The Shorting Premium and Asset Pricing Anomalies

Main Results and their Relevance for the Q-group

We document large returns to shorting and reveal a tight relationship between this shorting premium and the returns to many well-known cross-sectional return anomalies. Utilizing a new database on the fees paid to borrow US equities (short fees), we find four main results. First, short fees are a strong predictor of the cross-section of stock returns, both gross *and* net of short fees: the portfolio of cheap-minus-expensive-to-short stocks (CME portfolio) has a large monthly gross return of 1.43%, a net-of-fees return of 0.91%, and a 1.53% four-factor alpha. Second, short fees are substantially higher for the stocks shorted by each of the eight well-known anomalies we study. Third, short fees interact strongly with the returns to anomalies: the anomalies disappear within the 80% of stocks that have low short fees, but are highly amplified among those with high fees.

We propose a joint explanation for these first three findings. The shorting premium represents compensation for the concentration of short risk borne by the small minority of investors who do most shorting. Because this risk is on the short side, it raises prices rather than lowers them. This hypothesis leads to our fourth set of results. Proxying for short risk using the return on the CME portfolio, we demonstrate that a Fama-French + CME factor model largely captures the anomaly returns within both high- and low-fee stocks.

Our findings have many important implications for the practice of investment management. They suggest that the shorting premium is due to limited shorting capital. This limited capital demands a large return for shorting because highly shorted stocks co-move strongly, creating an undiversifiable risk that it must bear. Shorting therefore represents an attractive opportunity for new capital to earn a large return premium, but doing so exposes investment managers to an undiversifiable risk. Similarly, profiting from well-known anomalies requires bearing largely this same risk. Shorting capital appears to have increased slowly over time. If it continues to do so, then the price of short risk should decrease, decreasing the shorting premium and anomaly returns.

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ABSTRACT

Short-rebate fees are a strong predictor of the cross-section of stock returns, both gross *and* net of fees. We document a large "shorting premium": the cheap-minus-expensive-to-short (CME) portfolio of stocks has a monthly average gross return of 1.43%, a net return of 0.91%, and a 1.53% four-factor alpha. We show that short fees interact strongly with the returns to eight of the largest and most well-known cross-sectional anomalies. The anomalies effectively disappear within the 80% of stocks that have low short fees, but are greatly amplified among those with high fees. We propose a joint explanation for these findings: the shorting premium is compensation for the concentrated short risk borne by the small fraction of investors who do most shorting. Because it is on the short side, it raises prices rather than lowers them. We proxy for this short risk using the CME portfolio return and demonstrate that a Fama-French + CME factor model largely captures the anomaly returns among both high- and low-fee stocks.

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1 Introduction

Asset pricing theory has long recognized that if an asset cannot be sold short then it may become overpriced, because investors who think it is overvalued are prevented from selling it (Miller, 1977). However, in practice U.S. equities are not typically subject to short-sales prohibitions. Arbitrageurs can sell shares short by borrowing them in the stock loan market. The price for doing so is a fee, or rebate, paid by the borrower to the lender (henceforth the "shorting fee"). There are at least two reasons why the shorting fee should contain information about the returns on the stock. The first is straightforward: the fee represents a payment stream that the stock owner can earn by lending the stock. The second is indirect: the shorting fee embeds information about the underlying demand to short the stock, a potentially important determinant of the stock's expected return.

In this paper, we demonstrate that shorting fees are highly predictive of the cross-section of stock returns. Our analysis is presented in two parts. In the first part, we show that low short-fee stocks earn much higher returns than high short-fee stocks. This is true for returns measured both gross *and* net of shorting fees. Moreover, the difference in returns is not explained by exposures to conventional risk factors. We call this difference in average returns the "shorting premium", because it represents the extra return earned by investors for shorting high short-fee stocks.

In the second part of the paper we show that there is a strong interaction between shorting fees and the returns to eight well-known, large cross-sectional return anomalies. Specifically, we show that these anomalies effectively disappear or are dramatically weakened among low-fee stocks, which represent 80% of all stocks and a higher fraction still of total market capitalization. In contrast, the anomalies are highly amplified among high-fee stocks, generating long-short portfolio returns that are very large even by the standards of the anomaly literature. Our findings show that shorting fees are instrumental to understanding the structure of these anomalies' returns.

We propose an explanation of these findings in which shorting high-fee stocks earns a large return because the risk involved in this is concentrated among a narrow subgroup of investors, an assumption that appears to be met in practice. Consistent with the theory, we demonstrate that augmenting the conventional four-factor model with a shorting risk factor, a portfolio long low-fee stocks and short high-fee stocks, allows it to explain much of, and in many cases all of, the average returns to these anomalies among both low- and high-fee stocks.

We begin by examining the distribution of short fees across stocks and the stock characteristics associated with high short-fees. Previous studies utilizing shorting fees have typically depended on datasets obtained from an individual participating institution in the stock loan market (D'Avolio (2002), Geczy, Musto and Reed (2002), Ofek, Richardson, and Whitelaw (2004), Cohen, Diether, and Malloy (2007)), and were consequently limited in terms of time series and cross-sectional coverage.[1] We make use of a new database that aggregates data from a large number of participants in the stock loan market and covers over 95% of US equities in the CRSP database. Moreover, compared to earlier studies our sample is quite long, spanning 2004-2012, which gives us enough power to study differences in expected returns.

We sort stocks into deciles based on their shorting fee at the end of each month. For each of the top eight deciles the average shorting fee is below 32 bps per annum, indicating that 80% of stocks are quite cheap to short. The stocks in the ninth decile are moderately expensive to short (75 bps per annum on average), while those in the tenth decile are quite expensive to short, with an average fee of 568 per annum. The aggregate market capitalizations of the expensive-to-short stocks are economically large: the average total market caps of the ninth and tenth deciles are roughly \$1.1 trillion and \$435 billion over the sample.

We examine the average returns on these decile portfolios over the following month. The average returns are flat across the eight cheap-to-short deciles, but drop precipitously in the ninth and tenth deciles. The average return on the tenth decile is -0.68% per month! The average return on a portfolio long the stocks in the first decile and short the stocks in the tenth decile–the cheap-minus-expensive (CME) portfolio–is a whopping 1.43% per month, and highly significant (t-stat 4.99) despite the short sample. This large average return cannot be explained by differential exposures to the conventional four Fama-French factors, as the CME portfolio's four-factor (FF4) alpha is 1.53% (t-stat 7.06). The return difference is even larger for the upper half of stocks in the decile ten portfolio (the "10b" portfolio): the cheap-minus-10b portfolio has a mean return of 2.14% per month and a 2.28% alpha.

The difference in returns is not accounted for by the shorting fees themselves. We document that the difference in net returns, while clearly smaller, remains very large. The average net return on the decile 10 stocks is -0.16% per month, the average net return of the CME portfolio is a highly significant 0.91% per month, and the cheap-minus-10b portfolio's

[1] The US stock loan market is decentralized and over-the-counter, which makes data collection a challenge.

average net return is 1.28% per month. Hence, high-short-fee stocks have low returns even from the viewpoint of an investor who lends them out and earns the fees.

We propose a theory for this large shorting premium. Under this theory, the marginal sellers of high-short fee stocks hold concentrated short positions in these stocks. For these investors, exposure to the *short* return of the high-fee stock portfolio represents a systematic risk, and is therefore priced. In other words, these investors do not sell high-fee stocks down to the "fair" price as perceived by the average investor in the economy. Rather, the prices of high-short fee stocks remain high because their subsequent low (even negative) average returns are compensation for the risk taken by the group of concentrated short sellers.

This explanation contrasts with most risk-based theories of the cross-section of returns in that the risk premium posited causes prices to increase rather than decrease.[2] The difference is due to a lack of perfect risk sharing, which arises under our theory because short sellers, who are marginal, hold concentrated short risk. The obvious question is why the buyers of these securities should be willing to hold them given their abysmally low returns. While this behavior is puzzling, it is implied by the very existence of high short fees, which requires that some owners of the underlying shares do not lend them out, and hence forego receiving their high lending fees. Hence, high short fees and inefficient investing behavior are necessarily connected.[3]

Next, we analyze the connection between short fees and the returns to eight large cross-sectional pricing anomalies: value-growth (Fama and French, 1992), momentum (Jegadeesh and Titman, 1993), idiosyncratic volatility (Ang et al., 2006), composite equity issuance (Daniel and Titman, 2006), financial distress (Campbell et al., 2008), max return (Bali et al., 2011), net stock issuance (Loughran and Ritter, 1995), and gross profitability (Novy-Marx, 2013). We first show that there is a close correspondence between a stock's short fee and its anomaly characteristics, especially among high short-fee stocks. A stock's short-fee decile is strongly positively related with its idiosyncratic volatility, financial distress, max return, net share issuance, and the magnitude of its momentum return. Moreover, book-to-market ratios and gross profitability are decreasing in the high short-fee deciles. The converse relationship also holds. Sorting stocks based on their anomaly characteristics, we find a strong relation between the decile number and the average shorting fee, particularly

[2]In such models a negative excess return, as exhibited by high-short fee stocks, must reflect a hedging premium that long investors pay to insure against a systematic risk.

[3]Some buyers may be institutions who are restricted from lending out their shares. This does not rationalize their behavior, as it is inefficient for these institutions to buy these securities in the first place.

at the higher characteristic deciles.

We then document a strong interaction between shorting fees and the returns to the anomalies. Except for momentum, the anomaly long-short portfolios returns are all large in our sample and have statistically significant FF4 alphas. To show the interaction with shorting fees, we first sort stocks into buckets based on their shorting fee. The low-fee bucket consists of the cheap-to-short stocks in the top eight short-fee deciles, while the high-fee stocks in the ninth and tenth deciles are further sorted into three buckets. We then form anomaly-based long-short portfolios within each of the four fee-based buckets, and examine their average returns.

The resulting patterns are striking. Within the low-fee bucket, all of the anomaly long-short average returns and corresponding FF4 alphas are small, with the exception of gross profitability, which remains sizable. Moreover, only one of the eight anomaly returns, and two of the FF4 alphas are statistically significant. This is the case despite the low-fee bucket containing 80% of all stocks, and an even greater fraction of total market cap, and despite the anomalies having large unconditional returns and alphas. In contrast, in the high-fee bucket the average returns and FF4 alphas are all very large and either statistically significant or close to it despite the short sample. For instance, the average unconditional return for the idiosyncratic volatility anomaly in our sample is 87 bps per month, its average return in the low-fee bucket is -5 bps per month, and its average return in the high-fee bucket is 176 bps per month.

Across the anomalies, the differences between the average anomaly returns and FF4 alphas of the low- and high-fee buckets are large and either significant or close to it. This includes momentum, which in our sample has a negative unconditional return. These results demonstrate a strong relationship between shorting fees and anomaly returns, and show that the anomalies are largely non-existent within the 80% of stocks that have low short fees.

We investigate the possibility that the anomalies' alphas reflect compensation for exposure to shorting risk, as suggested by our theory of the shorting premium. We proxy for this risk using the return on the CME portfolio and estimate alphas for all of the bucket-based anomaly portfolios using a model that augments the four Fama-French risk factors with the CME return factor. Our results are as follows. Within the low-fee bucket, all of the anomalies' FF4 + CME alphas are economically small and statistically insignificant. In the intermediate and high-fee buckets, there is a large decrease in the alphas, so that with one exception, all of the FF4 + CME alphas become statistically insignificant. For instance, the FF4 + CME alpha for idiosyncratic volatility decreases to an insignificant 37 bps per month from a highly significant FF4 alpha of 191 bps per month. The exception is the high-fee value-growth return, which is significant. With this exception, all of the differences in FF4 + CME alphas between the low- and high-fee buckets become smaller and are insignificant.

We also show that the size and liquidity of high-short fee firms have no role in generating the relationship we find with anomaly returns. To show this we construct for each high-fee anomaly portfolio a portfolio with the same size and anomaly characteristics, but using *only* low-fee stocks. The matched portfolio returns allow us to separate the role of short fees from firm size in generating the pattern we find. We find that for all anomalies the average returns and FF4 alphas of the matched portfolios are starkly different from their high-fee counterparts, and very similar to those of the *low-fee* bucket. The same is true for liquidity-matched portfolios. Hence, the size and liquidity of high-fee stocks appears to have no role in generating the relationships we find.

Finally, we extend our analysis to a longer sample covering 1980 to 2012 by using a proxy for shorting fees. Our proxy is the ratio of short interest to institutional ownership (denoted SIR_{IO}), which provides a rough measure of the demand for shorting (short interest) relative to available lending supply (institutional ownership). Although this proxy is a noisy signal of shorting fee, the longer available time series enables us to extend the results, albeit with noise, to a longer sample that significantly overlaps with those used in many cross-sectional return studies.

We find similar results overall. Sorting stocks into deciles using SIR_{IO}, we find a large and statistically significant average return of 1.48% per month on the corresponding CME portfolio, with a FF4 alpha of 1.54% per month. There is again a strong correspondence between the anomaly characteristics and SIR_{IO}. Sorting stocks into four buckets as before, but based on SIR_{IO}, we also find generally similar results. Average returns and alphas are significantly smaller in the low-fee bucket than in the high-fee bucket, though now the average returns and alphas in the low-fee bucket are mostly significant. The alphas are again greatly reduced under the FF4 + CME model, are insignificant for most of the portfolios, and have much smaller differences across the low and high-fee buckets

The findings in this paper build on previous work showing that shorting has an important impact on stock returns, and that short sellers earn high returns (Jones and Lamont (2002), Ofek, Richardson, and Whitelaw (2004), Cohen, Diether, and Malloy (2007), and Boehmer, Jones, and Zhang (2008)). It is also related to the work by Diether, Malloy, and Scherbina (2002), who show that differences of opinion, which create a demand for shorting, predict returns in the cross-section.

Our work also builds on studies which examine how cross-sectional predictability is related to markers of short sales constraints and limits-to-arbitrage: breadth of ownership (Chen, Hong and Stein, 2002), institutional ownership (Ali, Hwang, and Trombley (2003), Asquith, Pathak, and Ritter (2005), and Nagel (2005)), and short interest (Hanson and Sunderam, 2013). Our work extends these findings in several directions: (1) we document that there is a large shorting premium, (2) we use direct observations on shorting fees to condition anomaly returns and document the relationship between anomaly returns and shorting fees, (3) we propose a risk-based explanation for these findings, and (4) we estimate a model with a shorting-risk factor model and demonstrate that it largely captures the high-fee anomaly returns.

Several recent papers have focused on the returns to the short legs of anomalies. Hirshleifer, Teoh, and Yu (2011) argue that short arbitrage occurs primarily for firms in the top accrual decile. Avramov et. al. (2013) find that several anomaly returns are derived from taking short positions in high credit risk firms, which they argue may be hard to short sell. Stambaugh, Yu, and Yuan (2012) show that the short leg of various anomalies are more profitable following high investor sentiment, while Stambaugh, Yu, Yuan (2013) show that the negative relation between idiosyncratic volatility and average returns is stronger for stocks which appear in the short legs of various anomalies. However, none of these papers analyzes short fees or the net returns to these anomalies. Our results shows that high-short fee stocks predominate in the short legs of anomalies and drive their returns, and that the loadings of the high idiosyncratic volatility portfolios on the CME factor can explain their returns across short-fee buckets.

Some authors have questioned the importance of short fees in accounting for anomaly returns (Geczy, Musto, and Reed (2002)), the role of shorting constraints in explaining stock prices during the "internet bubble" (Battalio and Schultz (2006)), or whether short-sales constraints seriously hinder arbitrageurs (Ljungqvist and Qian (2013)). Our view is not necessarily at odds with theirs, because we argue that a large portion of the shorting premium is due to concentration of shorting risk, and not simply the direct cost imposed by high short fees.

