considered to positively relate to performance. On the other hand, younger hedge funds may be more motivated and spend more effort and time on their portfolio construction to attract new inflows. Moreover, younger funds tend to be more skilled than older funds, perhaps due to better education or greater command of new technology, such that they have a better chance of beating the market (Pastor, Stambaugh, and Taylor, 2014). Empirical evidence for the age-performance relation is mixed. For a European sample of mutual funds Otten and Bams (2002) find that younger funds perform better than older funds, whereas Ferreira, Keswani, Miguel, and Ramos (2013) find no relationship between age and performance for mutual funds. Pastor, Stambaugh, and Taylor (2014) find a positive age-performance relation but note that it is driven by industry and fund size. Thus, it is not clear whether and in what direction the effect of age exerts itself, when we focus on the short-sale performance of hedge funds.

We measure hedge fund age by deducting the inception year of the fund from the position date. As shown in Columns 2 and 3 of Table 6, we find a negative but statistically

insignificant effect of age on the short-selling performance of hedge funds. Similar to the size-performance relation, we observe in Columns 5 and 6 that the point estimate decreases economically to essentially zero when including all six factors. Overall, weak evidence indicates that younger hedge funds perform better in short sales, which can be explained by trading on misvaluation factors.

**Diversification in asset classes:** It is not clear how the diversification of hedge funds relates to managers' skills and ability to generate abnormal returns. Hedge funds may specialize in certain asset classes, sectors, industries, or geographic regions to distinguish themselves from other investors and thereby profit from their unique knowledge. However, diversification also can proxy for general knowledge in financial markets and relate positively to future risk-adjusted returns. Shawky, Dai, and Cumming (2012), for instance, find that diversification across asset classes is positively related to the alphas of hedge funds, whereas investing across different investment styles and regions is negatively related to performance. In the following, we investigate whether the positive relation between asset class diversification and performance also occurs in the short portfolios of hedge funds.

To measure the diversification of hedge funds' portfolios across asset classes, we use quarterly holding reports to calculate the relative share of market capitalization invested in equity on the total size of the long portfolio. A low equity share suggests that the fund uses other instruments and diversifies across asset classes. Therefore, we define a hedge fund as diversified if this relative share is *below* the median of the distribution. In Table 6, we report a positive and significant relation between diversification and short-sale performance. The portfolio of large short positions of diversified hedge funds outperforms the portfolio of other hedge funds by more than 5 bp per day. This finding is robust across both models, which suggests that diversification is also a useful predictor of the short-sale performance of hedge funds when controlling for factor trading.

**Local informational advantage:** One of the most interesting questions to investors and researchers in the mutual and hedge fund field is whether local investors have local

informational advantages and generate superior performance when they undertake nearby investments. In their seminal paper, Coval and Moskowitz (2001) provide evidence for a home advantage, showing that mutual fund managers generate higher returns by investing in better performing local stocks relative to other nearby located stocks they do not invest in. However, Sulaeman (2014) finds that this differences in returns is not limited to local returns but also present for distant stocks. Specifically, distant stocks held by mutual funds also outperform distant stocks not held by mutual funds. In terms of the hedge fund industry, evidence about whether such differences exist remains uncertain. However, if there is any local informational advantage in asset management, then one would expect that such an effect would be particularly strong for the informed traders, i.e. hedge fund managers. Moreover, because short selling is a very risky investment strategy, this local informational advantage effect might be of particular interest and importance.

We apply a very simple approach to measure whether a hedge fund is local. We obtain, from *Factset*, information about whether a hedge fund is located in Europe or another location. Because our sample consists of European stocks, one would expect that if there is a local or domestic informational advantage, hedge funds headquartered in Europe should outperform other hedge funds. This definition is very broadly encompassing and represents a first step toward providing evidence of a local advantage. The next section deals with the cross section of single positions and offers a more accurate analysis on this topic. However, even by just applying such a simple proxy, we obtain very interesting results. Columns 2, 3, 5, and 6 reveal a strong, positive relation between the location of the fund and future short-sale performance. European hedge funds outperform non-European funds by 8.51 (6.59) bp per day after the three-factor (six-factor) return adjustment. This effect is by far the strongest with respect to the economic magnitude of our analysis. In our specifications, we control for experience in European stocks using the relative share of European stocks in the long equity portfolio. This first result is consistent with a local informational advantage; we test it further in the next section.

**Shorting activity:** Lastly, we test whether investors' shorting activity predicts their short-sale performance. To the best of our knowledge, this variable has yet to be used as a predictor in such a setting. On the one hand, shorting activity might capture experience in short sales, such that we would expect a positive coefficient estimate. On the other hand, one might expect diseconomies of scale, similar to the effect of the size variable in the fund literature (Chen, Hong, Huang, and Kubik, 2004). Specifically, the more a hedge fund is involved in short selling, the more difficult it is to find profitable investments.

To test the direction of the effect, we employ two proxies for shorting activity. First, a natural choice is the market capitalization of all large short positions that we observe for each investor. Second, as a simpler proxy, we use the number of stocks that an investor has shorted in our sample of SSPs. We update both proxies daily and lag them by one trading day. In Columns 2, 3, 5, and 6 we observe that the sign for both variables is negative, which favors the diseconomies of scale hypothesis; however, the effect is not significantly different from zero at any conventional level.[17]

## 4.2 The cross section of positions

In the second part of our cross-sectional analysis, we conduct estimations on the position level. With this disaggregation, we are able to test additional hypotheses, for example within hedge funds. We estimate our coefficients using a rich panel of investor-stock-day observations. Similar to the previous analysis, we use panel regressions in the spirit of Hoechle, Schmid, and Zimmermann (2012) with Driscoll and Kraay (1998) standard errors. To account for the size of the short position in estimating the effects, we weight the observations by the lagged market value of the SSPs. All explanatory variables from quarterly holdings data are lagged by one quarter. All other variables are lagged by one day unless otherwise stated. In Table 7 we test several hypotheses and gradually introduce fixed effects on different levels. Columns 1 to 6 report estimation coefficients for the Fama

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[17]Including both proxies for shorting activity in the same specification might cause some concern. Although the two variables are not highly correlated, we include the two proxies separately into the specifications. The regression estimates remain qualitatively similar.

and French (1993) three-factor model while Columns 7 to 12 contain the estimates of the six-factor model that includes the misvaluation-related factors.

We motivate our first two variables of interest from the example in Figure 1. *Belgacom* attracted the interest of many short sellers that sequentially crossed the SSP threshold and speculated on a falling stock price. We know from prior literature that some short sellers process better public information (Engelberg, Reed, and Ringgenberg, 2012) or have superior private information (Cohen, Diether, and Malloy, 2007). In both cases, the information comes with some level of uncertainty and potentially contains noisy signals. However, the number of short sellers in each stock should be inversely related to the uncertainty of a (negative) signal. Therefore, we expect that the number of investors shorting a stock is positively related to the position's performance. The second observation we make from Figure 1 is the difference in the entry and exit of the significant short positions across investors. For example, *AKO Capital LLP* was the first investor in our sample that entered an SSP in *Belgacom*, closely followed by *Marshall Wace LLP*. More than half a year later, *Pennant Capital Management LLC* and *Luxor Capital Group LP* entered a large short position. A natural question that arises is whether the timing of these short sellers matters for the profitability of the position. More specifically, do first-movers have an advantage by entering the large position earlier than others? An early entry might signal that the hedge fund manager has received private information before its competitors or that the hedge fund is faster and better in processing public information. In both cases, we expect that first movers outperform other investors.

