The Shorting Premium
and
Asset Pricing Anomalies

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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 1.31%, a net-of-fees return of 0.78%, and a 1.44% 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.

JEL: G11, G12, G14

Keywords: shorting premium, stock lending fees, anomalies, cross-section, concentrated risk, differences of opinion

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1 Introduction

Asset pricing theory has long recognized that market efficiency can depend strongly on participants who are willing and able to short sell overvalued securities. Miller (1977) argued that an asset that cannot be shorted will be overpriced when there are differences of opinion about its value, because investors with negative views cannot sell it. This theory puts the focus on short-selling constraints as the friction that limits short selling and allows mispricings to persist, an idea that has been influential in shaping the literature. However, this idea has not proven very successful at explaining perhaps the most well-known examples of overpricing, the cross-sectional anomalies in US stock returns. A main reason is that US stocks are not typically subject to short-sales prohibitions, and in almost all cases can be sold short (e.g., D'Avolio (2002)). Arbitrageurs can short shares by paying a fee (the "short fee") to borrow them in the stock loan market. Moreover, even when the cost of these fees is taken into account, short-sales constraints appear unable to explain anomalies because their average returns significantly exceed their fees (Geczy, Musto, and Reed (2002), Battalio and Schultz (2006)).

In this paper we show that focusing on short-sales constraints gives a very incomplete picture of the importance of short selling, and we demonstrate that short fees are highly informative about the cross-section of returns and return anomalies. This is due to what we call the "shorting premium", the large net-of-fee returns earned for shorting high short-fee stocks. We argue that this shorting premium reflects compensation demanded by arbitrageurs for bearing the risk involved in shorting high-fee stocks.

Our findings reveal large returns to shorting and tight relationships between short fees and eight large, well-known cross-sectional anomalies. Utilizing an extensive new database on US stock shorting fees, we find four main results. First, we show that shorting high short-fee stocks earns much higher returns than shorting low short-fee stocks, both gross *and* net of fees. This is captured by the return on the cheap-minus-expensive-to-short (CME) portfolio of stocks, which has an average monthly gross return of 1.31% and an average net-of-fees return of 0.78%. Moreover, its Fama-French four factor (FF4) alpha is 1.44% per month, so the CME portfolio's average return is not due to exposures to conventional risk factors. We call this average return the shorting premium.

Second, we reveal a relationship between short fees and the returns to eight well-known cross-sectional anomalies. We show that for each anomaly, short fees are substantially higher for the decile of stocks designated for shorting by the anomaly. Hence, short fees identify stocks that are overpriced according to the anomalies. However, the short fees do not cancel out the anomaly returns; as with the shorting premium itself, the anomalies' net-of-fee returns remain large.

Yet, this is far from the end of the story. Our third findings shows that conditioning on short fees has a powerful effect on anomaly returns. We demonstrate that anomaly returns effectively disappear when we look only within the set of low-fee stocks, a group which represents 80% of all stocks and an even greater fraction of total market capitalization. This finding suggests that anomaly returns are concentrated among high-fee stocks, which we show is indeed the case. We show that among high-fee stocks the anomalies are highly amplified, generating long-short returns that are very large even by the standards of the anomaly literature. We further demonstrate that the relationship between high fees and large anomaly returns is *not* due to the the size or liquidity of high-fee firms. Among low-fee firms with the same size and liquidity as high-fee stocks, anomaly returns are no higher than for low-fee firms in general.

We propose a joint explanation for these first three findings: the shorting premium represents compensation for the risk involved in shorting high-fee stocks. We argue that this risk is undiversifiable and therefore demands a premium. Moreover, the premium is large because in practice the risk is concentrated in the portfolios of the small minority of market participants who do substantial shorting. Because the risk is on the short side, the resulting premium raises prices rather than lowering them, as would normally be the case with a risk premium. In other words, short sellers stop shorting high-fee stocks well in advance of the point in which their prices decrease to the "fair" price as perceived by the average investor in the economy (and as measured by an econometrician using a conventional pricing model). Rather, the prices of high-short fee stocks remain 'high' because their subsequent low (even negative) average returns represent compensation for the concentrated short risk taken on by short sellers.