The remainder of the paper is organized as follows. Section 2 describes the Data. Section 3 documents the relationship between shorting fees and the cross-section of average returns. Section 4 examines the interaction between shorting fees and anomaly returns and estimates alphas from the FF4 + CME model. Section 5 extends the analysis to the long sample by using SIR_{IO} as a proxy for shorting fees. Section 6 concludes.

2 Data

We obtain data on stock lending fees from *Markit Security Finance* (MSF).[4] MSF collects self-reported data on the actual (as opposed to quoted) rates on security loans from over 100 participants in the securities lending market. The full dataset covers June 2002 to October 2012. However, in the initial part of the data the sample is monthly and covers mostly large-cap companies. By 2004 the coverage expands to include almost all US stocks, and the data frequency is daily. In order to avoid biases, we therefore begin our sample in January 2004.

We obtain returns data data by matching the MSF data to the CRSP database and obtain accounting information by matching with Compustat. We retain only common stocks (share codes 10 and 11 in the CRSP database). To ensure that our results are not driven by micro-cap stocks or low share price observations, we drop all observations for which a stock is in the bottom 10% of either the firm size or stock price distribution.[5] The results remain very similar if we change (or eliminate) these percentile cutoff values. When we construct the various anomaly portfolios we also drop any firms that are missing the data required to calculate the the associated characteristic.

MSF reports the value-weighted average lending fee for each security over the past 1, 3, 7, and 30 days, where the value weight assigned to a loan is the dollar value of the outstanding balance of the loan for that transaction, divided by the total dollar value of outstanding balances over that time. In keeping with the literature we analyze trading strategies that are rebalanced monthly, and therefore we use the 30-day average value-weighted fee as our

[4] MSF is formerly known as *DataExplorers*.

[5] This causes roughly 15% of the observations to be dropped in each month. We do not use a fixed cutoff for the share price because, owing to the drop in share prices in 2008-2009, this would create tremendous variation in the percentage of observations dropped. For example, the shares of a number of large financial institutions (e.g., Citigroup) traded at very low dollar values during this period.

measure of a stock's shorting fee. If an observation is missing the 30-day average value-weighted fee, we drop it from the sample.

The security lending activity covered by the MSF database over our sample period includes over 95% of the US equities in the CRSP database, and approximately 85% of borrowing activity in the US security lending market. This coverage is significantly larger than what was available to previous studies, which tended to rely on data collected from a single institution in the stock loan market. The availability of multiple sources for the lending data helps ensure that it accurately captures the full cross-section of the lending market.

We also construct a proxy for the borrowing fee in order to extend our analysis to a longer sample. This proxy, denoted SIR_{IO}, is the total short interest in a stock divided by the number of shares held by institutional investors (Short Interest Ratio relative to Institutional Ownership). We obtain the short interest data from Compustat and the institutional ownership data from Thomson Reuters 13F. The data is available going back to March 1980. The numerator and denominator have been used separately in previous work to proxy for, respectively, the demand for and supply of shares for shorting. The numerator reflects equilibrium demand for shorting the stock. The denominator represents a measure of the effective supply of borrowable shares, because institutional investors are much more likely than non-institutional investors to lend out their shares (D'Avolio, 2002). By combining demand and supply information, SIR_{IO} acts as a proxy for the underlying borrowing fee on the stock.

2.1 Summary Statistics

Table 1 reports yearly summary statistics for aggregate US equity shorting for the sample. Column two gives the number of individual stocks contained in our dataset in each year. It shows that the coverage of our dataset is very extensive, with loan fee data available for over three thousand individual stocks throughout the sample. The number of stocks declines towards the end of the sample, mirroring a decline in the number of US stock listings.

All of the remaining columns, except the second-to-last, provide equal-weighted averages of various stock characteristics. The average market capitalization of firms in the dataset ranges from a low of \$3.00 billion in 2009 to a high of \$4.77 billion in 2012. The average book-to-market (B/M) ratio ranges from a low of 0.51 in 2007 to a high of 0.99 in 2009. Both the size and B/M ratio patterns follow the trends in the overall market over this time. The columns labeled IOR (institutional ownership ratio) and SIR (short interest ratio) represent the two components used to create our lending fee proxy, SIR_{IO}. IOR gives the fraction of shares held by institutions, and can be viewed as a proxy for the supply of borrowable shares. Roughly 60% of shares are held by institutions on average, and this exhibits only minor variation over this time period. SIR is shares shorted as a fraction of total shares outstanding, and can be viewed as a noisy proxy for shorting demand. It exhibits substantial variation, increasing from a low of 4.3% in 2005 to a high of 7.2% of shares outstanding in 2008, and then dropping sharply at the beginning of the financial crisis.

The column labeled SIR_{IO} gives our long-sample shorting-fee proxy. This is the ratio of SIR and IOR. Like SIR, it exhibits substantial variation, rising steadily until 2008, with a peak value of 11.3%, and then dropping during the financial crisis. The next column gives aggregate short interest for each year, the average (daily) dollar value of shares borrowed in each month of that year. It exhibits roughly the same pattern as SIR_{IO}. Figure 1 plots the monthly time series of this quantity (shaded area). Aggregate short interest peaks in August 2008 at a value of of \$562 billion, drops sharply at the end of 2008 and early 2009, and recovers back to around \$400 billion by 2012.

The final column of Table 1 shows the equal-weighted average annual shorting fee. The average fee can be substantial. For instance, in 2012 the (equal-weighted) average fee was 99 basis points. It is important to be careful in interpreting this number because, as we show below, the majority of firms have low fees, while high-fee firms are smaller than average. Nevertheless, the average fee shows that significant shorting fees are prevalent. The table further shows that, like the other measures of shorting activity, the average shorting fee varies substantially over time. Figure 1 plots the time series of the equal-weighted fee (solid line). The year with the highest fee is 2008, averaging 126 basis points. Average fee then drops sharply in 2009 to 68 basis points, and rebounds gradually afterwards. The figure also plots the average fee weighted by the dollar value of stocks' short interest (dashed line). This measure tends to be smaller than equal-weighted fee, but tracks its time variation closely.

3 Shorting Fees and the Cross-section of Returns

We examine the distribution of shorting fees across stocks and analyze the predictive power of shorting fees for the cross-section of returns, both gross and net of fees. To that end, we sort stocks into deciles at the end of each month based on their volume-weighted lending fee over the previous 30 days, and examine their returns over the following month. Panel A of Table 2 presents equal-weighted average returns and characteristics of the decile portfolios for our sample, January 2004 to October 2012. The decile 1 stocks, labeled "cheap," have the lowest shorting fees, while the stocks in decile 10, labeled "expensive," have the highest. Panel B further sorts the decile ten stocks into halves by shorting fee to obtain portfolios 10a and 10b, and reports the set of statistics for each half. We examine this refined sort to obtain a finer picture of the very expensive-to-short stocks.

The table reports the average short fee (over the previous 30 days) for each portfolio at the time of formation. Short fees are low for most stocks. They are below 31 bps on average for each of the first eight deciles. Hence, on average, around 80% of stocks are cheap to short. However, for the remaining 20% of stocks, the shorting fees can be substantial. The average short fee for decile nine rises to 78 bps, while average short fees in decile ten are very large, with an average of 568 bps. For perspective, this is roughly the same magnitude as the equity premium or the value premium. Investors who own these stocks and do not lend them out forgo a very substantial stream of payments. Moreover, that the very fact that these stocks command a high shorting fee implies that such investors must hold a large fraction of the shares.

Table 2 reports the average monthly returns gross of fees ("Gross Ret") for the deciles. Like shorting fees, the gross returns are essentially flat across the cheap-to-short stocks which comprise the top eight deciles. However, average returns are lower on the expensive-to-short stocks of the ninth and tenth deciles. In particular, the most expensive-to-short stocks earn a very low–indeed *negative*–average return of -0.68% per month. The average return of a portfolio which goes long the cheapest-to-short stocks and short the most expensive-to-short stocks (henceforth the cheap-minus-expensive, or CME, portfolio) is an impressive 1.43% per month. This value is highly significant (t-stat of 4.99) despite the relatively short sample.

This large average return does not reflect a difference in the loadings of cheap- and expensive-to short stocks on conventional risk factors. This is indicated by the last column in the table, labeled "FF4α", which gives the Fama-French four factor (FF4) alphas for the decile portfolios. The FF4 alpha of the expensive-to-short portfolio is -1.42% per month and the alpha of the CME portfolio is a highly significant 1.53% per month.

Perhaps surprisingly, the average long-short return remains large even after netting out shorting fees. To compute the net return, we calculate portfolio returns using the net monthly return on each stock, computed as the gross return plus the average past 30 days shorting fee on the stock (converted to a monthly quantity). The average net returns are reported in the column labeled "Net Ret". As the table shows, even when netting out short fees the CME portfolio earns a very substantial 0.91% average net return, which is again highly significant.

Panel B show that the results are more dramatic still if we restrict attention to portfolio 10b, the more expensive-to-short half of stocks in the decile 10 portfolio. The shorting fee on these stocks is very large, with an average of 908 bps per annum. The average gross return on the 10b portfolio is an abysmally low -1.40% per month. Consequently, the average return of the 1-minus-10b portfolio is a highly significant 2.14% per month! Again, the FF4 alpha is even larger, at 2.28% per month (t-statistic 7.87). The return on the spread portfolio remains large even after accounting for the shorting fees. The average net return on the 10b portfolio is -0.52% per month, giving a highly significant average 1-minus-10b portfolio net return of 1.28% per month.

Finally, Table 2 shows that the dollar amounts involved in the portfolios of expensive-to-short stocks are economically large. The total market capitalization of the tenth decile portfolio is on average \$435B over the sample. When the ninth decile portfolio is included, the total market cap grows to \$1.54 trillion. Hence, whereas only 10-20% of stocks have significant shorting fees, the total dollar amounts involved are still economically large.

3.1 Relation to Anomaly Characteristics

Table 2 further reports several characteristics of stocks in the decile portfolios, calculated at portfolio formation. We focus on characteristics associated with the anomalies that we study. The table shows that in general, expensive-to-short stocks have extreme values of the anomaly characteristics. They have far higher momentum returns, idiosyncratic volatility, max returns, financial distress, and new share issuance than do stocks in the other deciles, as well as far lower gross profitability. This is even more clearly the case for the stocks in portfolio 10b.

Overall there is a strong association between the characteristic and decile rankings, with this relationship strengthening at the high deciles, where the variation in shorting fees is largest. The weakest relationship is for the book-to-market ratio. Interestingly, past momentum returns are actually the highest among the expensive-to-short stocks. However, this masks an underlying bi-modal relationship. As we show below, both low and high momentum stocks have relatively high shorting fees. The same is true for the book-to-market ratio. Hence, the expensive-to-short portfolio actually overweights both extreme high and low book-to-market and momentum stocks.

Table 2 also shows that there is a strong positive relationship between short fees and SIR_{IO} (short interest as a fraction of institutional ownership), our long-sample proxy for the shorting fee. As with the short fees themselves, there is little variation in SIR_{IO} in the first six or seven deciles, with SIR_{IO} remaining around 6%. However, beginning with the eighth decile, SIR_{IO} increases strongly, reaching values of 26.5% and 34.4% for the decile-10 and 10b portfolios.

Finally, the table shows how average market capitalization varies with the shorting fee. The stocks with almost zero short fees tend to be very large on average. Market capitalization is then effectively flat at $2-to-3 billion on average from the third to the ninth deciles. The expensive-to-short stocks are on average the smallest. Yet, even these stocks have a sizable average market cap of $1.30B. The very expensive-to-short stocks of portfolio 10b tend to be a bit smaller still, with an average market cap just under $1B.

3.2 The Shorting Premium

Our main findings to this point are as follows. First, sorting on shorting fees induces a very large spread in gross returns. In particular, expensive-to-short stocks earn very low–in fact, negative–average gross returns. This spread in average gross returns is captured by the average return on the CME portfolio, which we call the "shorting premium". Importantly, the shorting premium cannot be explained by the loading of the CME portfolio on conventional risk factors, as the FF4 alpha of the CME portfolio is even larger than its average return. At a minimum, the large gross shorting premium shows that investors who own expensive-to-short stocks and do not lend them out earn very low returns. This provides an apparently clear example of example of inefficient investing behavior.[6]

Second, netting out shorting fees explains only a fraction of the shorting premium. The shorting premium calculated using net (of fee) returns is still very large. Hence, even investors who do lend out their shares earn very low total returns on expensive-to-short stocks. This finding does not follow from existing theories about asset prices in the presence of shorting restrictions (e.g., Miller 1977). These theories predict that an inability to short assets leads to their prices being too high because investors with negative views are prevented from selling them. Such shorting prohibitions are akin to an infinite shorting fee. However, this is not the case in the data. Investors can pay to short stocks and our results show that stock prices are still too high even when netting out the fees required to do so. This result is not explained by theories of hard short-sales constraints.

We propose an alternative theory to explain these findings. The theory we propose is that the shorting premium represents a risk premium which is earned by short investors as compensation for taking shorting risk. We assume that the marginal sellers in expensive-to-short stocks are investors who hold concentrated short positions in these stocks. As a result, a systematic risk for these investors is the covariance of a stock's *short* return with the return on the expensive-to-short stock portfolio. We proxy for this risk using the return on the CME portfolio. The average return on this portfolio–the shorting premium–measures the price these short sellers charge for taking on this shorting risk.

The existence of a large shorting risk premium implies that short sellers do not sell the expensive-to-short stocks all the way down to the "fair" price as perceived by an average investor in the economy. Instead, prices of expensive-to-short stocks remain high, and their subsequent realized returns are low, to compensate short sellers for taking on short risk. Hence, the risk premium *increases* prices. This effect contrasts with the usual impact of a risk premium, which is to lower prices. The difference with the usual case arises from a lack of risk sharing; shorting risk is concentrated within a subgroup of investors, who are marginal in setting the prices of these stocks. In contrast, in a setting with full risk sharing, the marginal investor must be net long stocks and a risk premium reduces stock prices.

The assumption that shorting risk is concentrated in a narrow subgroup of investors appears to be met in practice. Ben-David, Franzoni, and Moussawi (2012) cite a Goldman

[6] This cannot not be rationalized from the fact that some institutions are restricted from loaning out their shares, as such institutions could (and should) sell these shares to other investors.

Sachs report which estimates that in March 2010 85% of all equity short positions going through Goldman's brokerage house were taken by hedge funds. They also calculate that the aggregate short interest ratio is similar to the fraction of total stock market capitalization controlled by equity hedge funds. It therefore seems plausible that shorting, and hence shorting risk, is concentrated among a relatively narrow group of investors/intermediaries.

We also find that there is co-movement among expensive-to-short stocks in excess of that implied by their loadings on the four Fama-French risk factors. We calculate the residuals from regressions of the returns of the cheap- and expensive-to-short portfolios on the four Fama-French factors. These represent the returns of the portfolios of the stocks' idiosyncratic returns based on the four factors. The standard deviation of the expensive-to-short portfolio's residual returns is 2.11%, substantially higher than the 0.83% standard deviation for the cheap-to-short portfolio. Dividing each portfolio idiosyncratic variance by the constituent stocks' average idiosyncratic variance gives the average correlation among the stocks. The average correlation among the expensive-to-short stocks is 37%, substantially higher than the correlations among the stocks in the eight cheapest-to-short deciles, which average 23%. This evidence is consistent with an additional source of common variation among expensive-to-short stocks.

Panel A of Table 3 reports the moments of the CME risk factor's monthly return. The mean return is the same as in Table 2. The standard deviation is 2.94% per month, comparable to the other risk factors. This implies a very high Sharpe ratio of 1.68 (1.07) for the CME portfolio's gross (net) return. The skewness and excess kurtosis are both negative, but not very large. The returns also exhibit what appears to be a relatively high positive autocorrelation. However, the autocorrelations of $mktrf$, HML, and umd are also high in this period, at 0.21, 0.35, and 0.25, respectively, so CME is not exceptional in this regard.