In Column 2 of Table 7, we find that short position days with more than one short seller outperform other position days by more than 3.03 bp in the Fama and French (1993) model. However, this result, as evident in the following specifications, is not robust across different models. With regard to the first-mover hypothesis, the binary variable *initiator*, which equals to 1 for the first investor to go short in one stock, is positively associated with the position's risk-adjusted return. This variable is not statistically significant in the first model, but we observe that a first-mover advantage is particularly strong when we account

for trading on mispricing factors. Therefore, it is especially important to enter a position as a first mover when it comes to stock picking and not *simply* trading on well-known misvaluation factors. Economically speaking, initiators earn 2.92 bp higher returns than other hedge funds. From the descriptive statistics we observe that approximately 30% of the positions are defined as initiators, that is positions opened when no other investor was short in the corresponding stock. These positions include scenarios similar to our example in Figure 1, as well as cases in which an investor enters a short position as an initiator and remains the only short seller throughout the entire SSP episode. We call these positions "singles" and believe that they do not necessarily signal skill or the possession of private information. Two-thirds of these initiators remain the only short sellers in their episode. If initiators are not followed by other investors, then the first-movers are not necessarily led by reliable or distinct signals. We hypothesize that the positions of initiators followed by other hedge funds throughout their episodes (we refer to them as "initiator leader"), yield particularly strong positive returns. The drawback of this measure is that an initiator leader can be determined only ex post. However, the advantage is that it is closer to the definition of an *informed* first-mover. Indeed, we find that initiators followed by other investors earn significantly higher returns of 2.38 (3.09) bp than other investors in the three-factor (six-factor) model. Again, the first-mover advantage is stronger for the six-factor model. We also note that the first-mover advantage is robust across different specifications. When we account for fund-, week-, fee bucket-, and country-fixed effects, the economic magnitude of the coefficient is even greater. This result is in line with recent findings by Siegmann, Stefanova, and Zamojski (2013), who document a first-mover advantage in the hedge fund industry by clustering hedge funds on the basis of several characteristics. To the best of our knowledge, we are the first to provide direct evidence of such an effect in short-sale positions. In addition, the initiator leader variable subsumes the effect of multiple investors, which thereby suggests that mainly first-movers profit from a strong agreement among hedge funds.

We now focus on the local advantage of hedge funds. In the cross-sectional analysis on the hedge fund-level, we provide initial evidence of the local advantage of European hedge funds relative to others. To rule out the possibility that this effect is driven by institutional differences between European and, mainly, U.S. funds, we test the local advantage hypothesis, using position-level data. These detailed panel data allow us to test an even stronger research question: Do positions where the hedge fund and the company of the shorted stock are headquartered in the same country outperform other positions? We include in the panel regression a dummy variable that equals 1 if the stock and fund are headquartered in the same country. The local advantage is present even on the position level and even when accounting for time-constant, unobservable fund characteristics. In short, same-country positions outperform other positions on average by approximately 4 bp per day. Funds tend to hold domestic stocks, and the share of local stocks might proxy for experience in a particular country. Therefore, we define country experience as a dummy variable equal to 1 if the hedge fund holds stocks headquartered in the same country as its short position. However, the country experience variable is insignificant throughout all specifications and does not subsume the local advantage effect.

In addition to the geographical channel, hedge funds may obtain knowledge and gain experience in certain industries (e.g., Kempf, Manconi, and Spalt, 2014).The reporting entity for our short positions (and quarterly holdings data) is the institution, and not the fund, so we cannot consider the experience of a single manager as a proxy for the institution's experience in certain industries. Instead, we take a simpler approach and rely on data from quarterly long equity holdings. Specifically, we define a hedge fund as experienced in an industry if the past quarter's industry holding was non-zero. By using an industry share of zero as the threshold for experience, we conservatively avoid any subjectivity in the choice of the threshold. As is evident in Table 1, approximately 80% of all positions are held by hedge funds with experience in the industry in which the shorted company operates.[18] In Table 7 we report the coefficient of the industry experience

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[18]Short and long positions in the same industry might capture the hedging strategies of investors, which would imply a negative relation between the same industry dummy and returns. However, the quarterly

dummy and find a positive effect. Although the effect is not statistically significant for the three-factor model specifications of Columns 1 to 5, the industry experience effect is statistically and economically significant if we account for time-invariant, unobservable fund characteristics (Column 6). Moreover, we observe that industry experience exerts a very strong effect when we adjust the returns for trading on mispricing factors (Columns 7 to 12). All in all, these findings are in line with the hypothesis that industry matters within funds and is associated with stock-picking skills.

With our data set, we can observe the holding period of the large short positions. We use this advantage to test whether the holding period has a role in explaining the cross section of short-sale performance. We proceed in an exploratory manner. On the one hand, positions with short holding periods can be very profitable investment opportunities, in which the hedge fund must short and cover its short positions quickly to realize the gains. In extreme events such as airplane crashes or natural disasters, the stock prices adapt very quickly to the efficient stock price. On the other hand, some positions might be short-term positions, because of temporary price reactions in the "wrong" direction. As suggested by Shleifer and Vishny (1997), such price movements trigger either margin calls or even force the fund to cover its short position, though the price of the stock is above its fundamental value. In this case, we expect that short-term positions are highly unprofitable. Our regression results suggest an underperformance of short-term positions by more than 17 bp per day – an effect that is economically and statistically significant at the 1% level. Although around 26% of SSP episodes are categorized as short-term, these positions represent only 1% of investor-stock-*day* observations.

Finally, we investigate whether short positions in emerging countries are more profitable. Literature on market efficiency and capital market anomalies suggests that market efficiency might be lower in emerging markets due to two main reasons. First, the number of informed investors is lower in these countries, which leads to higher profits due to lower competition among investors. Second, it is on average more expensive to invest or short sell in emerging

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share of certain industry holdings is very persistent (as we expect experience to be) and rather unsuitable for capturing short-term hedging purposes.

countries, leading to more arbitrage opportunities and higher gross profits of short sales. Our sample consists of two emerging countries with short-sale positions. Although the number of observations is relatively low, we add this binary variable to the specification in Column 4 and find that the profitability of short positions is significantly higher in emerging countries for the Fama and French (1993) model. However, when we include borrowing fee bucket-fixed effects obtained from the *Markit* database, we find that the effect can be explained by the difference in fees. This specification illustrates that the borrowing fee is an important determinant in the cross section of positions, but it does not affect the findings associated with the previous explanatory variables.

## 5  Conclusion

Using a novel data set of significant short positions in the EU, we find that the largest group of short-sellers, hedge funds, generate a significant and positive Fama and French (1993) risk-adjusted return on average. The return can be explained by trading on mispricing-related capital market anomalies momentum, betting-against-beta, and, to some extent, quality-minus-junk. The data set offers a rich cross section of stocks *and* investors. We exploit this advantage and document that local, diversified, and active hedge funds outperform other funds. On a more detailed level, we show that positions of first-movers, local, and industry-experienced hedge funds significantly outperform other positions. Finally, we find that short-term positions are associated with extremely negative returns.

We conclude that short sellers, as a group, earn positive risk-adjusted returns by trading on well-known mispricing factors. Our research does not address the impact of the regulation on market efficiency or, more precisely, on capital market anomalies. For example, the EU transparency regulation reveals short sellers' positions and potential arbitrage opportunities. Such regulations seemingly should increase the efficiency and decrease the profitability of capital market anomalies. This topic provides an area for further investigation.

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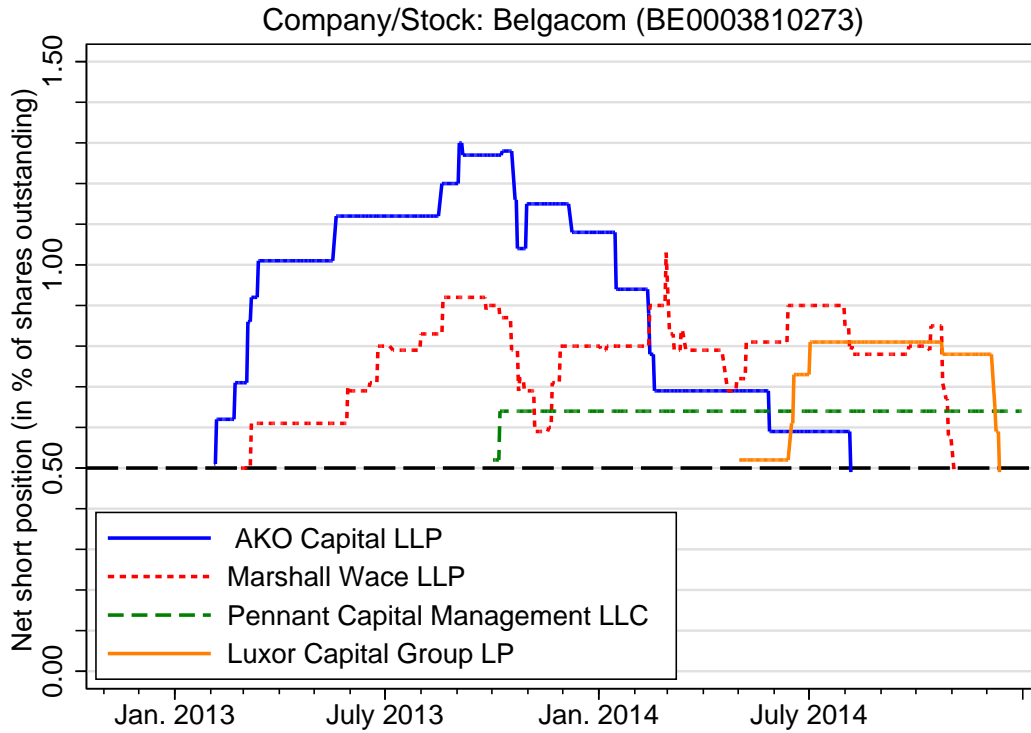
**Figure 1:**