This theory provides the tests which lead to our fourth set of findings. Proxying for short risk using the return on the CME portfolio, we demonstrate that the addition of a CME factor to the conventional pricing model leads to dramatic reductions in anomaly alphas, and that the resulting FF4 + CME model largely captures anomaly returns among all stocks. Lending further support to the idea that high-fee stocks are exposed to an additional source of undiversifiable risk, we show that the return variance of a fixed portfolio of stocks rises in event time as the underlying stocks enter the expensive-to-short portfolio.

We begin our analysis with an examination of the distribution of short fees across stocks and the characteristics associated with high short-fee stocks. Previous studies on 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 an extensive 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, our sample is much longer than that used in earlier studies, spanning 2004-2013, which gives us substantial power to study differences in expected returns.

To study the cross-section of stocks by short fee, we sort stocks into deciles based on their shorting fee at the end of each month. We find that for each of the top eight deciles the average shorting fee is below 30 bps per year, indicating that 80% of stocks are cheap to short. The stocks in the ninth decile are moderately expensive to short (71 bps per annum on average), while those in the tenth decile are quite expensive to short, with an average fee of 571 per annum. The aggregate market capitalizations of the ninth and tenth decile stocks is economically large, an average of roughly \$1.05 trillion and \$405 billion over the sample.

We examine the average returns on these decile portfolios over the following month. 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 -0.33% per month, while 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 highly significant 1.31% per month, with a Fama-French four factor (FF4) alpha of 1.44% per month (t-stat 6.87). The difference in net-of-fee returns, while smaller, remains very large, with the average net of fee return on the CME portfolio a highly significant 0.78% per month. Hence, shorting high-fee stocks earns large returns even net of fees.

Next, we analyze the relationship between short fees and the returns of 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

[1]Data collection has been a challenge because the US stock loan market is decentralized and over-the-counter.

(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. 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. Book-to-market ratios and gross profitability are decreasing in the high short-fee deciles. The converse also holds. Sorting stocks based on their anomaly characteristics, we find the stocks which are designated for shorting by the anomaly strategies have by far the highest shorting fees.

We then demonstrate the dependence of anomaly returns on short fees. To that end, we sort stocks into four buckets based on their shorting fee. We put all of the low-fee stocks into one bucket and sort the remaining stocks by fee into three high-fee 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. With one exception, the average long-short anomaly returns in the low-fee bucket are small and insignificant. Moreover, all eight FF4 alphas are much smaller than their unconditional counterparts, with only three of eight remaining significant. This is the case despite the fact that the low-fee bucket contains 80% of all stocks. At the same time, the average anomaly returns and FF4 alphas in the high-fee bucket are all very large and either statistically significant or close to it despite the short sample. For instance, the average unconditional idiosyncratic volatility anomaly return in our sample is 70 bps per month, whereas its average return in the low-fee bucket is -14 bps per month, and its average return in the high-fee bucket is 156 bps per month.

We then use the FF4+CME model to investigate the possibility that the anomalies' alphas reflect compensation for exposure to shorting risk, as our theory suggests. We find that within the low-fee bucket *all* of the anomalies' FF4 + CME alphas are economically small and statistically insignificant. Similarly, for the intermediate and highest fee buckets the CME factor results in a large decrease in the FF4 alphas, so that only 2 out of the 24 anomalies' FF4 + CME alphas are insignificant. For instance, while idiosyncratic volatility has an enormous FF4 alpha of 179 bps per month, its FF4 + CME is only an insignificant 23 bps per month. The exception is the high-fee value-growth return, which is significant. With this exception, all the differences in FF4 + CME alphas between the low- and high-fee buckets are insignificant.

To demonstrate the robustness of our results and provide a comparison with other studies, we also use a proxy for shorting fees to extend our analysis to a longer sample covering 1980 to 2013. Our proxy is the ratio of short interest to institutional ownership, denoted SIR_{IO}. It provides a rough measure of the demand for shorting (short interest) relative to lending supply (institutional ownership). While noisy, this proxy allows us to analyze a long sample that significantly overlaps with the samples used in many cross-sectional return studies.