Panel B of Table 3 shows the correlation of the CME portfolio with the four Fama-French factors. CME is negatively correlated with the market portfolio, indicating that investors who concentrate in shorting high-fee stocks do relatively poorly when the market is up. It is also negatively correlated with SMB, probably due to the relatively small size of expensive-to-short stocks, and with HML. Finally, CME is quite positively correlated with the momentum factor, UMD.

4 Relation to Asset Pricing Anomalies

We now investigate the relationship between the shorting premium and eight asset pricing anomalies: (1) value-growth, (2) momentum, (3) idiosyncratic volatility, (4) composite share issuance, (5), financial distress, (6) max return, (7) net stock issuance, and (8) gross profitability. We focus on these anomalies because they are associated with large spreads in average returns, have received substantial attention in the literature, and are plausibly related to shorting frictions.

4.1 Unconditional Returns

Panel A of Table 4 examines the returns of these anomalies over our 2004-2012 sample period. For each anomaly, we sort stocks into ten portfolios based on the corresponding characteristic. We order the deciles so that the stocks in the first decile are the ones which are normally taken to be the long leg (value stocks, winner stocks, low idiosyncratic volatility stocks, etc. . .), while the stocks in the tenth decile are the short leg. The top part of Panel A reports the average returns of each of the deciles, while the bottom part analyzes the corresponding anomaly long-short (decile one minus decile ten) portfolios.

The top row in the bottom part of Panel A gives the average gross return of the long-short portfolios. With the exception of momentum, the average gross returns are large. Due to the fairly short sample, only four of the eight average raw return spreads are either statistically significant or close to it.[7]

The second row in the bottom part of Panel A reports the net returns of the long-short portfolios. The net long-short returns are all below the gross returns, reflecting the higher average shorting fees of the stocks in the short leg of the portfolio. The reduction in going from gross to net returns is meaningful for all the portfolios, with a high of 21 bps per month for idiosyncratic volatility. Nevertheless, the average long-short net returns remain large, showing that a very substantial portion of these anomalies' returns remain after subtracting out shorting fees. This finding is perhaps not surprising at this point, given that we have already seen that sorting on shorting fees themselves produces a large spread in *net* returns.

The next row in the bottom of Panel A shows the FF4 alphas of the long-short gross

[7] All of the anomaly long-short average returns are significant in the long sample analyzed in Section 5.

returns.[8] The alphas are mostly larger, in several cases significantly so, than the average gross returns. With the exception of momentum, the alphas are also all highly statistically significant, despite the short sample. Therefore, exposures to the conventional risk factors cannot explain the large long-short anomaly returns.

The last row in the bottom of Panel A shows the alphas of the long-short returns relative to an asset-pricing model that includes the CME return as an additional risk factor, as suggested by our shorting premium theory. We analyze this model in greater detail below, but report the corresponding shorting-risk alphas here for completeness. The table shows that the inclusion of this CME factor leads to a very large reduction in the alphas for all the anomalies except value-growth. Indeed, with this exception, the long-short FF4+CME alphas all decrease and become insignificant. For instance, the alpha of the idiosyncratic volatility portfolio decreases from a highly significant FF4 value of 1.21% per month to an insignificant 0.07%.

Panel B of Table 4 reports the average shorting fee by decile for each anomaly. The pattern that emerges across all anomalies is that the average shorting fee is significantly higher for the tenth decile than for any of the other deciles. Moreover, shorting fees are generally increasing with the deciles, and particularly so for deciles five to ten, where the relationship is both monotonic and strong. For all of the anomalies the average shorting fee for the tenth decile exceeds 140 bps per annum, significantly higher than the average. The table makes clear that there is a concentration of high shorting fee stocks in the short leg of the anomalies.

4.2 Returns Conditional on Shorting Fees

Next, we examine the interaction between shorting fees and the long-short anomaly returns. To that end, we look at the returns to each anomaly conditional on stocks' shorting fees. We therefore sort stocks into four buckets based on their shorting fees: a low fee bucket ($F0$), two intermediate fee buckets ($F1$ and $F2$), and a high fee bucket ($F3$). We then look at the long-short return for each anomaly within each of the buckets.

[8]We focus on the alphas of the gross returns, rather than net returns, to provide an easier comparison both with the literature and our own long-sample analysis. The difference between gross and net alphas is very similar to the difference between the average gross and average net returns. Hence, looking at either gross or net alphas paints a very similar picture.

Into the low fee bucket we put the stocks from the top eight shorting-fee deciles, which contain the cheap-to-short stocks. We put all of these stocks into the low fee bucket because their shorting fees are uniformly small and have little variation, as illustrated in Table 2. We then sort the stocks within the low-fee bucket into deciles based on each of the anomaly characteristics (just as for the full sample of stocks), and look at the corresponding anomaly long-short returns.

We sort the remaining twenty percent of stocks–the ones with significant shorting fees– into three equal size buckets based on their shorting fee. This gives us the intermediate fee buckets ($F1$ and $F2$) and high fee bucket ($F3$). We create three buckets in order to capture the gradient of anomaly returns with respect to shorting fee while retaining a sufficient number of stocks within each bucket to create long-short portfolios. We then sort the stocks within each of these three buckets into terciles based on each of the anomaly characteristics and obtain the anomaly long-short returns as the difference between the returns of the first and third terciles.

This sequential sorting procedure provides us with a non-parametric and robust way of analyzing the interaction between high shorting fees and anomaly returns, and allows us to examine the extent to which high-short fee stocks are responsible for generating the large anomaly-based long-short returns.

Panel A of Table 5 shows the average gross monthly long-short returns for each of the anomalies within each of the buckets (32 in total). These are reported in the first four rows in the panel. The fifth row in the panel then examines the difference between the average return of the long-short portfolio in the low fee ($F0$) and high fee ($F3$) buckets. This allows us to assess whether there is a difference in the size of the average anomaly return between the low and high short-fee stocks.

The results exhibit several striking patterns. First, except for gross profitability, all of the average long-short returns within the low-fee bucket ($F0$) are small and statistically insignificant, and only the average return of gross profitability exceeds 25 bps per month in absolute value. This is in stark contrast to the unconditional long-short returns, which are much larger. Indeed, in most of the cases the difference relative to the unconditional return is quite remarkable. For example, for idiosyncratic volatility (*ivol*), which has an unconditional return of 87 bps per month, the average low-fee bucket long-short return is -5 bps! Similarly, the average low-fee long-short momentum return is actually negative, while the average low-fee return of the max return strategy is just 2 bps.

Recall that the low-fee bucket contains the top eight deciles of all stocks sorted by shorting fee. This means it contains 80% of all stocks and, given the larger average size of the firms in these deciles, a still larger percentage of total market capitalization. Hence, Table 5 shows that this very large and economically important subgroup of stocks exhibits little in the way of anomalous returns within our sample (where shorting fees are available). Moreover, we emphasize that this is the case despite the fact that these anomalies *are* present unconditionally in this sample.

The second pattern that emerges is that the average anomaly long-short returns increase strongly with the level of shorting fees. In general, the average long-short return in the $F1$ bucket is higher than that in the low fee bucket. The average return in the $F2$ bucket is larger still and of similar magnitude to the unconditional long-short anomaly returns. Finally, the average returns in the high fee bucket $F3$ are very large across all the anomalies. For instance, the average high-fee long-short return for idiosyncratic volatility is 1.76% per month (!) and highly statistically significant. Indeed, despite the short sample, all of the average returns in the $F3$ bucket are either statistically significant or close to it. This includes even the average return on momentum, which is effectively zero unconditionally.

The differences in average anomaly returns between the low- and high-fee buckets is summarized in the bottom row of panel A. The differences are very large. They are also statistically significant at the 5% level in all cases except momentum and gross profitability, though in the case of momentum the point estimate, 87 bps per month, is very large.

To summarize, Panel A shows that there is little evidence of average return differences associated with these anomalies within the eighty percent of stocks that have low shorting fees. Instead, the anomalies are concentrated among high short-fee stocks, where the average anomaly returns are very large, especially among the highest short-fee stocks. Indeed, even in the case of momentum, which fails to exhibit any return spread unconditionally, the long-short average return is large for the group of high-fee stocks.

The fee-sorted buckets are rebalanced monthly. To help understand the dynamics of the stocks across these bucket, Figure 2 plots their transition matrix for periods of one, three, six, and twelve months. The transition matrix shows that while stocks do transition across the buckets over time, their assignments are fairly persistent. For instance, about 45% of the stocks in the highest fee bucket ($F3$) in a given month are in this bucket again twelve months later, while about 20% have transitioned into the low-fee bucket by this point. The intermediate fee buckets have the greatest probability of switching, while the low fee stocks are the least likely to do so.

4.2.1 Four Factor Alphas

Panel B of Table 5 reports the FF4 alphas corresponding to the average returns in Panel A. These exhibit very similar patterns to the average returns. The alphas for the low-fee anomaly long-short returns are much smaller than the unconditional alphas, and, with the exception of composite share issuance and gross profitability, are not statistically significant. Hence, there is little apparent mispricing associated with these anomalies among the low fee stocks, which constitute 80% of all stocks and an even greater fraction of total market capitalization.

The alphas increase in the intermediate fee buckets, and again generally increase as we move up from the $F1$ bucket to the $F2$ bucket. Moreover, despite the short sample, the $F2$ alphas are statistically significant or close to it, with the exception of momentum and gross profitability. Moving to the high fee ($F3$) bucket, the alphas are all very large, including momentum. Despite the short sample they are also highly statistically significant, except for momentum, which has a t-statistic of 1.56.

The bottom row of Panel B gives the alpha for the difference in long-short returns between the high and low fee buckets ($F3$ minus $F0$). The alphas are all large and statistically significant or nearly so. Panel B therefore shows that the FF4 alphas of these anomalies display the same patterns as the average returns. Despite being unconditionally large, these alphas are close to zero in most cases for low fee stocks, and are by far the largest among the high-fee stocks.

4.3 The FF4 + CME Model

We now consider the possibility that the large return spreads and positive alphas we find for the high short fee buckets reflect compensation for exposure to shorting risk. As discussed above, if investors holding concentrated short positions in high short-fee stocks are marginal in setting the prices of these stocks, then exposure to the risk of the high short-fee stock portfolio will be a factor determining stocks' expected returns. We proxy for this portfolio's return, and hence shorting risk, using the return on the CME portfolio. We then augment the four conventional risk factors with this fifth shorting-risk factor to create a new model of expected stock returns, the FF4 + CME model.

Panel C of Table 5 reports the alphas of the anomaly long-short portfolios based on the FF4 + CME factor model. The table shows that the alphas are all close to zero and insignificant for the low fee bucket, $F0$. The main difference relative to the FF4 alphas is that even the composite share issuance and gross profitability alphas are insignificant, due to a reduction in their magnitude from 37 bps and 69 bps per month to 2 bps and 28 bps, respectively. Hence, for the low fee stocks there is no evidence of mispricing with respect to the FF4 + CME model for any of these eight well-known anomalies. This is the case despite the fact that: (1) the unconditional FF4 alphas are large and statistically significant for seven of the eight anomalies, and (2) the low fee bucket contains 80% of all stocks and a still larger fraction of the total market capitalization.

Turning to the $F1$ bucket, the FF4 + CME alphas are insignificant for all of the anomalies, including idiosyncratic volatility and max return, which had highly significant FF4 alphas. Hence, there is again no evidence of mispricing relative to the FF4 + CME model. The situation is similar for the even higher short fee stocks in the $F2$ bucket. The FF4 + CME alphas are all insignificant, although the alpha for value-growth has a t-statistic of 1.47. In contrast, all the anomalies except momentum had $F2$-bucket FF4 alphas that were significant or nearly so. Hence, the FF4 + CME model clearly does a much better job in capturing these average returns.

The results are most striking for the stocks in the high-fee bucket ($F3$). The FF4 + CME alphas are in general much smaller than the FF4 alphas. Of the eight alphas, seven are insignificant. The reduction in alphas from the FF4 model is particularly dramatic for idiosyncratic volatility, distress, max return, net share issuance, and gross profitability. For example, for idiosyncratic volatility the high-fee long-short portfolio has a FF4 alpha of 1.91% per month (t-stat of 4.14), which decreases to 0.37% per month (t-stat 0.75) under the FF4 + CME model. As a result, the FF4 + CME alphas are insignificant for all four shorting-fee buckets across seven of the eight anomalies: composite share issuance, distress, idiosyncratic volatility, max return, momentum, net share issuance, and gross profitability. The single exception is the value-growth return of the high-fee bucket, whose FF4 + CME alpha is significant and larger than under the FF4 model.

The bottom row of Panel C gives the FF4 + CME alphas for the difference in long-short returns between the high- and low-fee buckets. In contrast to the differences in average returns and FF4 alphas, which were significant with one exception, the differences in FF4 + CME alphas are all insignificant save for value-growth, which is due to the high alpha of its high-fee long-short portfolio. Therefore, it appears that accounting for exposure to shorting risk equalizes risk-adjusted average returns between low- and high-fee stocks by capturing the very high average anomaly returns among the high-fee stocks.

Figure 3 plots a comparison of predicted average returns versus realized average returns for the FF4 and FF4 + CME models. Each anomaly is plotted separately. Within each plot, the points are comprised of the extreme characteristic-sorted portfolios within each of the four fee-sorted buckets. Hence, each plot shows eight different portfolios: the decile one and ten portfolios from the $F0$ bucket, and the first and third terciles from the $F1$, $F2$, and $F3$ buckets.

The figure shows a much superior fit of the FF4 + CME model. This is particularly the case for the low-return portfolios among this group of portfolios, which typically lie significantly below the forty-five degree line. The FF4 model is unable to account for the low, and sometimes negative, average returns of a number of these portfolios. However, the fit of the FF4 model is reasonable for the higher return portfolios. In contrast, the fit of the FF4 + CME model appears to be quite good. It is able to capture the returns to the low-return portfolios and even the very negative average returns exhibited by some of the distress, idiosyncratic volatility, gross profitability, and max return portfolios.

Our findings support two related hypotheses. First, the absence of significant anomaly returns or FF4 alphas within the low fee stocks supports the view that some kind of market frictions associated with the presence of high short fees–limited risk sharing in the case of our concentrated short-risk hypothesis–are responsible for the large returns to these anomalies. This view is further supported by our finding of a strong positive relationship between stocks' short fees and average anomaly returns. Second, the ability of the FF4 + CME model to capture the large average anomaly returns within the high fee stocks supports the theory that differences in stocks' exposures to the high short-fee portfolio explains the interaction of anomaly returns and short fees.

4.4 Can Size or Liquidity Account for the Returns?

Table 2 shows that high short-fee stocks are generally smaller than average. The average size of a firm in the highest short-fee decile during the sample period is $1.3 Billion, making it a small mid-cap stock. Hong, Lim, and Stein (2000) find that momentum returns decrease sharply with firm size. One may wonder then if the large anomaly returns we find in the high-fee buckets are actually due to the small average size of these firms rather than their high short fees. Similarly, because smaller firms are generally less liquid, one might alternatively wonder if the large anomaly returns are driven by low liquidity rather than high short fees.

One piece of evidence against this possibility is the large increase in anomaly returns we see in going from the intermediate-fee bucket $F1$ to the high-fee bucket $F3$ in Table 5. This suggests that it is actually high short fees, not size or liquidity, that accounts for the large anomaly returns. Still, a direct test of this hypothesis is desirable.[9]

We provide such a test by creating size and anomaly-characteristic matched portfolios for each of the high-fee anomaly portfolios in Table 5. The key is that we create these matched portfolios using only stocks from the low-fee ($F0$) bucket. That is, for each long and short leg of the anomaly portfolios in buckets $F1$-$F3$, we create a matching portfolio consisting of only low-fee stocks that has the same size and anomaly characteristics. Creating such a matching portfolio is not difficult because the low-fee ($F0$) bucket contains 80% of all stocks, and hence provides a large universe from which to create characteristic-matched portfolios. We then take the difference between the returns of the matched long and short legs to be the matched long-short return.