**Example of short position disclosures**

This figure shows the net short position disclosures of four investors for the stock *Belgacom* (ISIN: BE0003810273) during the sample period from November 1, 2012, to December 31, 2014. The black dashed line at 0.50% represents the disclosure threshold above which net short positions must be disclosed. Above the threshold, net short positions have to be published at every 0.10% threshold.
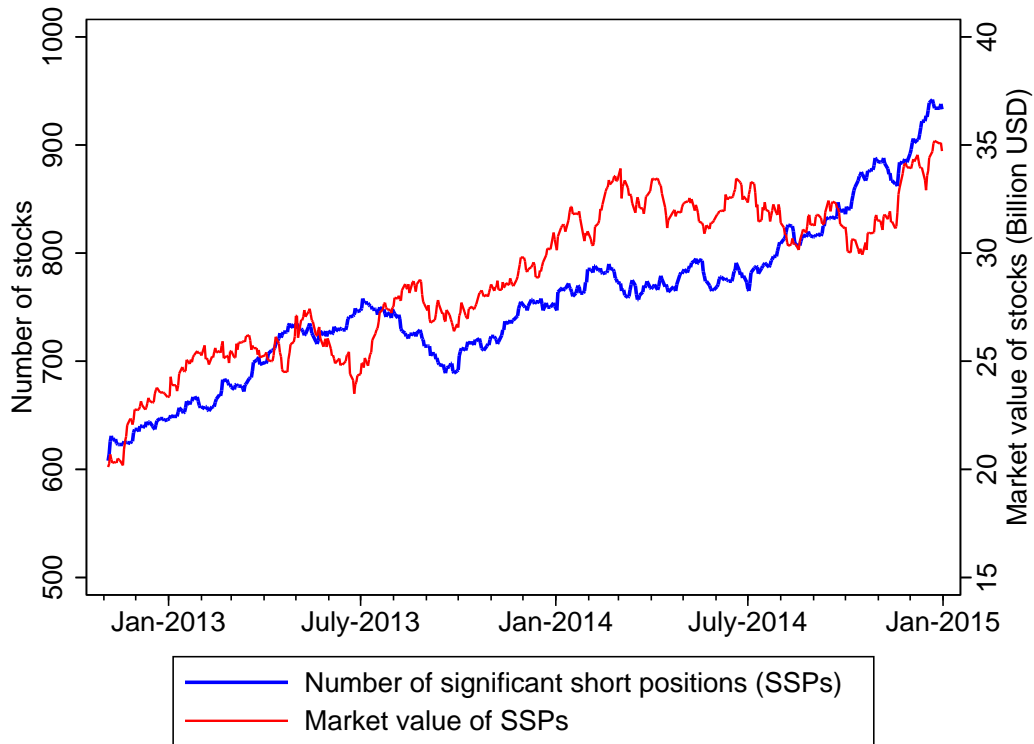
**Figure 2: Open significant short positions over time**

This figure shows the number of stocks with significant short positions (SSPs) and the market value of the SSPs over the sample period from November 1, 2012, to December 31, 2014.

**(a)** Variation of the entry date
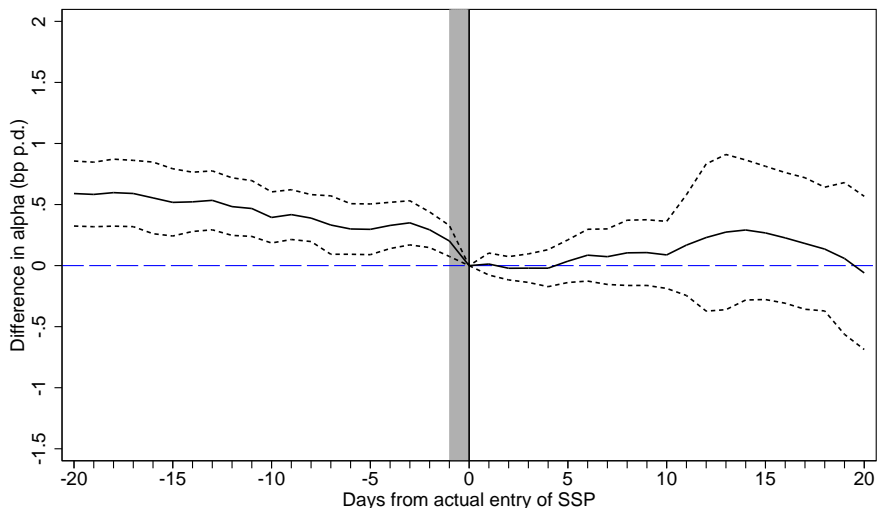


**(b)** Variation of the exit date
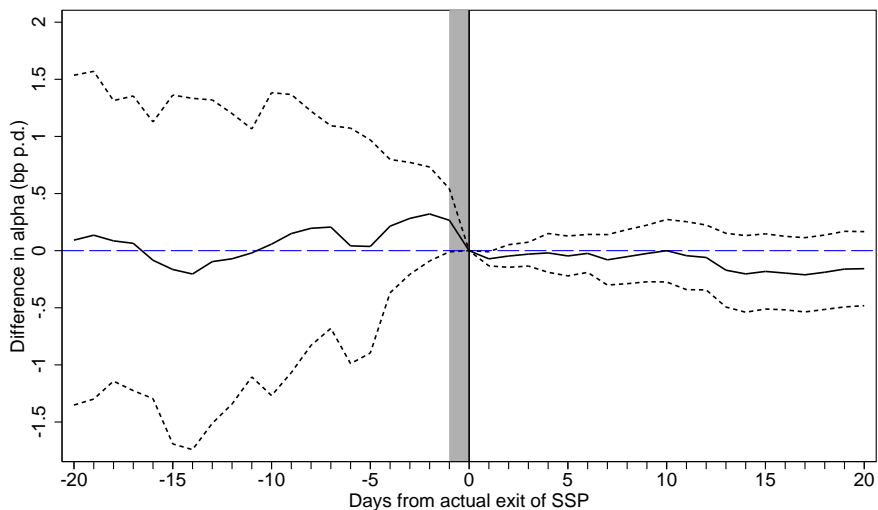
**Figure 3:**
**Variation of the entry and exit date and its effect on performance**

This figure displays the effect on the Fama and French (1993) three-factor alpha if the entry or exit date is varied. In Figure 3(a), the value-weighted investment strategy of Table 3, Column 5, is performed and compared against investment strategies that invest up to 20 trading days earlier (left-hand side) or 20 trading days later (right-hand side), holding the exit date constant. In Figure 3(b), the benchmark value-weighted investment strategy is compared against investment strategies that invest up to 20 trading days shorter (left-hand side) or 20 trading days longer (right-hand side), holding the entry date constant. The table shows the difference in Fama and French (1993) three-factor alpha (solid line) and 95% confidence intervals (dotted lines). The shaded areas between -1 and 0 indicates the uncertainty about whether investors opened/closed the position at the end of the day ($t = 0$), which is the conservative assumption of the original investment strategy, or at the beginning of the day ($t = -1$).

**Table 1:**
**Summary statistics: Position-stock-level and Investor-level data**

This table shows a list of sample characteristics of variables on the position level (Panel A) and hedge fund level (Panel B). For each variable in Panel A, we calculate the mean within each SSP and then calculate the descriptive statistics across positions. Net Short Position denotes the average magnitude of the large short position as a fraction of the number of shares outstanding. Number of Investors counts the number of investors in a stock on a given day. Holding period is the number of days from entering to closing a large short position. Fee Bucket is defined as in the *Markit* database, where stocks with the cheapest-to-borrow fee are in bucket 0 and stocks with the most expensive fee are in bucket 5. All other variables are defined in Section 4.