Overall we find similar, striking results. Sorting stocks into deciles based on SIR_{IO}, we again find a large and statistically significant spread of 1.42% per month between the average returns of low- and high-SIR_{IO} stocks, with a 1.51% per month FF4 alpha (t-stat 8.97). There is a strong correspondence between anomaly characteristics and SIR_{IO} and average anomaly returns and alphas are significantly smaller for low-SIR_{IO} stocks than for high-SIR_{IO} stocks. Moreover, we again find that adding a shorting risk factor into the conventional pricing model reduces alphas dramatically, with many becoming insignificant. One difference is that while anomaly returns among low SIR_{IO} stocks are substantially smaller than among high SIR_{IO} stocks, they remain mostly significant, perhaps in part as a result of noise in the short-fee proxy.

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 (Figlewski (1981), 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 for short sales constraints and limits-to-arbitrage: breadth of ownership (Chen, Hong and Stein, 2002), institutional ownership (Ali, Hwang, and Trombley (2003), and Asquith, Pathak, and Ritter (2005)), and short interest (Hanson and Sunderam, 2013). Nagel (2005) shows that low institutional ownership is associated with greater underperformance for stocks with high market-to-book, analyst forecast dispersion, turnover, and volatility. 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)). We argue that a large portion of the returns to high short fee stocks is due to the shorting premium and not simply the direct cost imposed by high short fees.

From a theoretical perspective, our work is closely related to the literature on limits of arbitrage and the role played by financial institutions in the formation of asset prices (see Gromb and Vayanos (2010) for a survey). It is also closely related to work on how differences of opinion affect equilibrium asset prices, particularly when shorting is limited in some way (e.g., Harrison and Kreps (1978), Scheinkman and Xiong (2003), Hong and Stein (2003), Basak (2005), Hong, Scheinkman, and Xiong (2006)) and to models of securities lending and high short fees (Duffie (1996), Duffie, Garleanu, and Pedersen (2002)).

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).[2] MSF collects self-reported data on the actual (rather than quoted) rates on security loans from over 100 participants in the securities lending market. The full dataset covers June 2002 to December 2013. 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. We therefore begin our sample in January 2004.

We match the MSF data to the CRSP database to obtain returns data and obtain accounting information by matching to 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.[3] 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 data required to calculate the associated anomaly 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 fee is the dollar value of the outstanding balance of the loan for that transaction divided by the total dollar value of outstanding balances for that time period. In keeping with the literature, we analyze trading strategies that are rebalanced monthly, and therefore use the 30-day value-weighted average fee fee as our measure of a stock's shorting fee. If an observation is missing the 30-day value-weighted average 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 has been available to most previous studies, which have tended to rely on data collected from a single institution in the stock loan market. The use of multiple sources for the

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

[3] This causes roughly 15% of the observations to be dropped in each month. We avoid a fixed share price cutoff and use a percentile cutoff instead because, owing to the large drop in share prices in 2008-2009, a fixed price cutoff creates tremendous variation in the percentage of observations dropped. For instance, using a fixed share price cutoff would cause us to drop observations on a number of large financial institutions (e.g., Citigroup) that traded at very low dollar values during this time period.

lending data helps ensure that it is unbiased and accurately captures the full cross-section of the lending market.

To extend our analysis to a long sample, we construct a proxy for the shorting fee. This proxy, denoted SIR_{IO} (Short Interest Ratio relative to Institutional Ownership), is the total short interest in a stock divided by the number of shares held by institutional investors. We obtain the short interest data from Compustat and the institutional ownership data from Thomson Reuters 13F. We construct the proxy series going back to the first quarter of 1980, when the 13F data is first available. The numerator and denominator of this proxy 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} serves 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 average number of 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 in each year of the sample. The number of stocks declines towards the end of the sample, reflecting 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 \$5.86 billion in 2013. The average book-to-market (B/M) ratio ranges from a low of 0.51 in 2007 to a high of 1.00 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% in 2008, before dropping sharply after the beginning of the financial crisis.

The column labeled SIR_{IO} gives the ratio of SIR and IOR and is our long-sample proxy for shorting fee. It also exhibits substantial variation, rising steadily until 2008, with a peak value of 11.3%, and then dropping after the start of the financial crisis. The following column gives average aggregate short interest for each year, the average dollar value of shares borrowed (per day) in that year. Figure 1 plots the time series of this quantity at the monthly frequency (shaded area). It shows that aggregate short interest rose steadily from the beginning of the sample until its August 2008 peak of $562 billion. It then dropped sharply by early 2009 to $250 billion, and subsequently trended back up for the remainder of the sample, rising to $500 billion by 2013.