We compare the average returns and alphas of the matched anomaly long-short returns to their high-fee counterparts from Table 5. If the large returns we find in Table 5 are actually due to firm size, then the we should that the matched anomaly portfolios display similarly large returns. In particular, these returns should be large and significant even though they are created using low-fee stocks. Moreover, the matched anomaly returns should increase strongly as we move from the matching portfolios for the $F1$ bucket to those of the $F3$ bucket. To assess the possibility that liquidity accounts for our findings, we perform the same analysis using portfolios matched on liquidity and anomaly-characteristics.

[9]Note that whether or not this is the case the majority of our findings would hold unchanged, including the finding that anomaly returns are concentrated in a small subsection of stocks, and that the FF4+CME-based factor model is able to capture these anomaly returns. However, the interpretation of these results is affected by the answer to this question.

We create matching portfolios by applying the approach of Daniel, Grinblatt, Titman, and Wermers (1997) to the universe of low-fee ($F0$) stocks. We first sort these stocks into size quintiles based on NYSE breakpoints. We then sort each size quintile into deciles based on the given anomaly characteristic. The resulting set of 5 x 10 portfolios gives the benchmark characteristic portfolios. We then assign each stock in each intermediate- and high-fee anomaly long or short portfolio to a benchmark portfolio by first finding the closest match to its size and then its anomaly characteristic. The assigned benchmark portfolio returns are then equal-weighted to obtain the matching long or short portfolio return. The difference between the matched long and short returns then gives the matched anomaly long-short return.

This approach uses only low-fee stocks to create long and short portfolios that have the same size and anomaly characteristics as their high-fee counterparts, thereby allowing us to separate the effect of size and high short fees on the magnitude of the anomaly returns. We follow the same procedure using Amihud's (2002) measure of liquidity to create liquidity and anomaly-characteristic matched portfolios, and separate the affect of liquidity on the anomaly returns.

Table 6 presents the results for the size and anomaly-characteristic matched portfolios. Panel A shows the average monthly returns. The average anomaly returns are small and far from significant across all anomalies and buckets save for the case of gross profitability. In the case of gross profitability the average return is no larger than it was for the low-fee ($F0$) bucket in Table 5, where it was also significant. Hence, across all anomalies and fee buckets the average returns in Table 6 are the same as those in the low-fee ($F0$) bucket of Table 5, in stark contrast to the much larger anomaly returns of the $F1$ through $F3$ buckets.

Table 6 further shows that, in sharp contrast with Table 5, the matching anomaly returns do not increase from the $F1$ to the $F3$ bucket. Instead the matched returns are completely flat across buckets. Consequently, the returns for the $F1$, and especially the $F2$ and $F3$ buckets, are far larger than their matched counterparts.

In summary, Panel A of Table 6 clearly shows that the (small) average size of the high-fee firms does *not* account for the large anomaly returns we find in this sample. Panel A actually reveals something further and perhaps surprising. It shows that the anomaly returns are *no* larger among small stocks than on average if high short-fee firms are excluded. This is an interesting finding by itself and it may explain why some studies (such as Hong, Lim, and

Stein (2000)) have found that anomaly returns are only large outside the large stocks.

Panel B of Table 6 shows the FF4 alphas for the matched portfolios. The FF4 alphas follow the same pattern as the raw returns and closely resemble the alphas in the low-fee ($F0$) bucket in Table 5. Again the matched-portfolio alphas are flat across the three buckets, in sharp contrast to the strong increase in alphas shown in Table 5. Hence, panel B reinforces the conclusion of panel A: size does not account for the large anomaly returns we find among the high-fee firms.

For completeness, Panel C reports the FF4+CME alphas of the matched portfolios. The FF4+CME alphas are even smaller than the already small FF4 alphas, consistent with earlier findings. Note that this is the case even though the matched portfolios consist solely of low short-fee stocks.

Table 7 presents the results for the liquidity and anomaly-characteristic matched portfolios. The results are very similar to those in Table 6. The matched average returns (panel A) mimic those of the anomaly returns among the low-fee stocks in Table 5. They are small and insignificant across all anomalies and buckets, besides gross profitability, where the matched return is again the same as in the $F0$ bucket of Table 5. Again the matched anomaly returns are flat across buckets, in stark contrast to the strongly increasing pattern displayed in Table 5. The FF4 alphas (panel B) again mirror the raw returns and closely resemble those of the low-fee bucket. Hence, Table 7 shows that liquidity cannot for the large anomaly returns we find in the sample of high-fee firms.

5 Long Sample Analysis

In this section we extend a similar analysis to a longer sample using a proxy for shorting fees. Our proxy is the variable SIR_{IO}, short interest as fraction of shares owned by institutions. Although our sample of shorting fee data is the longest and broadest that has been studied (to our knowledge), its time series is short in comparison to typical studies of the cross-section of expected returns. While this time series length is clearly sufficient to allow us to document significant anomaly alphas, it is nevertheless interesting to extend the sample backwards so that it has greater overlap with sample periods used in previous cross-sectional studies. Of course the drawback to using a proxy is that it may provide only a rough measure of shorting fees and hence introduce substantial noise into the analysis.

Using SIR_{IO} allows us to extend the sample back to April 1980. Hence, our long sample covers April 1980 to October 2012. Table 8 undertakes a similar analysis to Table 2, using SIR_{IO} as the sorting variable in place of shorting fee. We again sort all stocks into ten deciles at the end of each month, but now by their value of SIR_{IO} rather than their shorting fee. The table structure follows that in Table 8. The rows again report equal-weighted averages of returns and characteristics for the stocks in the decile portfolios over the long sample period.

The third column gives the average value of SIR_{IO} for each decile. The pattern displayed is broadly similar to that of shorting fee in Table 2. That is, there is not much variability in SIR_{IO} in the top eight deciles, which all have low average SIR_{IO} values. This is consistent with our earlier finding that shorting fees are low for most stocks. Moreover, similar to shorting fees, SIR_{IO} rises strongly in the ninth and especially tenth deciles.

The pattern in average returns also bears a strong similarity to that in Table 2. Average returns are quite flat across the top seven deciles, but decrease markedly starting with the eighth decile. As with shorting fees, there is a large drop in the average return between the ninth and tenth deciles, and the average return of the tenth decile is negative. Consequently, the average return of a portfolio which goes long the lowest SIR_{IO} stocks and short the highest SIR_{IO} stocks is a very large and highly statistically significant 1.48% per month. In keeping with our existing terminology, we refer to this portfolio as the SIR_{IO}-based CME portfolio.

The table also shows that the difference in average returns across the deciles is, again, not captured by differences in these portfolios' loadings on conventional risk factors. The Fama-French four factor (FF4) alpha (labeled "FF4α") of the high SIR_{IO} portfolio is -1.09% per month, and the alpha of the CME portfolio is a highly significant 1.54% per month! We highlight that this FF4 alpha is larger for this long-sample period than that of any of the well-known anomalies we study, as shown below.

For completeness, panel B mirrors the corresponding panel in Table 2. It shows that the return differences are more dramatic still if we look at portfolio 10b, the lower half of stocks in the decile 10 portfolio based on their SIR_{IO} value. The average SIR_{IO} value for these stocks is a tremendous 81.8%, so these are stocks where the amount of shorting is very large relative to the potential total supply. The average raw return on the 10b portfolio is -0.46% per month, resulting in an average monthly return on the 1-minus-10b portfolio of 1.88%.

The FF4 alpha is again even larger, at 1.96% per month, with a t-statistic of 9.83.

5.1 Characteristics

Table 8 also reports the average anomaly characteristics for each of the deciles at the time of portfolio formation. The patterns displayed are similar to those of the shorting-fee-sorted deciles. The decile ten stocks have extreme values of the anomaly characteristics. They have the highest average momentum returns, idiosyncratic volatility, max return, financial distress, and net share issuance. They also have the lowest book-to-market ratios and gross profitability. The stocks in portfolio 10b extend these patterns further.

There is again a close correspondence between the characteristic and decile rankings, with the relationship always strengthening at the high deciles. A contrast with the the shorting-fee-sorted deciles is that the relationship between SIR_{IO} and idiosyncratic volatility is not perfectly monotonic, whereas the relationship between SIR_{IO} and momentum or book-to-market ratio is monotonic.

Finally, table 8 shows the average market capitalization for each decile. With the exception of the first decile, which has the smallest stocks, market capitalization is decreasing in the decile number. Nevertheless, the aggregate market caps of the ninth and tenth deciles are economically large. The ratio of the average market cap in the tenth decile to the largest average market cap across deciles (the second decile) is similar to the corresponding value for the shorting-fee deciles. This suggests that, as in the case of shorting fees, the average stock in the tenth decile should be categorized as a (smallish) mid-cap stock.

5.2 CME Portfolio

Panel A of Table 9 looks at moments of the return on the SIR_{IO}-based CME portfolio. The mean return is the same as in Table 8. The standard deviation is around 5% per month. This implies a high annual Sharpe ratio of 1.03. The skewness and excess kurtosis are positive, but not very large, and the returns also exhibit a small positive autocorrelation.

Panel B of Table 9 shows the correlation of the SIR_{IO}-based CME portfolio with the four Fama-French factors. As in the short sample, CME is negatively correlated with the overall market, indicating that investors who concentrate in shorting stocks with high SIR_{IO}

do relatively poorly when the market is up. CME is again also negatively correlated with SMB and positively correlated with UMD. However, the correlation of CME with HML is now quite positive, rather than negative.

5.3 Unconditional Anomaly Returns

Table 10 documents the returns to the eight anomalies over the long sample period, April 1980 to October 2012. The structure of the table is the same as in Table 4. The top row of the bottom part of the table reports the average return of each of the anomaly long-short portfolios. As the table shows, all of the average long-short returns are large and statistically significant.

The second row in the bottom part of Table 10 reports the FF4 alphas of the anomaly long-short portfolios. Except for momentum and to a lesser extent value-growth, the alphas are very similar to the average returns. They are very large, and with the exception of momentum, are even more statistically significant than the average returns. In the case of momentum, the FF4 alpha is much smaller than the average return, and is not statistically significant. In the case of value-growth, the FF4 alpha is still large (64 bps per month), and highly statistically significant. Hence, with the exception of momentum, the large unconditional anomaly long-short returns cannot be explained by their exposures to the conventional four risk factors.

The last row in the bottom part of Panel A gives the alphas of the anomaly long-short returns relative to the FF4 + CME model, using the SIR_{IO}-based CME portfolio for the CME factor. The inclusion of the CME factor leads to a large reduction in the magnitudes of the alphas of all the anomalies except for the already small momentum alpha. Only the composite share issuance, net share, and gross profitability issuance alphas remain highly significant, while the max return alpha is marginally significant. Yet, even in those cases the alpha estimates decrease dramatically from their high FF4 values. The largest reductions in alphas are for distress, idiosyncratic volatility and max return, where the alphas are each reduced by at least 1.16% per month. This striking reduction in alphas is consistent with our short-sample results. It shows that a single risk factor, a proxy for exposure to shorting risk, goes very far towards explaining the average returns to these eight well-known anomalies.

Panel B of Table 10 reports the average SIR_{IO} by decile for each anomaly. There is a clear pattern. For all the anomalies decile ten stocks have by far the highest SIR_{IO}. Hence, there is a clear concentration of highly shorted stocks in the short legs of these anomalies. In addition, SIR_{IO} is generally increasing in the deciles, particularly for deciles five to ten. The main exception to this pattern is momentum, where there is high shorting of the one decile. These patterns are similar to those for short fees shown in Table 4.

5.4 Returns Conditional on Shorting Fees

Next, we replicate the analysis of Table 5 using SIR_{IO} in place of the shorting fee, thereby allowing us to examine the interaction between a short-fee proxy and anomaly returns in the long sample. Table 11 shows the results. The structure mirrors that of Table 5. As in Table 5, the "low fee" bucket consists of the stocks in the top eight SIR_{IO} deciles. The ninth and tenth deciles are sorted into the three "high fee" buckets. In creating the anomaly long-short returns, the low fee bucket is sorted into ten deciles based on the corresponding anomaly characteristics, while each of the high fee buckets is sorted into three terciles. The long-short portfolio returns are then given by the difference between the returns of the extreme portfolios within each bucket.

Panel A again shows the average returns for each of the four buckets. As in Table 5, there is a clear pattern of average anomaly long-short returns increasing strongly as we move from the low- to the high-fee buckets. In most cases the average long-short return in the first intermediate-fee bucket, $F1$, is higher than that in the low fee bucket, while the average return in the $F2$ bucket is larger still. The high fee bucket $F3$ always has the largest average return, and by a large margin in most cases. For example, the high-fee bucket's average long-short return for idiosyncratic volatility is an incredible 2.24%(!) per month. Even the smallest average $F3$-based long-short return is a very high 97 bps per month.

The bottom row of panel A formally examines the difference between the average long-short return of each anomaly in the low and high fee buckets. The differences are large, and with the exception of value-growth and gross profitability, highly statistically significant. Value-growth exhibits the smallest difference, 34 bps per month, with a t-stat of 1.52.

A difference relative to our findings in Table 5 is that the average returns in the low-fee bucket of Table 11 are statistically significant in all but one case. It is possible that this is difference is due to our use of a proxy for shorting fee in sorting the stocks into buckets. Any noise in this proxy will make the associated sorting imprecise and hence blur the difference in average returns across buckets.

5.4.1 Four Factor Alphas

Panel B of Table 11 reports the FF4 alphas for the long-short portfolios. The alphas exhibit similar patterns to the average returns. The alphas for the low fee bucket are smaller than the unconditional alphas, whereas the high-fee ($F3$) alphas are by far the largest. The bottom row of Panel B examines the difference in FF4 alphas between the high and low fee buckets ($F3$ minus $F1$). The difference in alphas is large, and in most of the cases highly statistically significant. Hence, the dependence of average returns on SIR_{IO} shown in panel A carries over to the corresponding FF4 alphas.

A difference relative to panel B of Table 5 is that, besides the case of momentum, the low-fee alphas are statistically significant. As in the case of the average returns, this difference may be due in part to the use of an imperfect proxy for shorting fee in sorting the stocks into buckets.

5.5 CME Alphas

We now use the SIR_{IO}-based CME portfolio to proxy for the shorting risk factor in the long sample. Panel C of Table 11 reports the long-sample alphas of the long-short anomaly portfolios relative to this SIR_{IO}-based version of the FF4 + CME model. Relative to their FF4 counterparts, the alphas in the $F0$ bucket become significantly smaller. For example, the alphas of financial distress and max return are reduced from 102 bps and 100 bps per month, respectively, under the FF4 model, to 27 bps and 19 bps per month under the FF4 + CME model. Except for the momentum alpha, which is insignificant under both models, all the alphas decrease substantially in magnitude. Moreover, the alphas are now insignificant for five of the anomalies. Arguably only the net share issuance alpha (46 bps) and gross profitability alpha (62 bps) are economically large. Therefore, among the low fee stocks there mostly weak evidence of anomalous returns relative to the FF4 + CME model.

The FF4 + CME alphas of the anomaly long-short returns in the $F1$ and $F2$ buckets are all fairly small and statistically insignificant. Indeed, with one exception the alpha magnitudes are less than 40 bps per month across all sixteen portfolios. In comparison, the FF4 alphas are much larger and also generally statistically significant. The dramatic decrease in alphas shows how accounting for shorting risk exposure using the CME portfolio allows the model to capture the expected returns to these portfolios.

Turning to the high fee ($F3$) bucket, across all anomalies there is a striking reduction in alphas in going from the FF4 model to the FF4 + CME model. For example, the alphas of idiosyncratic volatility, financial distress, and max return decrease from 206 bps, 162 bps, and 215 bps per month, respectively, to 91 bps, 46 bps, and 110 bps per month. Whereas all eight anomalies' FF4 alphas are significant at the 5% level, only the alphas of idiosyncratic volatility, max return, and net share issuance remain so under the FF4 + CME model. These anomalies' alphas were so large under the FF4 model that they remain significant despite the large reductions in their magnitudes (105 bps, 105 bps, and 59 bps, respectively).