| Variable | N | Mean | SD | Percentiles: 10th | 25th | 50th | 75th | 90th |
|---|---|---|---|---|---|---|---|---|
| **Panel A: Position-stock level data** | | | | | | | | |
| Net Short Position (in %) | 4404 | 0.75 | 0.39 | 0.50 | 0.52 | 0.60 | 0.80 | 1.18 |
| Number of Investors | 4404 | 3.21 | 2.40 | 0.94 | 1.10 | 2.63 | 4.48 | 6.80 |
| Dummy: Multiple Investors | 4404 | 0.69 | - | - | - | - | - | - |
| Holding Period | 4404 | 93.1 | 128.3 | 3.0 | 10.0 | 37.0 | 123.0 | 279.0 |
| Dummy: Holding Period < 10 days | 4404 | 0.26 | - | - | - | - | - | - |
| Fee Bucket $(0-5)$ | 4307 | 1.46 | 1.65 | 0.00 | 0.00 | 0.86 | 2.51 | 4.22 |
| Dummy: Cheapest to Borrow | 4307 | 0.46 | - | - | - | - | - | - |
| Dummy: Initiator | 4404 | 0.32 | - | - | - | - | - | - |
| Dummy: Initiator Leader | 4404 | 0.08 | - | - | - | - | - | - |
| Dummy: Industry Experience | 3822 | 0.82 | - | - | - | - | - | - |
| Dummy: Same Country | 4192 | 0.25 | - | - | - | - | - | - |
| Dummy: Country Experience | 3831 | 0.66 | - | - | - | - | - | - |
| Dummy: Emerging Market | 4404 | 0.01 | - | - | - | - | - | - |
| **Panel B: Hedge fund-level data** | | | | | | | | |
| Turnover | 195 | 0.11 | 0.15 | 0.05 | 0.07 | 0.09 | 0.12 | 0.18 |
| Dummy: Other instruments | 226 | 0.42 | - | - | - | - | - | - |
| Dummy: European fund | 226 | 0.33 | - | - | - | - | - | - |
| Share of European stocks | 195 | 0.24 | 0.32 | 0.02 | 0.04 | 0.08 | 0.31 | 0.88 |
| Fund MV (in Million US) | 195 | 2338.04 | 6286.21 | 41.62 | 241.99 | 685.32 | 2190.91 | 4642.49 |
| Age (in years) | 205 | 15 | 11.29 | 6 | 9 | 13 | 19 | 25 |
| MV of SSPs (in Million US) | 226 | 104.74 | 292.07 | 2.82 | 10.95 | 28.85 | 93.47 | 229.00 |
| Number of SSPs | 226 | 2.56 | 4.16 | 0.86 | 0.95 | 1.05 | 2.20 | 5.38 |

**Table 2:**
**Short positions by investor type**

This table shows the sample of SSPs categorized by investor type. Column 1 shows the number of investors, Column 3 shows the number of days with an open SSPs, and Column 5 indicates the time-series average of the market value (in Million USD) of the SSPs. Columns 2, 4, and 6 contain the percentage shares with respect to these figures.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Number of Investors | | Days of SSPs | | Market Value of SSPs | |
| Hedge Fund | 226 | 63.1% | 279159 | 67.9% | 21976.1 | 78.0% |
| Mutual Fund | 7 | 2.0% | 29597 | 7.2% | 1610.9 | 5.7% |
| Other Investment Adviser | 38 | 10.6% | 65672 | 16.0% | 1624.4 | 5.8% |
| Broker | 16 | 4.5% | 8617 | 2.1% | 1041.5 | 3.7% |
| Individual | 3 | 0.8% | 72 | 0.0% | 6.3 | 0.0% |
| Other | 41 | 11.5% | 16186 | 3.9% | 901.9 | 3.2% |
| Uncategorized | 27 | 7.5% | 11773 | 2.9% | 1024.6 | 3.6% |
| | | | | | | |
| Total | 358 | 100.0% | 411076 | 100.0% | 28185.6 | 100.0% |

**Table 3:**

**Performance of short sales: Calendar-time approach**

This table shows the performance of short sales using a calendar time approach. We form several investment strategies that imitate the short selling of investors: a stock is shorted, whenever an SSP is opened, and it not shorted anymore, when the SSP is closed. Portfolios are formed each day using equal weighting (EW), value-weighting (VW), and weighting by the market value of short positions (SPW). The portfolio returns are then regressed on the market excess return (MKTRF), the size (SMB) and value (HML) factors, the momentum factor (WML), the betting-against-beta factor (BAB), and the quality-minus-junk (QMJ) factor. The table reports factor loadings and alphas, as well as t-values computed with Newey-West standard errors in parentheses. For all coefficients except the market beta, the null hypothesis is that the coefficient is zero. For the market beta (MKTRF), the null hypothesis is that the beta equals -1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Panel A provides the results for hedge funds, Panel B for other investors, and Panel C displays the difference in alphas between hedge funds and other investors.

| | (1) EW | (2) VW | (3) SPW | (4) EW | (5) VW | (6) SPW | (7) EW | (8) VW | (9) SPW | (10) EW | (11) VW | (12) SPW |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| **Panel A: Hedge funds** | | | | | | | | | | | | |
| MKTRF | -1.14*** | -1.13*** | -1.12*** | -1.22*** | -1.10*** | -1.10*** | -1.24*** | -1.13*** | -1.13*** | -1.21*** | -1.10*** | -1.11*** |
| | (-4.78) | (-6.65) | (-5.66) | (-6.95) | (-4.20) | (-4.16) | (-7.35) | (-4.97) | (-4.72) | (-7.16) | (-3.69) | (-3.94) |
| SMB | | | | -0.41*** | -0.05 | -0.08* | -0.41*** | -0.06 | -0.09** | -0.52*** | -0.12*** | -0.17*** |
| | | | | (-11.28) | (-1.22) | (-1.83) | (-10.65) | (-1.49) | (-2.06) | (-10.67) | (-2.61) | (-3.68) |
| HML | | | | -0.55*** | -0.43*** | -0.42*** | -0.51*** | -0.37*** | -0.36*** | -0.29*** | -0.20*** | -0.21*** |
| | | | | (-8.11) | (-7.19) | (-7.00) | (-7.92) | (-7.24) | (-6.42) | (-3.39) | (-3.66) | (-3.25) |
| WML | | | | | | | 0.11 | 0.21*** | 0.19*** | 0.20*** | 0.26*** | 0.25*** |
| | | | | | | | (1.49) | (3.48) | (3.36) | (3.17) | (5.08) | (4.82) |
| BAB | | | | | | | | | | 0.29*** | 0.17*** | 0.20*** |
| | | | | | | | | | | (6.05) | (4.23) | (4.62) |
| QMJ | | | | | | | | | | 0.18** | 0.16** | 0.11 |
| | | | | | | | | | | (2.04) | (2.32) | (1.45) |
| $\alpha$ | 1.94 | 1.94* | 1.73 | 2.88** | 2.29** | 2.11* | 2.17 | 0.96 | 0.91 | -0.47 | -0.90 | -0.89 |
| | (1.01) | (1.67) | (1.36) | (2.24) | (2.02) | (1.78) | (1.39) | (0.80) | (0.70) | (-0.38) | (-0.83) | (-0.79) |
| $R^2$ | 86.64 | 89.28 | 88.44 | 90 | 90.56 | 89.67 | 90.12 | 91 | 90.03 | 91.87 | 91.79 | 90.92 |

Table 3 – Continued

**Panel B: Other investors**

| | (1) EW | (2) VW | (3) SPW | (4) EW | (5) VW | (6) SPW | (7) EW | (8) VW | (9) SPW | (10) EW | (11) VW | (12) SPW |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| MKTRF | -0.99 | -1.10*** | -1.08*** | -1.11*** | -1.07** | -1.08** | -1.12*** | -1.07** | -1.08** | -1.11*** | -1.03 | -1.05 |
| | (0.39) | (-5.47) | (-3.95) | (-3.68) | (-2.44) | (-2.36) | (-3.77) | (-2.39) | (-2.38) | (-2.94) | (-0.76) | (-1.24) |
| SMB | | | | -0.46*** | -0.05 | -0.09** | -0.46*** | -0.05 | -0.09** | -0.57*** | -0.11* | -0.17** |
| | | | | (-9.80) | (-1.11) | (-2.01) | (-10.20) | (-1.24) | (-2.01) | (-10.04) | (-1.72) | (-2.55) |
| HML | | | | -0.33*** | -0.40*** | -0.36*** | -0.30*** | -0.40*** | -0.36*** | -0.13* | -0.17*** | -0.16*** |
| | | | | (-5.34) | (-7.88) | (-6.34) | (-4.96) | (-6.81) | (-5.90) | (-1.71) | (-3.44) | (-2.59) |
| WML | | | | | | | 0.08 | 0.00 | 0.00 | 0.16*** | 0.07 | 0.07* |
| | | | | | | | (1.39) | (0.04) | (0.05) | (2.96) | (1.59) | (1.74) |
| BAB | | | | | | | | | | 0.27*** | 0.19*** | 0.22*** |
| | | | | | | | | | | (5.82) | (4.77) | (5.23) |
| QMJ | | | | | | | | | | 0.12 | 0.23*** | 0.17** |
| | | | | | | | | | | (1.44) | (2.90) | (2.08) |
| α | 1.28 | -0.48 | -0.56 | 2.16* | -0.14 | -0.20 | 1.64 | -0.16 | -0.22 | -0.58 | -2.49** | -2.36* |
| | (0.70) | (-0.37) | (-0.37) | (1.91) | (-0.13) | (-0.14) | (1.24) | (-0.12) | (-0.15) | (-0.49) | (-2.04) | (-1.65) |
| $R^2$ | 83.98 | 88.38 | 86.64 | 87.29 | 89.57 | 87.64 | 87.38 | 89.57 | 87.64 | 89.15 | 90.78 | 88.82 |