The rightmost column of Table 1 shows the equal-weighted average annual shorting fee across all stocks. The average fee can be substantial. For instance, in 2012 and 2013 the average fee was 96 and 67 basis points, respectively. Some care is required in interpreting these values because, as we show below, most firm have low fees and high-fee firms are smaller than average. Nevertheless, these values show that even average shorting fees can be significant. The table further shows that, like the other measures of shorting activity, the average shorting fee varies substantially over time. This is further plotted in Figure 1 (solid line). The average fee increases from the beginning of the sample, peaking at 126 basis points over 2008. The end of 2008 sees a sharp spike up in the average fee, which then drops sharply to an average of 68 basis points in 2009. Average fee then increases in 2011 before decreasing back to average levels in 2013. Figure 1 also plots average fee weighted by the dollar value of stocks' short interest (dashed line). This measure tends to be lower than the equal-weighted fee but closely tracks its variation over time.

3 Shorting Fees and the Cross-section of Returns

We begin by examining the distribution of shorting fees across stocks and analyze their predictive power 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 value-weighted shorting fee over the previous 30 days, and then examine their returns over the following month. Panel A of Table 2 presents equal-weighted average returns and characteristics for these decile portfolios over our sample, January 2004 to December 2013. The decile 1 stocks, labeled "Cheap," have the lowest shorting fees, while the stocks in decile 10, labeled "Expensive," have the highest. Panel B sorts the decile ten stocks further 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 third column reports the average short fee (over the past thirty days) for each decile at the time of formation. For most stocks short fees are low. They are below 30 bps on average for each of the first eight deciles. Hence, on average, around 80% of stocks are cheap to short. For the remaining 20% of stocks shorting fees are substantial. The average short fee for decile nine rises to 71 bps, while the average short fee for decile ten is a very large 571 bps per year. For perspective, this is roughly the same magnitude as the equity premium or the value premium. Hence, investors who own these stocks and do not lend them out forgo a very substantial stream of payments. Yet, the very existence of high short fee stocks implies that their shares must all come to rest in the portfolios of such non-lending investors, as noted by Duffie (1996) and D'Avolio (2002).

Figure 2 provides a detailed view of the distribution of short fees among the expensive-to-short stocks (the tenth decile) over the sample period. This distribution is fairly smooth. The 25th, 50th, and 75th percentile values of short fees in decile ten are 189 bps, 359 bps, and 696 bps per year, respectively, and the vast majority of the probability mass lie below 10% per year. Above this level the likelihood of short fees is small and fairly uniform up to a level of roughly 23% a year, and there remain some rare instances of even higher fees in the range of 30-45% per year.

Table 2 reports the average monthly returns gross of fees ("Gross Ret") for the deciles. The gross returns are flat across the cheap-to-short stocks comprising the top eight deciles. However, average returns are lower for the ninth and particularly the tenth deciles of stocks. In particular, the expensive-to-short stocks earn a very low–in fact *negative*–average gross return of -0.33% per month. Consequently, the average return of a portfolio which goes long the (first decile) cheap-to-short stocks and shorts the (tenth decile) expensive-to-short stocks (henceforth the cheap-minus-expensive, or CME, portfolio) is an impressive 1.31% per month, which is highly significant (5.00 t-stat) despite the relatively short sample.

The large average return of the CME portfolio does <u>not</u> reflect a difference in the loadings of cheap- and expensive-to short stocks on conventional risk factors. The last column in the table, labeled "FF4α", reports the Fama-French four factor (FF4) alphas of the decile portfolios. It shows that the FF4 alpha of the expensive-to-short portfolio is -1.33% per month, which results in a large and highly significant FF4 alpha of 1.44% per month for the CME portfolio.

The table also shows that the average long-short return remains large after netting out shorting fees. To compute the net return on the long-short portfolio, we calculate the decile portfolio returns using the net monthly return on each stock, which is calculated as the gross return plus the value-weighted past 30 days shorting fee for the stock (converted to a monthly quantity). The average net returns are reported in the column labeled "Net Ret". The table shows that the CME portfolio continues to earn a very substantial average net return of 0.78% per month, which is again highly significant (3.01 t-stat).