The bottom row of Panel C again examines the difference anomaly alphas between the low-fee and high-fee buckets. This difference is only significant in the case of idiosyncratic volatility and max return. The remaining differences are all under 20 bps. In contrast, the differences in average returns and FF4 alphas were almost all significant and large. This finding corroborates that in the short sample, and again shows that accounting for exposure to shorting risk using the CME portfolio effectively equalizes risk-adjusted returns across the low and high fee stocks. In both the long and short sample, an important component of this equalization is the model's ability to capture the very high returns to these anomalies in the high fee bucket.

Figure 4 plots a comparison of predicted average returns versus realized average returns for the FF4 and the SIR-based FF4 + CME models in the long sample. Each anomaly is plotted separately and the points are the extreme characteristic-sorted portfolios within each of the four fee-sorted buckets.

The figure shows a much superior fit of the FF4 + CME model across all the anomalies. This is particularly true for the low-return portfolios, which typically lie significantly below the forty-five degree line for the FF4 model. In contrast, the fit of the FF4 + CME model is quite good for both the low- and high- return portfolios, though it is not able to do as good a job capturing some of the very low-return portfolios as was the short-fee-based version of CME model in the short sample. Nevertheless, in all cases the model provides a good fit and one that is clearly significantly better than the FF4 model.

In summary, the SIR-based FF4 + CME model is mostly able to capture the average returns of all these anomalies in the long sample, corroborating our short-sample findings. We again find that average returns and FF4 alphas are strongly increasing in shorting fee, proxied by SIR_{IO}. The differences largely disappear, and the alphas mostly eliminated, once compensation for exposure to the CME factor is taken into account. The results further support the theory that compensation for exposure to shorting risk is a significant component of the expected returns to these anomalies.

5.6 Size and Liquidity Matched Portfolios

We repeat the analysis of section 4.4 on the long sample in order to separate the influence of high SIR on anomaly returns from that of firm size or stock liquidity. Following the same procedure as in section 4.4, we use only low-SIR_{IO} ($F0$ bucket) stocks to create size-matched and liquidity-matched portfolios for the anomaly portfolios in buckets $F1$ to $F3$ of Table 11.

Table 12 reports the results for the size (and anomaly-characteristic) matched portfolios. Across all anomalies and buckets the matched portfolio returns are very similar to the returns for the low-SIR_{IO} ($F0$) bucket in Table 11. While the average returns are usually significant, this was already the case in the $F0$ bucket in Table 4.4. The key point is that the returns are substantially smaller than for the $F1$ through $F3$ buckets in Table 11. Moreover, in going from the $F1$ to the $F3$ buckets the matched returns are generally flat or at most slightly increasing, in stark contrast to the large increases found in Table 11. As a consequence, in all cases the high-SIR_{IO} ($F3$) anomaly returns are far larger their matched returns. The same patterns hold for the FF4 alphas (panel B) of the matched portfolios. Hence, panels A and B of Table 12 show that firm size does *not* account for the highly amplified anomaly returns we find in the sample of high-SIR_{IO} firms.

For completeness, Panel C reports the FF4+CME alphas of the matched portfolios. In almost all cases these alphas are smaller–often substantially–than the FF4 alphas, and in most cases they are now insignificant or marginally significant.

Finally, Table 13 reports the results for the liquidity and anomaly-characteristic matched portfolios. The results are very similar to those of the size matched portfolios, and show that stock liquidity does not account for the highly amplified anomaly returns we find in the sample of high-SIR_{IO} firms.

6 Conclusion

There is tremendous cross-sectional variation in stocks' shorting fees. In our sample (January 2004 to October 2012) stocks in the top ten (five) percentile of shorting fees have an average shorting fee of 582 (908) bps per annum. The total market capitalization of such stocks is economically large. In our sample, the average total market capitalizations of the ninth and tenth deciles of stocks sorted by shorting fees are \$1.1 trillion and \$415 billion, respectively.

We show that shorting fees are highly predictive of the cross-section of returns. The high short-fee stocks have very negative average returns in our sample. The average return on the portfolio long cheap-to-short and short expensive-to-short stocks (the CME portfolio) is a highly significant 1.45% per month. We refer to this expected return as the shorting premium, because it represents the excess return earned investors who short the portfolio of high-fee stocks. Surprisingly perhaps, the large cross-sectional differences in average returns remain even when the returns are measured net of the shorting fees themselves. The average net return on the high-short fee stocks is also negative, and the net shorting premium– the net average return on the CME portfolio–is a highly significant 0.92% per month.

The shorting premium cannot be explained by the CME portfolio's exposure to the four Fama-French factors. Its four-factor alpha is 1.55% per month, even larger than its average return. The average return and alpha are substantially larger still if one shorts only the top 5% of stocks by shorting fee, our so-called 1-minus-10b portfolio. It has an average gross return of 2.13% per month, average net return of 1.27% per month, and a tremendous Fama-French 4-factor alpha of 2.27% per month.

We further show that there is a strong association between shorting fees and the characteristics associated with well-known asset-pricing anomalies: the book-to-market ratio, past returns (momentum), idiosyncratic volatility, cumulative equity issuance, financial distress, the previous' month's maximum return, net share issuance, and gross profitability. When stocks are sorted based on these anomaly characteristics, the upper deciles exhibit a strong increase in average short fees, and the average short fee is by far the largest for the decile ten portfolio.

Short fees themselves do not cancel out the returns on the anomalies. That is, the average net returns of the anomaly long-short portfolios are still large, and their Fama-French four factor alphas are large and significant. This is not surprising in light of our finding that the shorting premium itself is large, even net of fees. Yet, the connection between shorting fees and these anomalies goes beyond testing whether they have non-zero net returns.

We decompose the returns to the eight anomalies by conditioning the long-short portfolios on stocks' short fees, and find several striking patterns. First, among the set of low short-fee stocks, the average anomaly long-short returns are small and insignificant. This is surprising because low-fee stocks constitute 80% of all stocks and an even greater fraction of total market capitalization, and because these anomalies do display significant unconditional average returns in our sample. This finding indicates that these anomalies may not exist among the great majority of stocks.

Second, we show that the average anomaly long-short returns increase with the level of shorting fees. In particular, the anomaly returns are highly amplified among the highest-fee stocks. The same patterns hold for the Fama-French four-factor alphas: they are small and generally insignificant for low-fee stocks and are very large and significant within the group of high-fee stocks. Based on our findings the anomaly returns appear to be concentrated among the high-fee stocks.

We propose a theory that can jointly explain the large shorting premium and the interaction between anomaly returns and shorting fees. This theory posits that shorting is concentrated in the portfolios of a narrow minority of market participants, and that these shorts are marginal in setting the prices of high short-fee stocks. The first assumption is supported by evidence that most shorting is carried out by hedge funds. The second is consistent with the fact that the existence of significant short fees requires that some long investors not lend out their shares, despite the high fees that can be earned by doing so. Given that these long investors already earn inefficiently low returns on these shares, it is plausible that they are also insensitive to their prices at the margin.

If these assumptions are met, then the shorts will require a risk premium to compensate them for the concentrated short risk they bear in their portfolios. This risk premium will then appear as the shorting premium. In contrast to most other risk premiums, and in particular any risk premium in a model with perfect risk sharing, the short-risk premium will cause prices to increase rather than decrease.

The theory further implies that stocks which load positively on the risk of the concentrated short-risk portfolio will earn a short-risk (i.e., negative) premium. This may explain the very low returns earned by the anomalies within the group of high-fee stocks. To test this prediction we augment the conventional Fama-French model with the shorting-risk portfolio return proxied by return of the CME portfolio.

We find that this this Fama-French + CME factor model is able to capture a very large portion of the average returns to the eight anomalies, both within low- and high-fee stocks (32 portfolios in total). For almost all the portfolios, the Fama-French + CME alphas are small and insignificant. Most remarkably, there is a drastic reduction in the very large four-factor alphas exhibited by the anomalies amongst the high-fee stocks. As a result, risk-adjusted average returns are largely equated across the high- and low-fee anomaly portfolios.

Finally, we extend the analysis to a long sample using a proxy for short fees. We find largely similar results in the long-sample. Again, the average anomaly returns increase with the value of the proxy, as do the Fama-French four-factor alphas. Moreover, alphas are substantially decreased under a Fama-French + CME model based on the proxy, so that differences in risk-adjusted returns across low- and high-fee stocks become much smaller.

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Figure 1: Time Series of Aggregate Security Lending

The figure plots the time series of the aggregate securities lending amount and the average lending fee. The shaded area shows the aggregate total balance value, the aggregate dollar mount of shares borrowed in billions of dollars. The solid blue line plots and dashed red line report the equal weighted and, respectively, total balance value weighted, average lending fees across all stocks in basis points.

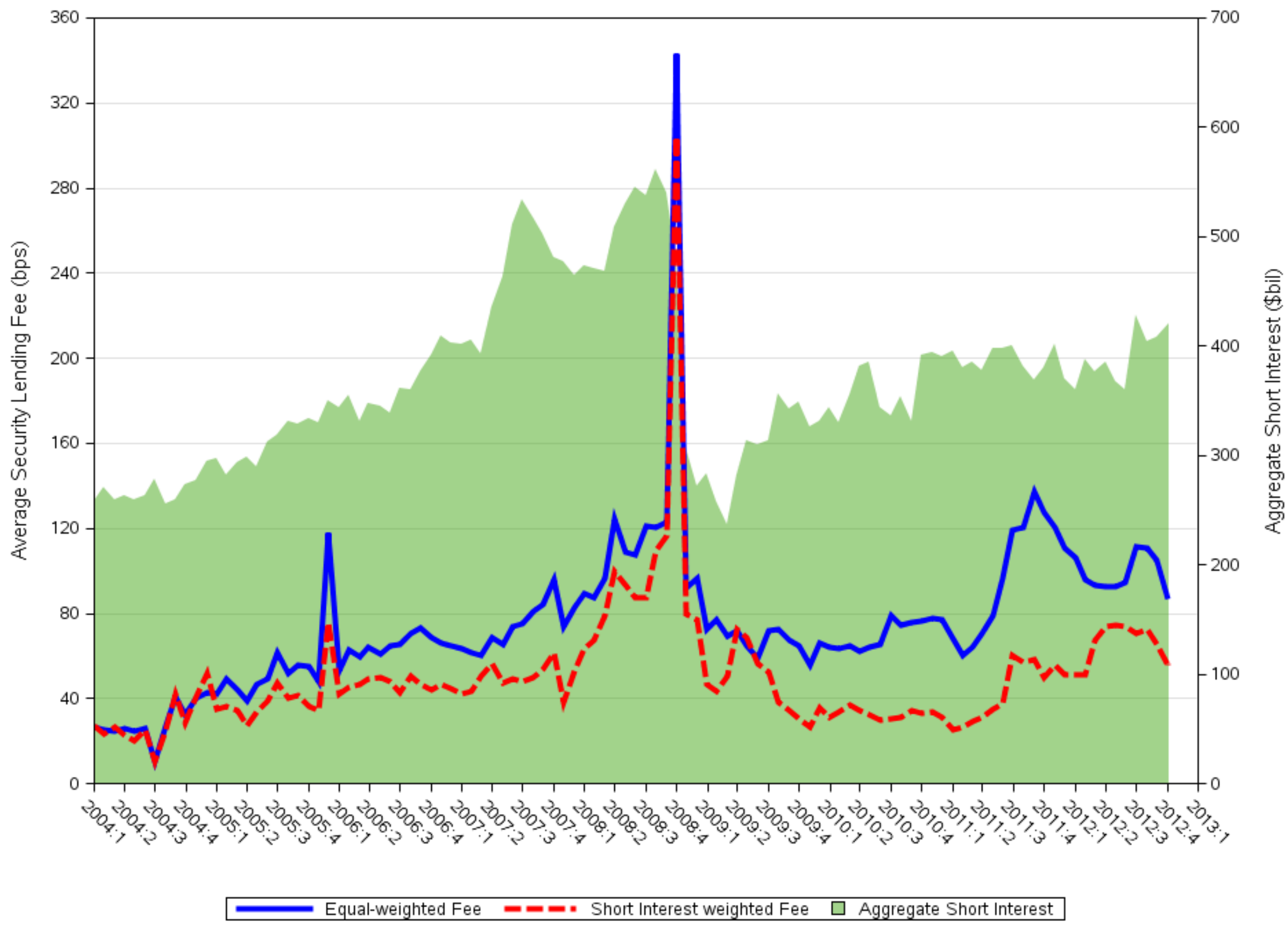

Figure 2: Transition Matrix of Stocks Based on Shorting Fee

The figure shows the transition matrix for stocks in the four short-fee-sorted buckets used in Table 5. The buckets are rebalanced monthly. The figure reports the probabilities that a stock will transition between the buckets over periods of one, three, six, and twelve months.

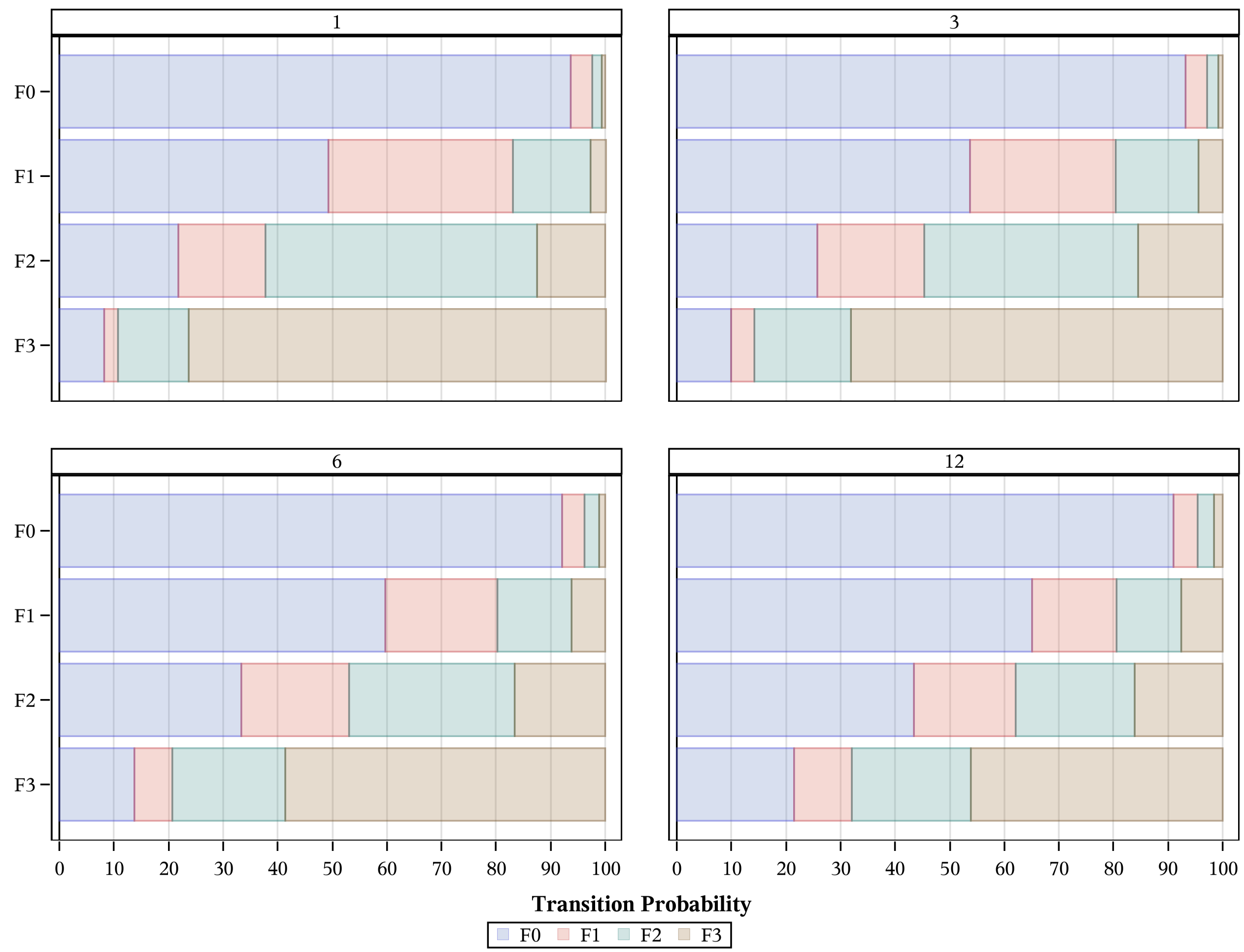

Figure 3: Realized versus Predicted Average Returns

For each anomaly, the figure plots the realized average monthly return versus the predicted average monthly return for each of the extreme anomaly-based portfolios within each the short-fee sorted buckets of Table 5. The blue circles are for the Fama-French four-factor (FF4) model, while the red pluses are for the FF4 + CME model. The sample period is January 2004 to October 2012.