**Panel C: Difference between hedge funds and other investors**

| | EW | VW | SPW | EW | VW | SPW | EW | VW | SPW | EW | VW | SPW |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| α | 0.66 | 2.42** | 2.29** | 0.72 | 2.44** | 2.30** | 0.53 | 1.12 | 1.12 | 0.11 | 1.59* | 1.47 |
| | (0.83) | (2.42) | (2.25) | (0.90) | (2.22) | (2.28) | (0.57) | (1.32) | (1.32) | (0.13) | (1.72) | (1.47) |

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**Table 4:**
**Performance and factor loadings of hedge funds: average performance and cross-sectional distribution**

This table shows summary statistics of alphas and risk loadings of hedge funds. For each hedge fund we form a short-position-weighted portfolio and run a time-series regression to estimate factor loadings and alphas using various models (Panel A-D). The table shows the equally weighted (EW) mean in Column 1 of factor betas and alphas. Column 2 shows, for factor loadings, the percentage of hedge funds that trade on a specific factor (i.e., have a $\beta > 0$ for SMB, HML, WML, BAB, QMJ or $\beta < -1$ for MKTRF); for the alphas, it shows the percentage of hedge funds with a positive alpha. The table furthermore provides standard deviation (S.D.) and the 10th through 90th percentiles in Columns 3-8. Columns 9 contains short-position-weighted (SPW) averages of factor loadings and alphas. The table shows t-statistics for average alphas in parentheses.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) |
|---|---|---|---|---|---|---|---|---|---|
| | Mean (EW) | | S.D. | Percentiles | | | | | Mean (SPW) |
| | | | | 10 | 25 | 50 | 75 | 90 | |
| **Panel A: CAPM** | | | | | | | | | |
| MKTRF | -1.12 | 34.2% | 0.35 | -1.46 | -1.28 | -1.12 | -0.93 | -0.77 | -1.10 |
| $\alpha$ | 3.85 | 54.9% | 17.11 | -10.99 | -4.69 | 1.00 | 8.96 | 23.84 | 2.83 |
| | (2.86) | | | | | | | | (2.69) |
| **Panel B: Fama-French three-factor model** | | | | | | | | | |
| MKTRF | -1.22 | 22.2% | 0.47 | -1.67 | -1.35 | -1.16 | -1.01 | -0.83 | -1.09 |
| SMB | -0.45 | 19.5% | 0.64 | -1.31 | -0.62 | -0.34 | -0.07 | 0.13 | -0.11 |
| HML | -0.53 | 25.4% | 0.93 | -1.54 | -0.92 | -0.43 | 0.02 | 0.36 | -0.42 |
| $\alpha$ | 4.35 | 59.9% | 17.50 | -11.06 | -4.48 | 1.23 | 9.51 | 26.02 | 3.24 |
| | (3.16) | | | | | | | | (3.10) |
| **Panel C: Carhart four-factor model** | | | | | | | | | |
| MKTRF | -1.21 | 23.1% | 0.41 | -1.68 | -1.39 | -1.17 | -1.00 | -0.85 | -1.11 |
| SMB | -0.44 | 20.6% | 0.61 | -1.16 | -0.65 | -0.33 | -0.04 | 0.13 | -0.11 |
| HML | -0.51 | 24.1% | 1.04 | -1.46 | -0.92 | -0.37 | -0.02 | 0.33 | -0.37 |
| WML | 0.00 | 47.9% | 0.74 | -0.66 | -0.34 | -0.02 | 0.36 | 0.87 | 0.14 |
| $\alpha$ | 4.26 | 59.8% | 17.23 | -9.59 | -4.26 | 1.18 | 8.54 | 22.00 | 2.17 |
| | (3.14) | | | | | | | | (2.34) |
| **Panel D: six-factor model** | | | | | | | | | |
| MKTRF | -1.19 | 25.9% | 0.44 | -1.68 | -1.35 | -1.15 | -0.98 | -0.82 | -1.10 |
| SMB | -0.58 | 13.1% | 0.78 | -1.39 | -0.80 | -0.42 | -0.15 | 0.08 | -0.19 |
| HML | -0.30 | 32.1% | 0.93 | -1.30 | -0.62 | -0.24 | 0.12 | 0.55 | -0.25 |
| WML | 0.08 | 54.9% | 0.83 | -0.57 | -0.27 | 0.04 | 0.44 | 1.02 | 0.20 |
| BAB | 0.35 | 87.4% | 0.64 | -0.09 | 0.10 | 0.28 | 0.44 | 0.86 | 0.19 |
| QMJ | 0.16 | 54.3% | 1.05 | -0.68 | -0.31 | 0.07 | 0.50 | 1.14 | 0.08 |
| $\alpha$ | 1.62 | 46.3% | 16.89 | -13.71 | -6.25 | -0.59 | 6.03 | 19.95 | 0.69 |
| | (1.22) | | | | | | | | (0.63) |

**Table 5:**
**Average factor-adjusted performance and factor loadings of SSPs**
This table shows the average factor-adjusted performance of short positions and their risk factor exposure. We first estimate factor loadings and alphas for each stock, based on the past 200 trading days. The table reports equal-, value- and short-position-weighted averages of factor loadings and alphas for various factor models (Panel A through D). For alphas, t-statistics are provided in parentheses. Columns 1 to 3 show the performance of all positions in the sample period, Columns 4 to 6 show the performance for completed positions only.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | All positions | | | Completed positions | | |
| | EW | VW | SPW | EW | VW | SPW |
| **Panel A: CAPM** | | | | | | |
| MKTRF | -1.17 | -1.15 | -1.15 | -1.17 | -1.14 | -1.14 |
| $\alpha$ | 1.24 | 2.02 | 1.76 | 2.18 | 4.01 | 3.97 |
| | (0.77) | (1.85) | (1.47) | (0.97) | (2.55) | (2.52) |
| **Panel B: Fama-French model** | | | | | | |
| MKTRF | -1.26 | -1.13 | -1.14 | -1.26 | -1.13 | -1.14 |
| SMB | -0.43 | -0.08 | -0.11 | -0.50 | -0.13 | -0.17 |
| HML | -0.46 | -0.37 | -0.37 | -0.53 | -0.43 | -0.43 |
| $\alpha$ | 2.34 | 3.21 | 2.95 | 4.37 | 5.70 | 5.82 |
| | (1.76) | (3.03) | (2.60) | (2.20) | (3.88) | (4.14) |
| **Panel C: Carhart model** | | | | | | |
| MKTRF | -1.21 | -1.12 | -1.12 | -1.23 | -1.12 | -1.13 |
| SMB | -0.36 | -0.05 | -0.07 | -0.42 | -0.09 | -0.11 |
| HML | -0.31 | -0.28 | -0.26 | -0.35 | -0.32 | -0.30 |
| WML | 0.13 | 0.16 | 0.18 | 0.23 | 0.20 | 0.22 |
| $\alpha$ | 0.53 | 1.36 | 0.85 | 1.78 | 3.67 | 3.56 |
| | (0.35) | (1.30) | (0.72) | (0.89) | (2.71) | (2.66) |
| **Panel D: Six-factor model** | | | | | | |
| MKTRF | -1.22 | -1.13 | -1.14 | -1.24 | -1.13 | -1.14 |
| SMB | -0.50 | -0.15 | -0.19 | -0.56 | -0.17 | -0.20 |
| HML | -0.20 | -0.21 | -0.21 | -0.19 | -0.21 | -0.19 |
| WML | 0.21 | 0.22 | 0.24 | 0.31 | 0.27 | 0.30 |
| QMJ | 0.11 | 0.03 | 0.00 | 0.13 | 0.06 | 0.06 |
| BAB | 0.30 | 0.20 | 0.22 | 0.29 | 0.16 | 0.17 |
| $\alpha$ | -1.21 | 0.27 | -0.11 | -0.32 | 2.45 | 2.19 |
| | (-0.91) | (0.28) | (-0.11) | (-0.17) | (1.72) | (1.65) |