Panel B show that average returns are even more dramatic if one examines portfolio 10b, the more expensive half of stocks in the decile 10 portfolio. The shorting fee on these stocks is very large, with an average of 921 bps per annum. Their average gross return is an abysmally low -0.99% per month, resulting in a highly significant 1.97% per month average return on the 1-minus-10b portfolio. Once more the FF4 alpha is even larger, at 2.14% per month (7.85 t-stat). Moreover, the return on the 1-minus-10b portfolio remains large even after accounting for the cost of shorting fees. The average net return on the 10b portfolio is -0.08% per month, resulting in a 1.07% per month average net return on the 1-minus-10b portfolio.

Table 2 also shows that the dollar amounts involved in the ninth and tenth decile portfolios are economically large. On average the total market capitalization of the tenth decile portfolio is \$405B over the sample. Including the ninth decile portfolio, the average total market capitalization of stocks with substantial shorting fees grows to \$1.45 trillion. This shows that even though only 10-20% of stocks have significant shorting fees, the total dollar values of companies that are expensive to short is economically large.

3.1 Relation to Anomaly Characteristics

Table 2 also reports averages for several characteristics of stocks in the decile portfolios, calculated at the time of portfolio formation. We focus on characteristics associated with the anomalies we study. The table shows that expensive-to-short stocks tend to 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. These features are even more pronounced for the stocks in portfolio 10b.

Overall, there is a strong association between the characteristic and decile rankings, with this relationship between the two strengthening in the high deciles, where the variation in shorting fees is also largest. Perhaps the weakest relationship is with 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 winner and loser stocks have relatively high shorting fees and in fact shorting fees are higher for the loser stocks. The situation is similar for the book-to-market ratio.

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 proxy for the shorting fee in the long sample. 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, starting with the eighth decile SIR_{IO} increases strongly, reaching values of 26.7% and 34.7% for the tenth decile and 10b portfolios, respectively.

Finally, the table shows how average market capitalization varies with the shorting fee. Stocks with the lowest short fees tend to be very large on average. Market capitalization is then effectively flat at roughly $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 the market cap of these stocks is sizable, with an average of $1.22B. The very expensive-to-short stocks in portfolio 10b tend to be a bit smaller, with an average market cap of roughly $0.9B.

3.2 The Shorting Premium

Table 2 shows that sorting on short fees induces a large spread in average returns, because expensive-to-short stocks earn very low average returns both gross and net of fees. The CME portfolio captures this spread in average returns, which we call the "shorting premium". Table 2 further shows that the shorting premium is not due to the exposure of the CME portfolio to conventional risk factors, as its FF4 alpha is even larger than its average return.

We note that the existence of high short fees, and the corresponding very low–in fact negative–average returns of expensive-to-short stocks, are an apparently clear example of inefficient investing behavior. Although some institutions may be prohibited from loaning out their shares, this does not rationalize such investing behavior because they would be better off selling their high-fee shares to investors who can collect the high fees. That they do not do this implies that they are significantly more optimistic about these high-fee stocks' prospects than are other investors. The stocks' subsequent low average returns show that this optimism is not subsequently borne out.

Table 2 further shows that the shorting premium remains very large even when the cost of shorting fees is netted out. This means that even investors who do lend out their shares earn very low total returns on expensive-to-short stocks. This finding is not explained by theories of overpricing based on short sales constraints, such as Miller (1977), which predict that assets become overpriced because investors who know they are overvalued cannot sell them. Generalized to a setting where stocks can be borrowed for a fee, this prediction becomes that short fees should increase until shorting is unprofitable. However, Table 2 shows that this is not the case. Empirically, short fees are sufficiently low that shorting high-fee stocks is highly profitable. Put another way, even when short fees are accounted for, short sellers do not short high-fee stocks down to the "fair" price according to conventional pricing models, thereby giving rise to the shorting premium.