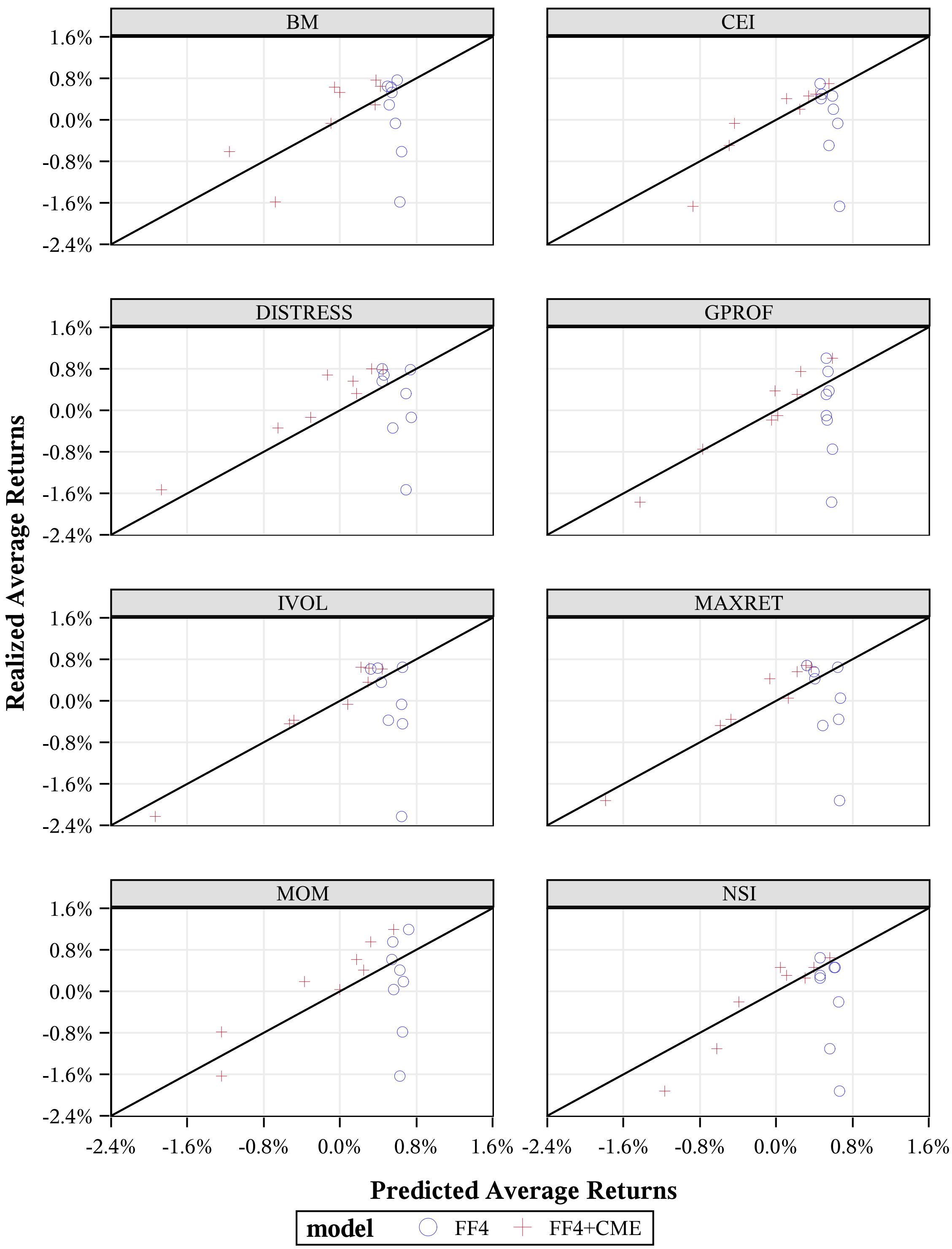

Figure 4: Realized versus Predicted Average Returns (long sample)

For each anomaly, the figure plots the realized average monthly return versus the predicted average monthly return for each of the extreme anomaly-based portfolios within each the short-fee sorted buckets of Table 11. The blue circles are for the Fama-French four-factor (FF4) model, while the red pluses are for the FF4 + CME model (based on SIR_{IO}). The sample period is April 1980 to October 2012.

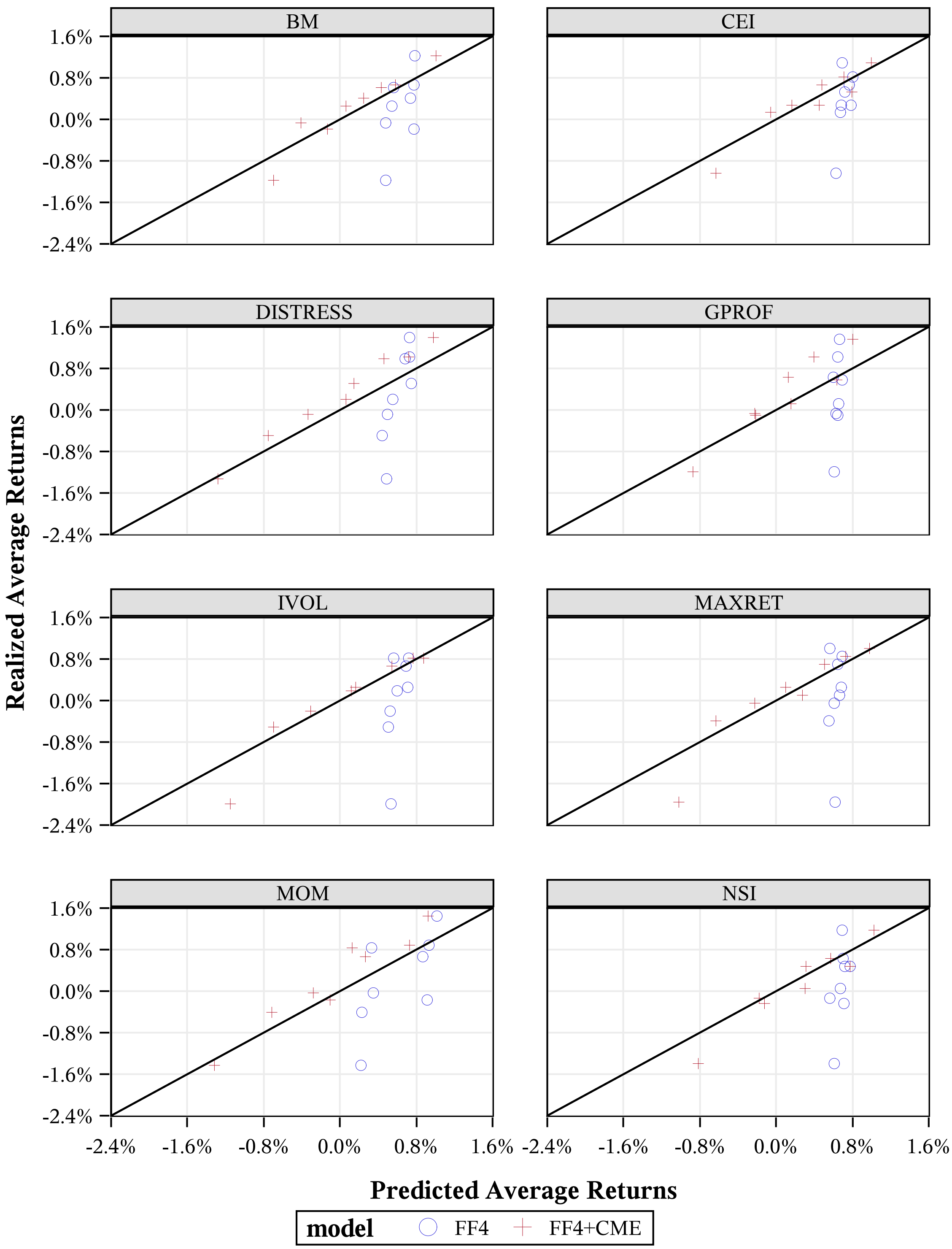

Table 1: **Summary Statistics**

The table reports data summary statistics. The figures reported for a given year are averages for the months in that year. IOR is institutional ownership ratio, the ratio of shares held by institutions to total common shares outstanding; SIR is the short interest ratio, the ratio of short interest to total shares outstanding; SIR_{IO} is short interest divided by shares held by institutions; Aggregate Short Interest is the total value of shares shorted for all stocks in dollars; Short Fee is the annual borrowing fee in basis points. All quantities except for Aggregate Short Interest are equal-weighted averages across stocks.

Year	No. Stocks	Market Cap. (\$*mil*)	B/M	IOR (%)	SIR (%)	SIR_{IO} (%)	Aggregate Short Interest (\$*bil*)	Short Fee (*bps*)
2004	3,071	3,958	0.58	59.2	4.4	8.0	268	29
2005	3,434	3,901	0.51	60.1	4.3	8.3	314	55
2006	3,525	4,090	0.52	62.3	5.1	9.0	364	65
2007	3,647	4,380	0.51	64.6	6.1	9.9	466	74
2008	3,560	3,792	0.59	65.0	7.2	11.3	474	126
2009	3,355	3,005	0.99	60.6	4.7	8.4	309	68
2010	3,282	3,780	0.84	60.1	4.9	9.4	361	70
2011	3,194	4,494	0.69	63.2	5.0	8.8	387	98
2012	3,121	4,770	0.77	63.0	5.1	9.1	390	99

Table 2: **Cross-section of Returns by Shorting Fee**

At the end of each month from January 2004 to October 2012 we sort stocks into deciles by their shorting fee. Only stocks above the tenth percentile of both market capitalization and share price are included. The table reports equal-weighted averages of the monthly decile portfolio returns and stock characteristics. Decile 1 contains the cheapest-to-short stocks, while decile 10 contains the most expensive-to-short stocks. Short Fee is the annual borrowing fee in basis points; *mktcap* is market capitalization; B/M is the book-to-market ratio; *mom* is the average return over the previous twelve months; *ivol* is the idiosyncratic volatility; *cei* is composite equity issuance; *distress* is financial distress. *Gross Ret* is the return gross of shorting fees; *Net Ret* is the return net of shorting fees. $FF4\,\alpha$ is the Fama-French 4-factor alpha. Returns are in percent.

Fee Decile	No. Stocks	Short Fee (*bps*)	SIR_{IO} (%)	*mktcap* (\$ *bil*)	B/M	*mom* (%)	*ivol* (%)	*cei*	*distress*	*maxret* (%)	*nsi*	*Gross Ret* (%)	*Net Ret* (%)	$FF4\,\alpha$ (%)
Panel A: Portfolio Characteristics and Returns by Decile														
1 (Cheap)	336	3	4.6	15.33	0.61	9.06	1.69	0.04	-8.35	4.77	0.02	0.74	0.76	0.12
2	336	9	6.0	5.94	0.63	9.24	1.88	0.06	-8.36	5.25	0.02	0.77	0.78	0.12
3	336	11	6.7	3.34	0.63	9.15	1.98	0.08	-8.32	5.48	0.03	0.86	0.87	0.17
4	336	12	6.7	2.13	0.66	9.02	2.08	0.09	-8.32	5.72	0.03	0.81	0.82	0.14
5	336	13	6.3	1.88	0.69	8.91	2.18	0.10	-8.22	5.93	0.03	0.89	0.91	0.19
6	336	15	6.3	1.74	0.71	8.22	2.26	0.10	-8.24	6.09	0.04	0.89	0.90	0.20
7	336	19	7.1	2.56	0.72	9.00	2.33	0.10	-8.21	6.30	0.04	0.86	0.88	0.17
8	336	31	9.0	2.87	0.71	9.42	2.49	0.15	-8.02	6.64	0.05	0.86	0.88	0.16
9	336	75	12.5	3.30	0.68	9.29	2.73	0.21	-7.75	7.15	0.07	0.53	0.59	-0.14
10 (Expensive)	336	568	26.5	1.30	0.64	11.59	3.47	0.44	-2.49	8.94	0.12	-0.68	-0.16	-1.42
$1-10$ Return												1.43	0.91	1.53
(t-stat)												(4.99)	(3.24)	(7.06)
Panel B: Highest Fee Decile														
$10a$ (Expensive)	168	228	18.4	1.66	0.66	9.63	3.18	0.34	-7.44	8.22	0.10	0.03	0.20	-0.67
$10b$ (Expensive)	168	908	34.4	0.93	0.63	13.53	3.76	0.54	2.71	9.66	0.15	-1.40	-0.52	-2.16
$1-10b$ Return												2.14	1.28	2.28
(t-stat)												(5.86)	(3.56)	(7.87)

Table 3: **Summary Statistics for the CME factor**

Summary statistics for the monthly return of the CME (cheap-minus-expensive) factor. Panel A reports moments of the CME return. Panel B gives the correlation matrix for the return of the CME portfolio and the four Fama-French factors, $MKTRF$, SMB, HML, and UMD. The sample is January 2004 to October 2012.

Panel A: Moments					
N	Mean(%)	Std. Dev.(%)	Skewness	Kurtosis	AC(1)
108	1.43	2.94	-0.49	1.89	0.27
Panel B: Correlations					
	CME	$MKTRF$	SMB	HML	UMD
CME	1.00	-0.38	-0.49	-0.31	0.50
$MKTRF$		1.00	0.48	0.33	-0.35
SMB			1.00	0.19	-0.10
HML				1.00	-0.32
UMD					1.00

Table 4: **Anomaly Returns and Shorting Fees**

The table reports the returns and shorting fees by decile for seven anomalies. For each anomaly, stocks are sorted into deciles so that decile 1 is the long leg of the anomaly strategy and decile 10 is the short leg. The upper part of Panel A reports the average monthly returns for each anomaly decile. The lower part reports the average return on the long-short portfolio ("L-S"), which is long the stocks in decile 1 and short the stocks in decile 10, its FF4 alpha, and its FF4 + CME model alpha. Panel B reports the average annual shorting fee in basis points for the stocks in each anomaly decile. The anomalies are: value-growth (B/M), momentum (mom), idiosyncratic volatility ($ivol$), composite equity issuance (cei), financial distress ($distress$), max return ($maxret$), and net share issuance (nsi). The sample is January 2004 to October 2012.