**Table 6:**

**Determinants of hedge funds' short-sale performance**

This table shows the results of a panel regression of hedge funds' alpha values on their characteristics. Each hedge fund portfolio is calculated by weighting all SSP of a fund by the market value of the SSP at each point of time. Then, the alphas are regressed on a list of fund characteristics. Specifications in Columns 1 to 3 use the Fama and French (1993) three-factor alpha as a dependent variable, and specifications in Columns 4 to 6 use the six-factor alpha. The table reports standardized coefficient estimates (except for dummy variables) and t-values computed by Driscoll and Kraay (1998) standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
| | Three-factor alpha | | | Six-factor alpha | | |
| ln(Turnover) | | 1.18 | | | 0.83 | |
| | | (1.05) | | | (0.75) | |
| Turnover Top Quartile | | | 5.60** | | | 4.54* |
| | | | (2.06) | | | (1.73) |
| ln(MV Holdings) | | 1.66 | 2.03* | | -0.53 | -0.22 |
| | | (1.38) | (1.69) | | (-0.46) | (-0.19) |
| ln(Age) | | -1.04 | -1.34 | | 0.22 | -0.03 |
| | | (-0.98) | (-1.26) | | (0.21) | (-0.03) |
| Other Fin. Instruments | | 5.43*** | 5.60*** | | 5.27** | 5.44*** |
| | | (2.60) | (2.66) | | (2.56) | (2.63) |
| European Headquarter | | 8.51*** | 8.91*** | | 6.59** | 6.94** |
| | | (2.73) | (2.84) | | (2.15) | (2.26) |
| Share of European Holdings | | -2.74* | -2.72* | | -3.27** | -3.27** |
| | | (-1.77) | (-1.79) | | (-2.18) | (-2.24) |
| ln(MV SSPs) | | -1.08 | -1.12 | | -1.07 | -1.10 |
| | | (-0.51) | (-0.54) | | (-0.54) | (-0.56) |
| ln(No of SSPs) | | -1.51 | -1.44 | | -1.16 | -1.11 |
| | | (-0.98) | (-0.95) | | (-0.77) | (-0.75) |
| Intercept | 3.72*** | 2.74 | 1.05 | 1.00 | 2.18 | 0.78 |
| | (3.08) | (1.33) | (0.47) | (0.86) | (1.03) | (0.35) |
| Week Fixed Effects | No | Yes | Yes | No | Yes | Yes |
| $R^2$ | 0.0000 | 0.0060 | 0.0061 | 0.0000 | 0.0056 | 0.0057 |
| Nobs | 63444 | 52183 | 52183 | 63444 | 52183 | 52183 |

## Table 7:
## Performance analysis: The cross section of short positions

This table shows the results of a WLS panel regressions of alphas of SSP episodes on several fund position characteristics, using the short positions' market values as weights. Specifications in Columns 1 to 5 use the Fama and French (1993) three-factor alpha as the dependent variable, and specifications in Columns 6 to 10 use the six-factor alpha. The table reports standardized coefficient estimates (except for dummy variables) and t-values computed by Driscoll-Kraay standard errors in parentheses. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | | | Three-factor alpha | | | | | | Six-factor alpha | | | |
| Multiple Investors | | 3.03** | 1.74 | 1.73 | 1.61 | 2.13* | | 1.85 | -0.02 | -0.01 | 0.16 | 0.80 |
| | | (2.07) | (1.25) | (1.24) | (1.20) | (1.80) | | (1.25) | (-0.01) | (-0.01) | (0.12) | (0.68) |
| Initiator | | 2.04 | | | | | | 2.92** | | | | |
| | | (1.26) | | | | | | (2.14) | | | | |
| Initiator Leader | | | 2.38* | 2.40* | 2.54* | 2.57* | | | 3.09** | 3.08** | 3.23** | 3.39** |
| | | | (1.82) | (1.85) | (1.94) | (1.82) | | | (2.34) | (2.34) | (2.44) | (2.46) |
| Same Country | | 4.15*** | 4.25*** | 4.24*** | 3.79*** | 4.65** | | 4.63*** | 4.80*** | 4.80*** | 4.24*** | 4.02* |
| | | (2.87) | (2.91) | (2.91) | (2.68) | (2.11) | | (3.28) | (3.44) | (3.44) | (3.18) | (1.81) |
| Country Experience | | 1.06 | 1.07 | 1.07 | 0.88 | -0.76 | | -0.49 | -0.46 | -0.46 | -0.60 | -1.96 |
| | | (0.52) | (0.52) | (0.53) | (0.44) | (-0.33) | | (-0.25) | (-0.22) | (-0.22) | (-0.30) | (-0.86) |
| Industry Experience | | 1.93 | 1.90 | 1.91 | 2.06 | 4.07** | | 2.84** | 2.80** | 2.79** | 3.04** | 5.14*** |
| | | (1.40) | (1.38) | (1.38) | (1.49) | (2.18) | | (2.04) | (2.01) | (2.01) | (2.19) | (2.74) |
| Holding Period < 10 days | | -18.10*** | -17.88*** | -17.86*** | -17.84*** | -17.26*** | | -17.74*** | -17.48*** | -17.49*** | -17.34*** | -16.89*** |
| | | (-3.42) | (-3.37) | (-3.37) | (-3.28) | (-2.84) | | (-3.00) | (-2.94) | (-2.94) | (-2.90) | (-2.68) |
| Emerging Country | | | | 11.41** | -6.88 | -9.95 | | | | 8.67 | -5.26 | -8.06 |
| | | | | (2.12) | (-0.74) | (-0.96) | | | | (1.50) | (-0.53) | (-0.76) |
| Intercept | 2.95*** | -0.81 | 0.35 | 0.35 | 2.01 | 3.69 | -0.11 | -1.80 | -0.02 | -0.01 | 1.28 | 9.72 |
| | (2.60) | (-0.24) | (0.09) | (0.09) | (0.49) | (0.53) | (-0.11) | (-0.48) | (-0.00) | (-0.00) | (0.30) | (1.43) |
| Country Fixed Effects | No | Yes | Yes | Yes | Yes | Yes | No | Yes | Yes | Yes | Yes | Yes |
| Fee Bucket Fixed Effects | No | No | No | No | Yes | Yes | No | No | No | No | Yes | Yes |
| Fund Fixed Effect | No | No | No | No | No | Yes | No | No | No | No | No | Yes |
| Week Fixed Effects | No | No | No | No | No | Yes | No | No | No | No | No | Yes |
| $R^2$ | 0.00 | 0.07 | 0.07 | 0.07 | 0.08 | 0.73 | 0.00 | 0.08 | 0.08 | 0.08 | 0.08 | 0.73 |
| Nobs | 278333 | 258389 | 258389 | 258389 | 249785 | 249785 | 278333 | 258389 | 258389 | 258389 | 249785 | 249785 |

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# A  Additional tables and figures

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2014-11-28

**Publication des positions courtes nettes importantes sur les actions**
Conformément à l'article 9 du Règlement Européen (EU) No 236/2012

**Public disclosure of significant net short positions in shares**
In accordance with Article 9 of Regulation (EU) No 236/2012

| | |
|---|---|
| **POSITION HOLDER** <br> **DETENTEUR DE LA POSITION** | **MARSHALL WACE LLP** |
| **NOM DE L'ÉMETTEUR** <br> **NAME OF THE ISSUER** | **AIR FRANCE-KLM** |
| **ISIN** | **FR0000031122** |
| **POSITION COURTE NETTE DETENUE EN %** <br> **NET SHORT POSITION SIZE IN PERCENTAGE** | **0.47** |
| **DATE DE POSITION (AAAA-MM-JJ)** <br> **POSITION DATE (YYYY-MM-DD)** | **2014-11-27** |