Anomaly	Anomalies							
Rank	B/M	mom	$ivol$	cei	$distress$	$maxret$	nsi	$gprof$
Panel A: Anomaly Strategy Returns (%)								
1 (Long)	0.85	0.84	0.74	0.78	0.87	0.74	0.66	0.99
2	0.78	0.67	0.82	0.70	0.86	0.79	0.69	0.83
3	0.74	0.67	0.79	0.84	0.82	0.87	0.63	0.87
4	0.81	0.81	0.73	0.84	0.80	0.78	0.68	0.84
5	0.64	0.72	0.74	0.83	0.92	0.80	0.90	0.90
6	0.76	0.75	0.81	0.97	0.88	0.70	0.89	0.75
7	0.64	0.86	0.76	0.78	0.86	0.68	0.84	0.69
8	0.61	0.77	0.75	0.80	0.93	0.64	0.80	0.61
9	0.46	0.65	0.52	0.60	0.70	0.51	0.45	0.13
10 (Short)	0.31	0.79	-0.13	0.17	0.18	0.03	0.11	-0.05
L-S Return	0.54	0.05	0.87	0.61	0.69	0.71	0.55	1.04
(t-stat)	(1.40)	(0.07)	(1.68)	(2.07)	(1.12)	(1.43)	(2.04)	(3.41)
L-S Net Fee Return	0.47	-0.03	0.66	0.51	0.52	0.55	0.42	0.93
(t-stat)	(1.21)	(0.05)	(1.27)	(1.75)	(0.86)	(1.11)	(1.58)	(3.05)
L-S FF4 α	0.45	0.19	1.21	0.77	0.99	1.04	0.69	1.07
(t-stat)	(2.24)	(0.65)	(4.36)	(3.38)	(3.87)	(4.09)	(3.28)	(3.55)
L-S FF4+CME α	0.65	0.14	0.07	0.14	0.50	0.23	0.02	0.41
(t-stat)	(2.67)	(0.40)	(0.27)	(0.54)	(1.68)	(0.84)	(0.08)	(1.16)
Panel B: Average Annual Shorting Fee (bps)								
1 (Long)	80	102	27	47	48	38	46	79
2	52	55	27	44	34	38	44	56
3	54	48	32	38	35	41	65	51
4	54	47	39	41	38	48	72	53
5	52	46	48	39	41	56	59	56
6	54	50	58	40	46	62	55	52
7	60	57	72	42	59	76	52	68
8	64	66	96	55	76	93	63	70
9	84	90	135	79	115	122	116	84
10 (Short)	150	170	224	142	206	184	165	186

Table 5: **Anomaly Returns Conditional on Shorting Fees**

We divide the short-fee-sorted deciles from Table 4 into four buckets. Deciles 1-8, the low-fee stocks, are placed into the $F0$ bucket. Deciles 9 and 10, the intermediate- and high-fee stocks, are further divided into three equal-sized buckets, $F1$ to $F3$, based on shorting fee, with $F3$ containing the highest short-fee stocks. We then sort the stocks within each bucket into portfolios based on the anomaly characteristic and let the bucket's long-short anomaly return be given by the difference between the returns on its extreme portfolios. Due to the larger number of stocks in the $F0$ bucket, it is sorted into deciles based on the anomaly characteristic, while $F1$ to $F3$ are sorted into terciles. Panel A reports the monthly anomaly long-short returns for each of the buckets. Panel B reports the corresponding FF4 alphas. Panel C reports the corresponding FF4 + CME alphas. The sample period is January 2004 to October 2012.

Fee Bucket	Anomalies *B/M*	*mom*	*ivol*	*cei*	*distress*	*maxret*	*nsi*	*gprof*
				Panel A: Monthly Returns (%)				
$F0$	0.13	-0.23	-0.05	0.24	-0.00	0.02	0.17	0.69
(t-stat)	(0.35)	(0.34)	(0.10)	(0.98)	(0.00)	(0.03)	(0.75)	(2.42)
$F1$	0.38	0.24	0.71	0.12	0.22	0.49	-0.28	0.71
(t-stat)	(1.06)	(0.44)	(1.86)	(0.31)	(0.40)	(1.18)	(0.78)	(2.07)
$F2$	0.69	-0.21	0.81	0.60	0.72	0.86	0.51	0.72
(t-stat)	(1.63)	(0.35)	(1.84)	(1.31)	(1.13)	(1.96)	(1.43)	(2.10)
$F3$	0.93	0.87	1.76	1.03	1.24	1.44	0.84	1.02
(t-stat)	(1.88)	(1.56)	(3.57)	(1.80)	(1.81)	(2.90)	(2.09)	(2.28)
$F3-F0$	0.80	1.10	1.81	0.79	1.24	1.43	0.67	0.32
(t-stat)	(2.08)	(1.49)	(3.60)	(1.61)	(2.12)	(3.24)	(2.00)	(0.91)
				Panel B: Fama-French 4-Factor Alphas (%)				
$F0$	0.03	-0.07	0.28	0.37	0.30	0.34	0.31	0.69
(t-stat)	(0.16)	(0.20)	(1.14)	(2.04)	(1.16)	(1.51)	(1.77)	(2.60)
$F1$	0.37	0.33	0.97	0.25	0.48	0.76	-0.12	0.69
(t-stat)	(1.24)	(0.93)	(3.52)	(0.71)	(1.58)	(2.54)	(0.38)	(2.11)
$F2$	0.73	-0.10	1.03	0.78	1.02	1.12	0.70	0.71
(t-stat)	(2.17)	(0.24)	(3.14)	(2.06)	(2.53)	(3.61)	(2.40)	(2.06)
$F3$	0.92	0.84	1.91	1.15	1.37	1.62	0.94	1.01
(t-stat)	(2.47)	(1.56)	(4.14)	(2.15)	(2.32)	(3.60)	(2.77)	(2.30)
$F3-F0$	0.90	0.91	1.62	0.78	1.07	1.28	0.63	0.32
(t-stat)	(2.42)	(1.49)	(3.72)	(1.58)	(1.95)	(3.13)	(2.05)	(0.89)
				Panel C: Fama-French 4-Factor + CME Alphas (%)				
$F0$	0.20	0.03	-0.29	0.02	0.13	0.08	-0.00	0.28
(t-stat)	(1.01)	(0.07)	(1.00)	(0.11)	(0.41)	(0.30)	(0.01)	(0.88)
$F1$	0.67	0.41	0.55	-0.01	0.43	0.51	-0.44	0.50
(t-stat)	(1.84)	(0.93)	(1.66)	(0.03)	(1.17)	(1.40)	(1.18)	(1.25)
$F2$	0.61	-0.58	-0.08	0.04	0.36	0.35	0.04	0.69
(t-stat)	(1.47)	(1.19)	(0.21)	(0.08)	(0.77)	(0.97)	(0.13)	(1.63)
$F3$	1.46	0.98	0.37	0.63	0.15	0.30	0.27	0.34
(t-stat)	(3.24)	(1.48)	(0.75)	(0.97)	(0.22)	(0.59)	(0.67)	(0.65)
$F3-F0$	1.26	0.95	0.66	0.61	0.02	0.22	0.27	0.06
(t-stat)	(2.78)	(1.27)	(1.30)	(1.00)	(0.04)	(0.46)	(0.73)	(0.14)

Table 6: **Low-Fee Size and Characteristic Matched Portfolios**

For each of the anomaly portfolios in buckets $F1$-$F3$ (the intermediate- and high-fee stocks) in Table 5, we create a size and anomaly-characteristic matched portfolio using only stocks from the low-fee ($F0$) bucket. The matched portfolios are formed by sorting the stocks in the $F0$ bucket into five quintiles by size and ten deciles by the corresponding anomaly characteristic. Each stock is assigned one of the 5 x 10 benchmark portfolios based on its size and anomaly-characteristic value. The assigned benchmark portfolios are then equal-weighted to obtain the matching portfolio. Matched long-short returns are given by the difference between the matched long portfolio return and the matched short portfolio return. Panel A reports the monthly anomaly long-short returns for each bucket. Panel B reports the corresponding FF4 alphas. Panel C reports the corresponding FF4 + CME alphas. The sample period is January 2004 to October 2012.

Fee	Anomalies							
Bucket	B/M	mom	$ivol$	cei	$distress$	$maxret$	nsi	$gprof$
				Panel A: Monthly Returns (%)				
$F1$	0.18	-0.19	-0.04	0.10	0.05	0.05	-0.03	0.53
(t-stat)	(0.69)	(0.45)	(0.13)	(0.48)	(0.11)	(0.16)	(0.14)	(2.12)
$F2$	0.21	-0.24	0.06	0.10	0.10	0.15	0.06	0.64
(t-stat)	(0.74)	(0.56)	(0.19)	(0.43)	(0.20)	(0.45)	(0.32)	(2.42)
$F3$	0.12	-0.21	0.09	0.15	0.05	0.09	0.13	0.57
(t-stat)	(0.42)	(0.43)	(0.28)	(0.56)	(0.10)	(0.29)	(0.62)	(2.08)
				Panel B: Fama-French 4-Factor Alphas (%)				
$F1$	0.16	-0.08	0.15	0.22	0.27	0.26	0.09	0.45
(t-stat)	(1.17)	(0.37)	(0.72)	(1.42)	(1.47)	(1.42)	(0.71)	(2.23)
$F2$	0.21	-0.12	0.24	0.22	0.34	0.35	0.18	0.57
(t-stat)	(1.39)	(0.53)	(1.06)	(1.25)	(1.49)	(1.81)	(1.30)	(2.52)
$F3$	0.13	-0.08	0.21	0.26	0.28	0.24	0.25	0.52
(t-stat)	(0.76)	(0.30)	(0.90)	(1.27)	(1.07)	(1.13)	(1.61)	(2.05)
				Panel C: Fama-French 4-Factor + CME Alphas (%)				
$F1$	0.44	-0.05	-0.31	0.03	0.12	0.00	-0.08	0.20
(t-stat)	(2.68)	(0.18)	(1.30)	(0.14)	(0.53)	(0.01)	(0.50)	(0.82)
$F2$	0.48	-0.14	-0.23	-0.04	0.07	0.08	0.04	0.32
(t-stat)	(2.66)	(0.51)	(0.88)	(0.20)	(0.26)	(0.36)	(0.22)	(1.17)
$F3$	0.27	-0.06	-0.23	-0.01	-0.05	-0.07	0.09	0.24
(t-stat)	(1.30)	(0.18)	(0.81)	(0.04)	(0.15)	(0.27)	(0.51)	(0.78)

Table 7: **Low-Fee Liquidity and Characteristic Matched Portfolios**

For each of the anomaly portfolios in buckets $F1$-$F3$ (the intermediate- and high-fee stocks) in Table 5, we create a liquidity and anomaly-characteristic matched portfolio using only stocks from the low-fee ($F0$) bucket. The matched portfolios are formed by sorting the stocks in the $F0$ bucket into five quintiles by their Amihud (2002) liquidity measure and ten deciles by their corresponding anomaly characteristic. Each stock is assigned one of the 5 x 10 benchmark portfolios based on its liquidity and anomaly-characteristic value. The assigned benchmark portfolios are then equal-weighted to obtain the matching portfolio. Matched long-short returns are given by the difference between the matched long portfolio return and the matched short portfolio return. Panel A reports the monthly anomaly long-short returns for each bucket. Panel B reports the corresponding FF4 alphas. Panel C reports the corresponding FF4 + CME alphas. The sample period is January 2004 to October 2012.

Fee	Anomalies							
Bucket	B/M	mom	$ivol$	cei	$distress$	$maxret$	nsi	$gprof$
Panel A: Monthly Returns (%)								
$F1$	0.26	-0.18	-0.03	0.08	0.10	0.06	-0.00	0.57
(t-stat)	(1.00)	(0.44)	(0.08)	(0.34)	(0.21)	(0.18)	(0.01)	(2.29)
$F2$	0.25	-0.13	0.09	0.03	0.11	0.11	0.07	0.61
(t-stat)	(0.85)	(0.29)	(0.26)	(0.13)	(0.22)	(0.36)	(0.37)	(2.34)
$F3$	0.18	-0.18	0.17	0.12	0.12	0.11	0.15	0.55
(t-stat)	(0.61)	(0.37)	(0.55)	(0.47)	(0.23)	(0.39)	(0.75)	(2.10)
Panel B: Fama-French 4-Factor Alphas (%)								
$F1$	0.24	-0.08	0.16	0.20	0.33	0.27	0.11	0.50
(t-stat)	(1.77)	(0.34)	(0.76)	(1.27)	(1.80)	(1.41)	(0.88)	(2.52)
$F2$	0.24	-0.00	0.26	0.15	0.36	0.31	0.19	0.54
(t-stat)	(1.62)	(0.02)	(1.16)	(0.87)	(1.54)	(1.61)	(1.36)	(2.46)
$F3$	0.17	-0.06	0.30	0.23	0.35	0.26	0.26	0.50
(t-stat)	(1.07)	(0.22)	(1.27)	(1.18)	(1.42)	(1.30)	(1.78)	(2.08)
Panel C: Fama-French 4-Factor + CME Alphas (%)								
$F1$	0.50	-0.03	-0.32	0.01	0.20	0.02	-0.08	0.32
(t-stat)	(3.08)	(0.11)	(1.29)	(0.04)	(0.88)	(0.07)	(0.54)	(1.32)
$F2$	0.49	-0.06	-0.19	-0.09	0.07	0.06	-0.02	0.31
(t-stat)	(2.74)	(0.20)	(0.72)	(0.46)	(0.24)	(0.27)	(0.11)	(1.17)
$F3$	0.30	-0.09	-0.15	-0.08	0.10	-0.07	0.02	0.17
(t-stat)	(1.55)	(0.29)	(0.53)	(0.35)	(0.34)	(0.28)	(0.12)	(0.59)

Table 8: **Cross Section of Returns by Short Interest to Institutional Ownership** (SIR_{IO})

At the end of each month from April 1980 to October 2012, we sort stocks into deciles by the ratio of their short interest to institutional ownership (SIR_{IO}). Only stocks above the tenth percentile of market capitalization and share price are included. The table reports equal-weighted averages of the monthly decile portfolio returns and stock characteristics. Decile 1 contains the stocks with the lowest SIR_{IO}, decile 10 the stocks with the highest SIR_{IO}. Returns are in percent; *mktcap* is market capitalization; B/M is the book-to-market ratio; *mom* is the average return over the previous twelve months; *ivol* is the idiosyncratic volatility; *cei* is composite equity issuance; *distress* is financial distress. *Ret* is the return; $FF4\,\alpha$ is the Fama-French 4-factor alpha. Panel B further splits the stocks in decile 10 by their SIR_{IO}.

SIR_{IO} Decile	No. Stocks	SIR_{IO} (%)	*mktcap* (\$ *bil*)	B/M	*mom* (%)	*ivol* (%)	*cei*	*distress*	*maxret* (%)	*nsi*	*gprof*	*Ret* (%)	$FF4\,\alpha$ (%)
Panel A: Portfolio Characteristics and Returns by Decile													
1 (Low)	340	0.1	0.36	1.00	7.66	2.68	0.01	-8.10	6.32	0.03	30.66	1.42	0.45
2	343	0.4	3.71	0.91	9.17	2.59	0.02	-8.14	6.26	0.03	32.48	1.44	0.40
3	345	0.9	3.70	0.85	9.38	2.46	0.02	-8.16	6.08	0.03	33.41	1.35	0.25
4	345	1.4	3.04	0.83	9.87	2.42	0.03	-8.18	6.03	0.03	33.91	1.40	0.25
5	346	2.1	2.85	0.81	10.41	2.42	0.04	-8.19	6.07	0.03	34.32	1.30	0.14
6	346	2.8	2.38	0.79	10.90	2.47	0.07	-8.15	6.27	0.04	33.87	1.30	0.14
7	346	4.0	1.81	0.78	11.17	2.60	0.10	-8.05	6.60	0.05	33.32	1.12	0.01
8	345	6.1	1.32	0.77	11.48	2.78	0.14	-7.94	7.03	0.06	32.77	0.98	-0.13
9	344	11.1	0.86	0.74	11.86	3.03	0.20	-7.74	7.67	0.06	31.38	0.79	-0.27
10 (High)	338	52.8	0.47	0.68	12.97	3.74	0.34	-6.17	9.42	0.09	26.67	-0.06	-1.09
$1-10$ Return												1.48	1.54
(t-stat)												(5.86)	(8.84)
Panel B: Highest SIR_{IO} Decile													
10a	172	22.4	0.51	0.69	11.39	3.42	0.28	-6.71	8.64	0.08	30.38	0.37	-0.65
10b	172	82.1	0.44	0.67	14.44	4.04	0.40	-5.63	10.19	0.11	22.96	-0.46	-1.51
$1-10b$ Return												1.88	1.96
(t-stat)												(6.95)	(9.84)

Table 9: **Summary Statistics for the SIR_{IO}-based CME factor (long sample)**

We use the SIR_{IO} proxy to construct a version of the monthly CME factor for the long sample, April 1980 to October 2012. The table presents summary statistics for the returns on this factor. Panel A reports moments of the CME factor. Panel B gives the correlation matrix for the returns of the CME factor and the four Fama-French factors, $MKTRF$, SMB, HML, and UMD.