**Figure A.1:**
**Example of a disclosure notification for significant net short positions**

This figure shows a disclosure notification for a significant net short position in the stock of *Air France-KLM*.
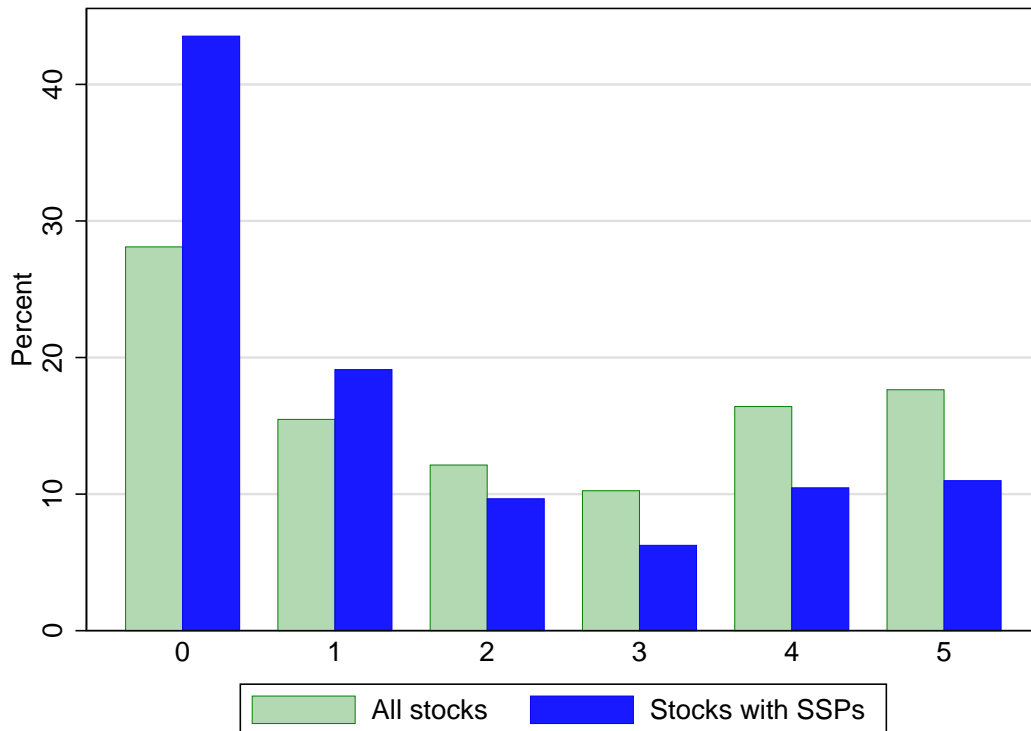
**Figure A.2: Distribution of stocks across borrowing fee buckets**

This figure shows the distribution of stocks across fee buckets for all stocks in Europe (*Markit* universe) and for stocks with significant short positions (SSPs) in the sample period November 1, 2012 - December 31, 2014. Information about borrowing costs is categorized by *Markit* in fee buckets ranging from 0 to 5, where 0 is the cheapest to borrow and 5 is the most expensive.

**(a)** Variation of the entry date
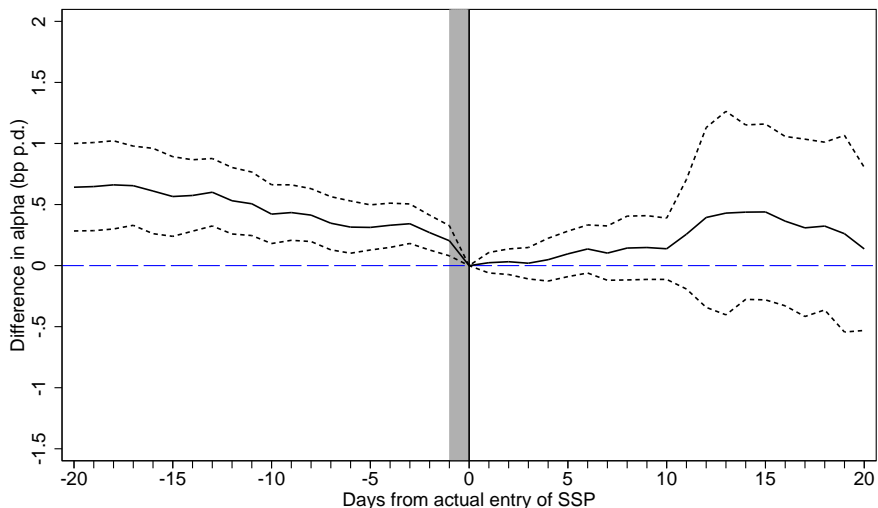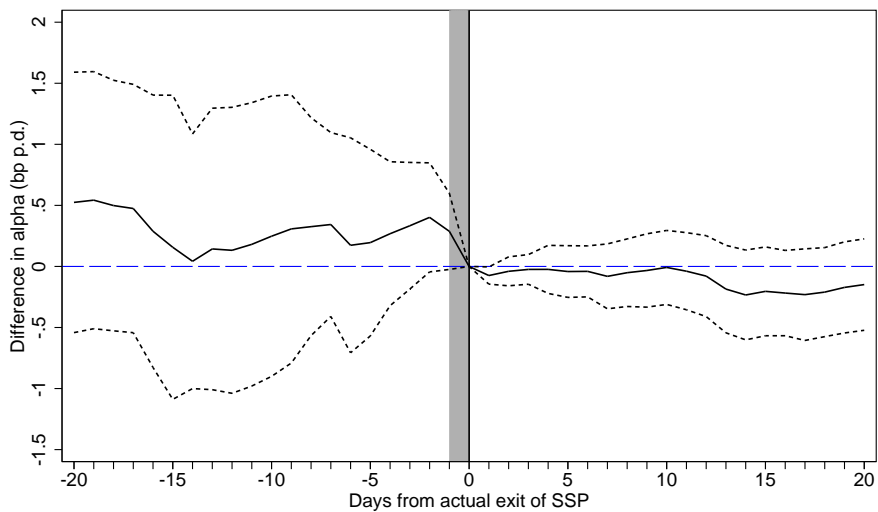


**(b)** Variation of the exit date



**Figure A.3:**
**Variation of the entry and exit date (six-factor alpha)**
This figure repeats the analysis of Figure 3 using the six-factor model instead of Fama and French's (1993) three-factor model to risk-adjust performance. The benchmark model is the value-weighted investment strategy in Table 3, Column 8.

**Table A.1:**
**Summary statistics: Short positions by country**
This table shows summary statistics for significant short positions (SSPs) by country, grouped into developed markets (Panel A) and emerging markets (Panel B). Column 1 shows the total number of open SSPs in the sample period November 1, 2012, to December 31, 2014. Column 2 reports the average number of SSPs per trading day, Column 3 details the average short position in percentage of shares outstanding, given that there is an SSP. The reported statistics are time-series averages of cross-sectional averages for each country. For the developed market of Luxembourg and the emerging markets of Bulgaria, Croatia, Cyprus, Czech Republic, Estonia, Latvia, Lithuania, Malta, Romania, Slovakia, and Slovenia among the EU 28, there were no SSP disclosures in the sample period. There was one disclosure of an SSP in Greece, but its duration was less than 2 days, so it was not included in the sample.

| | (1) | (2) | (3) |
|---|---|---|---|
| Country | Total number of open SSP days | Average number of SSPs per day | Average short position in percentage of shares |
| **Panel A: Developed markets** | | | |
| Austria | 3048 | 5.51 | 0.91 |
| Belgium | 12126 | 21.93 | 1.05 |
| Denmark | 7333 | 13.26 | 1.15 |
| Finland | 25387 | 45.91 | 0.97 |
| France | 36134 | 65.34 | 0.98 |
| Germany | 53588 | 96.90 | 0.96 |
| Ireland | 1050 | 1.90 | 0.96 |
| Italy | 33117 | 59.89 | 0.91 |
| Netherlands | 18610 | 33.65 | 1.04 |
| Portugal | 3514 | 6.35 | 0.92 |
| Spain | 26172 | 47.33 | 0.89 |
| Sweden | 31618 | 57.18 | 1.02 |
| United Kingdom | 151055 | 273.16 | 1.04 |
| **Panel B: Emerging markets** | | | |
| Hungary | 3375 | 6.10 | 0.79 |
| Poland | 4257 | 7.70 | 0.93 |

**Table A.2:**
**Summary statistics: Most active investors**
This table shows the most active investors, defined as having the highest average number of opened short positions per day, as displayed in Column 1. It also shows the average short position as a percentage of shares outstanding in Column 2.

| | (1) | (2) |
|---|---|---|
| Investor name | Average number of SSPs per day | Average short position in percentage of shares |
| BlackRock Investment Management (UK) Ltd. | 46.14 | 0.98 |
| AQR Capital Management LLC | 35.12 | 0.95 |
| OxFORD Asset Management LLP | 30.13 | 0.77 |
| Lansdowne Partners (UK) LLP | 29.51 | 1.45 |
| Marshall Wace LLP | 28.53 | 0.80 |
| BlackRock Fund Advisors | 25.34 | 0.73 |
| Odey Asset Management LLP | 23.25 | 1.22 |
| AKO Capital LLP | 21.94 | 1.39 |
| JPMorgan Asset Management (UK) Ltd. | 19.53 | 0.81 |
| Ennismore Fund Management Ltd. | 13.01 | 1.04 |
| Ziff Brothers Investments LLC | 11.56 | 1.03 |
| D. E. Shaw & Co. LP | 10.43 | 0.93 |
| Henderson Alternative Investment Advisor Ltd. | 9.92 | 0.83 |
| BlueCrest Capital Management (UK) LLP | 9.80 | 0.62 |
| CQS (UK) LLP | 9.41 | 0.96 |
| Lone Pine Capital LLC | 8.95 | 0.94 |
| TT International | 8.92 | 0.71 |
| Wellington Management Co. LLP | 8.89 | 0.86 |
| Discovery Capital Management LLC | 8.55 | 0.98 |
| Highbridge Capital Management LLC | 8.18 | 0.89 |

## Table A.3:
## Performance of short sales: Calendar-time approach with alternative (non-conservative) investment timing

This table shows the performance of short sales using a calendar time approach. We form several investment strategies that imitate the short-selling of investors: A stock is shorted whenever an SSP is opened, and it not shorted anymore, when the SSP is closed. Portfolios form each day using equal weighting (EW), value-weighting (VW), and weighting by the market value of short positions (SPW). The portfolio returns are then regressed on the market excess return (MKTRF), the size (SMB) and value (HML) factors, the momentum factor (WML), the betting-against-beta factor (BAB), and the quality-minus-junk (QMJ) factor. The table reports factor risk loadings and alphas, as well as t-values computed with Newey-West standard errors in parentheses. For all coefficients except the market beta, the null hypothesis is that the coefficient is zero. For the market beta (MKTRF), the null hypothesis is that the beta equals -1. *, **, and *** indicate significance at the 10%, 5%, and 1% levels, respectively. Panel A provides the results for hedge funds, Panel B for other investors, and Panel C displays the difference in alphas between hedge funds and other investors.

| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) | (9) | (10) | (11) | (12) |
|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | EW | VW | SPW | EW | VW | SPW | EW | VW | SPW | EW | VW | SPW |
| **Hedge funds** | | | | | | | | | | | | |
| MKTRF | -1.14*** | -1.13*** | -1.12*** | -1.22*** | -1.10*** | -1.10*** | -1.23*** | -1.13*** | -1.13*** | -1.21*** | -1.11*** | -1.11*** |
| | (-4.73) | (-6.81) | (-5.79) | (-7.24) | (-4.31) | (-4.19) | (-7.46) | (-5.07) | (-4.79) | (-7.33) | (-3.92) | (-4.15) |
| SMB | | | | -0.40*** | -0.05 | -0.07* | -0.41*** | -0.06 | -0.08** | -0.51*** | -0.12*** | -0.16*** |
| | | | | (-11.95) | (-1.21) | (-1.74) | (-11.24) | (-1.51) | (-2.00) | (-11.08) | (-2.62) | (-3.54) |
| HML | | | | -0.53*** | -0.41*** | -0.40*** | -0.50*** | -0.36*** | -0.34*** | -0.28*** | -0.19*** | -0.21*** |
| | | | | (-7.80) | (-6.98) | (-7.00) | (-7.58) | (-7.47) | (-6.83) | (-3.29) | (-3.64) | (-3.14) |
| WML | | | | | | | 0.11 | 0.20*** | 0.18*** | 0.19*** | 0.25*** | 0.24*** |
| | | | | | | | (1.53) | (3.48) | (3.41) | (3.11) | (5.02) | (4.85) |
| BAB | | | | | | | | | | 0.28*** | 0.17*** | 0.20*** |
| | | | | | | | | | | (5.69) | (4.09) | (4.58) |
| QMJ | | | | | | | | | | 0.17* | 0.15** | 0.10 |
| | | | | | | | | | | (1.94) | (2.24) | (1.39) |
| α | 2.52 | 2.61** | 2.35** | 3.43*** | 2.95*** | 2.71** | 2.73* | 1.66 | 1.52 | 0.23 | -0.07 | -0.15 |
| | (1.34) | (2.38) | (2.01) | (2.74) | (2.65) | (2.40) | (1.78) | (1.40) | (1.19) | (0.19) | (-0.07) | (-0.14) |
| $R^2$ | 87.06 | 89.92 | 89.36 | 90.33 | 91.1 | 90.49 | 90.45 | 91.52 | 90.84 | 92.05 | 92.23 | 91.66 |

**Table A.4:**
**Determinants of hedge funds' short-sale performance using Fama-MacBeth regressions**

This table shows the results of a panel regression of hedge funds' alpha on their characteristics using Fama and MacBeth (1973) regressions. Further information is provided in Table 6.

|  | (1) | (2) | (3) | (4) | (5) | (6) |
|---|---|---|---|---|---|---|
|  | Three-factor alpha | | | Six-factor alpha | | |
| ln(Turnover) |  | 1.30 |  |  | 0.94 |  |
|  |  | (1.13) |  |  | (0.83) |  |
| Turnover Top Quartile |  |  | 4.20 |  |  | 3.05 |
|  |  |  | (1.54) |  |  | (1.16) |
| ln(MV Holdings) |  | 1.62 | 1.82 |  | -0.49 | -0.36 |
|  |  | (1.33) | (1.50) |  | (-0.42) | (-0.31) |
| ln(Age) |  | -0.58 | -0.89 |  | 0.62 | 0.37 |
|  |  | (-0.55) | (-0.83) |  | (0.59) | (0.34) |
| Other Fin. Instruments |  | 5.48** | 5.63*** |  | 5.22** | 5.35*** |
|  |  | (2.57) | (2.67) |  | (2.49) | (2.59) |
| EU Headquarter |  | 7.99** | 7.64** |  | 6.06* | 5.63* |
|  |  | (2.42) | (2.34) |  | (1.90) | (1.78) |
| Relative EU Holdings |  | -2.11 | -1.72 |  | -2.64* | -2.25* |
|  |  | (-1.43) | (-1.22) |  | (-1.86) | (-1.65) |
| ln(MV LSP) |  | -0.69 | -0.76 |  | -0.67 | -0.71 |
|  |  | (-0.32) | (-0.35) |  | (-0.32) | (-0.35) |
| ln(No of LSP) |  | -1.70 | -1.41 |  | -1.37 | -1.10 |
|  |  | (-0.98) | (-0.82) |  | (-0.81) | (-0.65) |
| Intercept | 3.43*** | -0.92 | -2.04 | 0.70 | -3.05 | -3.86** |
|  | (2.85) | (-0.45) | (-1.02) | (0.60) | (-1.51) | (-2.00) |
| $R^2$ | 0.0000 | 0.1110 | 0.1110 | 0.0000 | 0.1112 | 0.1110 |
| Nobs | 63444 | 52183 | 52183 | 63444 | 52183 | 52183 |

# B   Sample construction

We collect the disclosures of significant short positions (SSPs) from all national competent authorities of the 28 EU member states in the sample period November 1, 2012, to December 31, 2014.[19] Accounting for ISIN changes, we obtain, for each instrument, its static characteristics and time series data (price, return, and market value data) from *Thomson Reuters Datastream*. Following Karolyi, Lee, and Van Dijk (2012), we define non-trading days as days on which 90% or more of the stocks show a zero return. We only keep stocks categorized by *Datastream* as equity (Variable TYPE equals EQ) and major issuance (variable MAJOR equals Y). Moreover, we exclude preferred stocks, depositary receipts, REITs, mutual funds, and stocks with other special features by screening the stocks' names. Noting Ince and Porter's (2006) concerns about return data from *Datastream*, we apply the following filters for daily return data, as proposed by Karolyi, Lee, and Van Dijk (2012) and Griffin, Kelly, and Nardari (2010): The return $r_t$ is set to missing if the current or lagged total return index (RI) is below 0.01. If $r_t$ or $r_{t-1} > 100\%$ and $(1 + r_{t+1})(1 + r_t) - 1 < 20\%$, then both $r_t$ and $r_{t-1}$ are set to missing. Moreover, any return greater than 200% is set to missing. Finally, we omit short position episodes, for which more than 80% of returns are missing or zero.

Because the SSP disclosures originate from 15 different authorities, we first standardize the variant spelling forms of the position holders' names, resulting in 359 unique investors in our sample. For these names, we manually research the corresponding unique investor identification number from *FactSet*. Three investors are apparently individuals. For the remaining investors, we find a corresponding *FactSet* identifier for all but 27. For the identified investors, we obtain investor characteristics, such as location, age, and type, as well as their long-side portfolio holdings. Finally, we complement our data set by including daily information on stock borrowing fees from *Markit*.

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[19]A summary of links to the national web sites can be obtained through: http://www.esma.europa.eu/system/files/ssr_websites_ss_positions.pdf.