Panel A: Moments					
N	Mean (%)	Std. Dev. (%)	Skewness	Kurtosis	AC(1)
390	1.48	4.99	-0.49	4.73	0.06
Panel B: Correlations					
	CME	$MKTRF$	SMB	HML	UMD
CME	1.00	-0.55	-0.55	0.47	0.19
$MKTRF$		1.00	0.22	-0.35	-0.14
SMB			1.00	-0.32	0.04
HML				1.00	-0.18
UMD					1.00

Table 10: **Anomaly Returns (long sample)**

For each anomaly, stocks are sorted into deciles so that decile 1 is the long leg of the anomaly strategy and decile 10 is the short leg. The upper part of Panel A reports the average monthly returns for each anomaly decile. The lower part reports the average return on the long-short portfolio ("L-S"), which is long the stocks in decile 1 and short the stocks in decile 10, its FF4 alpha, and its alpha from the FF4 + CME model using the SIR_{IO}-based CME factor. Panel B reports the average SIR_{IO} for the stocks in each anomaly decile. The sample is April 1980 to October 2012.

Anomaly Rank	Anomalies B/M	mom	$ivol$	cei	$distress$	$maxret$	nsi	$gprof$
Panel A: Anomaly Strategy Returns (%)								
1 (Long)	1.48	1.66	1.22	1.46	1.79	1.37	1.49	1.68
2	1.44	1.29	1.35	1.40	1.43	1.39	1.27	1.46
3	1.33	1.21	1.36	1.40	1.40	1.42	1.20	1.33
4	1.37	1.13	1.37	1.34	1.36	1.35	1.17	1.22
5	1.26	1.16	1.40	1.36	1.29	1.38	1.28	1.24
6	1.12	1.09	1.40	1.37	1.19	1.24	1.32	1.00
7	1.08	1.01	1.19	1.28	1.13	1.22	1.25	0.95
8	1.03	0.91	1.11	1.18	0.98	1.03	1.12	0.98
9	0.82	0.72	0.73	1.00	0.78	0.73	0.78	1.01
10 (Short)	0.54	0.73	-0.14	0.53	0.16	-0.10	0.40	0.54
L-S Ret	0.94	0.93	1.35	0.94	1.63	1.46	1.09	1.14
(t-stat)	(3.65)	(2.35)	(3.70)	(4.58)	(4.93)	(4.37)	(5.87)	(6.05)
L-S FF4 α	0.64	0.14	1.34	0.94	1.40	1.52	1.08	1.13
(t-stat)	(4.55)	(0.56)	(6.21)	(7.33)	(6.28)	(7.34)	(8.28)	(5.94)
L-S FF4+CME α	0.05	-0.25	0.19	0.47	0.26	0.35	0.48	0.53
(t-stat)	(0.39)	(0.94)	(1.01)	(3.68)	(1.29)	(2.02)	(3.93)	(2.73)
Panel B: Average SIR_{IO} (%)								
1	5.93	12.12	3.89	4.67	4.64	4.08	5.48	7.60
2	5.01	7.61	4.01	3.86	4.50	4.51	5.47	6.50
3	5.14	6.61	4.73	4.12	4.81	5.10	6.82	6.49
4	5.41	6.00	5.54	4.19	5.19	5.97	6.79	6.67
5	5.91	6.13	6.59	5.03	5.72	6.75	6.33	6.84
6	6.27	6.25	7.76	6.19	6.57	7.80	6.56	7.60
7	6.74	6.77	9.06	7.13	7.53	8.94	7.21	8.05
8	8.53	7.86	10.72	8.31	9.11	10.44	9.11	7.57
9	10.50	9.88	12.87	9.80	11.86	12.11	11.16	6.59
10	18.35	15.09	16.33	13.46	16.48	15.58	14.02	14.64

Table 11: **Anomaly Returns Conditional on SIR_{IO} (long sample)**

We divide the SIR_{IO}-sorted deciles from Table 10 into four buckets. Deciles 1-8 are placed into the $F0$ bucket. Deciles 9 and 10 are further divided into three equal-sized buckets, $F1$ to $F3$, based on SIR_{IO}, with $F3$ containing the highest SIR_{IO} stocks. We then sort the stocks within each bucket into portfolios based on the anomaly characteristic and let the bucket's long-short anomaly return be given by the difference between the returns on its extreme portfolios. Due to the larger number of stocks in the $F0$ bucket, it is sorted into deciles based on the anomaly characteristic, while $F1$ to $F3$ are sorted into terciles. Panel A reports the monthly long-short anomaly returns for each of the buckets. Panel B reports the corresponding FF4 alphas. Panel C reports the corresponding FF4 + CME alphas. The sample is April 1980 to October 2012.

SIR_{IO}	Anomalies							
Group	B/M	mom	$ivol$	cei	$distress$	$maxret$	nsi	$gprof$
				Panel A: Monthly Returns (%)				
$F0$	0.61	0.61	0.63	0.56	1.19	0.89	0.71	0.79
(t-stat)	(2.67)	(1.68)	(1.89)	(3.16)	(4.02)	(2.89)	(4.64)	(5.24)
$F1$	0.45	0.92	1.02	0.53	1.11	0.91	0.58	0.91
(t-stat)	(1.64)	(2.96)	(3.25)	(2.34)	(3.55)	(3.06)	(2.84)	(4.56)
$F2$	0.48	1.08	1.16	0.53	1.48	1.09	0.62	0.73
(t-stat)	(1.82)	(3.23)	(3.78)	(2.03)	(4.81)	(3.80)	(2.86)	(3.80)
$F3$	0.97	1.27	2.24	1.31	1.84	2.21	1.16	1.12
(t-stat)	(3.56)	(3.48)	(7.43)	(4.41)	(5.51)	(7.52)	(4.75)	(4.77)
$F3-F0$	0.34	0.65	1.61	0.75	0.65	1.31	0.45	0.34
(t-stat)	(1.52)	(2.43)	(6.55)	(3.07)	(2.49)	(5.31)	(2.16)	(1.55)
				Panel B: Fama-French 4-Factor Alphas (%)				
$F0$	0.40	-0.08	0.67	0.59	1.01	0.99	0.74	0.82
(t-stat)	(3.10)	(0.35)	(3.41)	(5.10)	(5.21)	(5.35)	(6.72)	(5.29)
$F1$	0.19	0.34	0.83	0.41	0.87	0.82	0.55	0.92
(t-stat)	(1.02)	(1.43)	(3.72)	(2.39)	(3.60)	(3.77)	(3.14)	(4.68)
$F2$	0.23	0.44	0.97	0.44	1.24	0.99	0.41	0.78
(t-stat)	(1.19)	(1.71)	(4.20)	(2.16)	(5.00)	(4.31)	(2.22)	(3.95)
$F3$	0.65	0.57	2.07	1.15	1.57	2.14	1.06	1.11
(t-stat)	(2.87)	(1.90)	(8.11)	(4.44)	(5.21)	(8.24)	(4.77)	(4.53)
$F3-F0$	0.24	0.65	1.40	0.57	0.56	1.15	0.32	0.29
(t-stat)	(1.03)	(2.42)	(6.14)	(2.25)	(2.13)	(4.87)	(1.50)	(1.27)
				Panel C: Fama-French 4-Factor + CME Alphas (%)				
$F0$	0.04	-0.18	-0.13	0.36	0.27	0.18	0.46	0.62
(t-stat)	(0.28)	(0.74)	(0.65)	(2.91)	(1.39)	(1.02)	(4.02)	(3.69)
$F1$	-0.10	-0.08	-0.05	0.28	0.05	-0.04	0.31	0.67
(t-stat)	(0.49)	(0.31)	(0.24)	(1.45)	(0.21)	(0.20)	(1.62)	(3.15)
$F2$	-0.17	0.10	-0.08	-0.01	0.26	-0.05	0.13	0.39
(t-stat)	(0.83)	(0.36)	(0.36)	(0.04)	(1.08)	(0.21)	(0.66)	(1.86)
$F3$	0.35	0.06	0.93	0.52	0.42	1.08	0.46	0.48
(t-stat)	(1.43)	(0.17)	(3.86)	(1.91)	(1.40)	(4.27)	(2.00)	(1.86)
$F3-F0$	0.29	0.24	1.06	0.16	0.15	0.90	-0.00	-0.14
(t-stat)	(1.17)	(0.82)	(4.28)	(0.61)	(0.53)	(3.51)	(0.00)	(0.60)

Table 12: **Low-SIR_{IO} Size and Characteristic Matched Portfolios (long sample)**

For each of the anomaly portfolios in buckets $F1$-$F3$ (the high-SIR_{IO} stocks) in Table 11, we create a size and anomaly-characteristic matched portfolio using only stocks from the low-SIR_{IO} ($F0$) bucket. The matched portfolios are formed by sorting the stocks in the $F0$ bucket into five quintiles by size and ten deciles by the corresponding anomaly characteristic. Each stock is assigned one of the 5 x 10 benchmark portfolios based on its size and anomaly-characteristic value. The assigned benchmark portfolios are then equal-weighted to obtain the matching portfolio. Matched long-short returns are given by the difference between the matched long portfolio return and the matched short portfolio return. Panel A reports the matched monthly long-short anomaly returns for each bucket. Panel B reports the corresponding FF4 alphas. Panel C reports the corresponding FF4 + CME alphas. The sample is April 1980 to October 2012.

SIR_{IO}	Anomalies							
Group	B/M	mom	$ivol$	cei	$distress$	$maxret$	nsi	$gprof$
Panel A: Monthly Returns (%)								
$F1$	0.56	0.43	0.48	0.35	0.66	0.60	0.34	0.56
(t-stat)	(2.85)	(1.48)	(1.87)	(2.37)	(2.78)	(2.55)	(2.62)	(4.88)
$F2$	0.53	0.40	0.63	0.53	0.79	0.72	0.37	0.61
(t-stat)	(2.58)	(1.34)	(2.55)	(3.68)	(3.29)	(3.21)	(2.88)	(5.04)
$F3$	0.53	0.62	0.94	0.59	1.02	1.00	0.45	0.66
(t-stat)	(2.59)	(2.01)	(4.10)	(4.15)	(4.20)	(4.77)	(3.33)	(4.86)
Panel B: Fama-French 4-Factor Alphas (%)								
$F1$	0.38	-0.13	0.38	0.39	0.45	0.56	0.33	0.58
(t-stat)	(3.46)	(0.68)	(2.45)	(4.17)	(3.00)	(3.75)	(3.65)	(5.76)
$F2$	0.34	-0.20	0.53	0.58	0.63	0.70	0.36	0.61
(t-stat)	(2.80)	(1.00)	(3.34)	(5.97)	(3.87)	(4.74)	(4.00)	(5.30)
$F3$	0.37	0.04	0.81	0.59	0.88	0.97	0.43	0.62
(t-stat)	(2.82)	(0.21)	(4.69)	(5.40)	(4.81)	(6.20)	(4.35)	(4.44)
Panel C: Fama-French 4-Factor + CME Alphas (%)								
$F1$	0.06	-0.16	-0.30	0.20	-0.13	-0.10	0.13	0.49
(t-stat)	(0.51)	(0.78)	(2.02)	(1.98)	(0.84)	(0.73)	(1.39)	(4.40)
$F2$	-0.01	-0.34	-0.16	0.46	0.03	0.04	0.16	0.44
(t-stat)	(0.05)	(1.56)	(1.04)	(4.32)	(0.21)	(0.25)	(1.64)	(3.52)
$F3$	-0.05	-0.11	0.06	0.45	0.23	0.30	0.23	0.39
(t-stat)	(0.41)	(0.48)	(0.35)	(3.75)	(1.25)	(2.00)	(2.22)	(2.59)

Table 13: **Low-SIR_{IO} Liquidity and Characteristic Matched Portfolios (long sample)**

For each of the anomaly portfolios in buckets $F1$-$F3$ (the high-SIR_{IO} stocks) in Table 11, we create a liquidity and anomaly-characteristic matched portfolio using only stocks from the low-SIR_{IO} ($F0$) bucket. The matched portfolios are formed by sorting the stocks in the $F0$ bucket into five quintiles by their Amihud (2002) liquidity measure and ten deciles by their corresponding anomaly characteristic. Each stock is assigned one of the 5 x 10 benchmark portfolios based on its liquidity and anomaly-characteristic value. The corresponding benchmark portfolios are then equal-weighted to obtain the matching portfolio. Matched long-short returns are given by the difference between the matched long portfolio return and the matched short portfolio return. Panel A reports the matched monthly long-short anomaly returns for each bucket. Panel B reports the corresponding FF4 alphas. Panel C reports the corresponding FF4 + CME alphas. The sample is April 1980 to October 2012.

SIR_{IO}	Anomalies							
Group	B/M	mom	$ivol$	cei	$distress$	$maxret$	nsi	$gprof$
Panel A: Monthly Returns (%)								
$F1$	0.49	0.35	0.44	0.35	0.53	0.56	0.31	0.52
(t-stat)	(2.62)	(1.20)	(1.66)	(2.45)	(2.20)	(2.28)	(2.33)	(4.46)
$F2$	0.47	0.35	0.58	0.51	0.67	0.62	0.40	0.58
(t-stat)	(2.42)	(1.15)	(2.25)	(3.70)	(2.72)	(2.59)	(3.21)	(4.74)
$F3$	0.50	0.51	0.85	0.55	0.82	0.86	0.46	0.60
(t-stat)	(2.50)	(1.66)	(3.56)	(4.11)	(3.29)	(3.85)	(3.57)	(4.38)
Panel B: Fama-French 4-Factor Alphas (%)								
$F1$	0.31	-0.21	0.35	0.40	0.35	0.53	0.30	0.55
(t-stat)	(2.94)	(1.12)	(2.26)	(4.51)	(2.31)	(3.48)	(3.37)	(5.37)
$F2$	0.29	-0.23	0.50	0.57	0.51	0.62	0.41	0.60
(t-stat)	(2.61)	(1.17)	(3.01)	(6.07)	(3.15)	(3.99)	(4.72)	(5.10)
$F3$	0.34	-0.06	0.73	0.59	0.69	0.83	0.46	0.59
(t-stat)	(2.73)	(0.28)	(4.13)	(5.93)	(3.87)	(5.12)	(5.18)	(4.19)
Panel C: Fama-French 4-Factor + CME Alphas (%)								
$F1$	0.02	-0.20	-0.33	0.21	-0.23	-0.14	0.10	0.42
(t-stat)	(0.22)	(0.98)	(2.21)	(2.18)	(1.58)	(0.96)	(1.02)	(3.82)
$F2$	-0.02	-0.32	-0.24	0.43	-0.13	-0.08	0.22	0.40
(t-stat)	(0.19)	(1.51)	(1.53)	(4.24)	(0.81)	(0.57)	(2.42)	(3.17)
$F3$	-0.04	-0.16	-0.06	0.46	0.00	0.11	0.31	0.32
(t-stat)	(0.30)	(0.71)	(0.38)	(4.29)	(0.02)	(0.71)	(3.18)	(2.13)