We propose a theory to explain this finding: the shorting premium is a risk premium demanded by short sellers as compensation for their exposure to undiversifiable shorting risk. We assume that there are differences of opinion, with overly optimistic investors pushing the prices of some stocks too high. Short sellers (arbitrageurs) short these stocks to profit from their mispricing. To do so they borrow these stocks and hence drive up their shorting fees. If the returns of these positions are correlated with each other, their risk is undiversifiable and the arbitrageurs will demand a risk premium–the shorting premium. If arbitrageurs' risk-bearing capacity is small relative to investors, they will bear concentrated short risk in their portfolios and demand a large risk premium. The result is that overvalued stocks will have high fees, but their net returns will still appear low from the vantage point of the average investor (and the conventional pricing model). In other words, short sellers stop shorting high-fee stocks while their prices are still 'high', because the subsequent low returns of these stocks serve as compensation for their short risk exposure.

Under this theory, the marginal seller in high-fee stocks is an arbitrageur who holds concentrated short positions. A systematic risk for this arbitrageur is the covariance of a stock's return with the return on the expensive-to-short stock portfolio. Arbitrageurs price this shorting risk in addition to other systematic risks priced by investors. We use a stock's covariance with the return on the CME portfolio to proxy for this shorting risk. The average return on the CME portfolio–the shorting premium–gives the price short sellers charge for this risk exposure.

We note that exposure to the shorting premium *increases* prices, in contrast to the usual impact of risk premiums, which is to lower them. The difference with the usual case arises from incomplete risk sharing and the resulting lack of a representative investor. Short risk is concentrated in the portfolios of a subgroup of investors (the short sellers), who are marginal in setting the prices and fees of these stocks. They therefore price this short risk differently than does the average investor in the economy, for whom this risk is not systematic. In contrast, in a setting with full risk sharing, the marginal investor is the average investor. He is therefore net long all stocks and any risk premium reduces stock prices.

There is strong evidence in favor of the assumption that shorting is concentrated among a relatively narrow subgroup of market participants. Almazan et. al. (2004) report that more than two thirds of mutual funds are prohibited from shorting by their charter, and that only 3% of mutual funds actually sell short. A lot of equity shorting is probably due to a subset of equity hedge funds. Ben-David, Franzoni, and Moussawi (2012) cite a report by Goldman Sachs that estimates that 85% of all equity short positions going through Goldman's brokerage house in March 2010 were taken by hedge funds. They also note that aggregate short interest is similar to the stock market capitalization controlled by equity hedge funds.

Panel A of Table 3 reports the moments of the CME factor's monthly return. The mean return was already given in Table 2. The standard deviation is 2.87% per month, which is comparable to the standard deviation of the four Fama-French factors. This implies that the annualized Sharpe ratio of the CME gross (net) return is a very high 1.58 (0.94). The skewness of CME returns is negative, but not very large. The returns also exhibit a positive autocorrelation that appears relatively high. However, $mktrf$, HML, and UMD also exhibit high autocorrelations 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 expensive-to-short stocks have comparatively high betas, negatively correlated with SMB and HML, and positively correlated with the UMD.

The fact that the CME return has substantial volatility despite containing over three hundred stocks in each leg indicates that its constituent stocks display substantial co-movement. To get a further sense of this, we calculate the residuals of the cheap- and expensive-to-short portfolios from regressions of their returns on the four Fama-French factors. The standard deviation of the expensive-to-short portfolio's residual is 2.11%, which is substantially higher than the 0.79% standard deviation of the cheap-to-short portfolio. Hence, it is the high-fee stocks in particular which display strong co-movement. Dividing the portfolio residual variance by the average idiosyncratic variance of its constituent stocks gives a rough measure of their average pairwise correlation. The average correlation among the expensive-to-short stocks is 39%, which is substantially higher than the correlations among the eight cheap-to-short deciles, which average 22% and range from 15% to 27%. This suggests that high-fee stocks load on an additional source of common variation.

In what follows we first document tight relationships between the shorting premium and cross-sectional anomalies. We then provide further evidence that covariance with the high-fee stock portfolio is a priced risk.

4 Relation to Asset Pricing Anomalies

We 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. Our aim is not to exhaust the set of documented anomalies. We focus on these anomalies because they are associated with large spreads in average returns and have received substantial attention in the literature.[4]

4.1 Unconditional Returns

Panel A of Table 4 examines the returns of these anomalies over our 2004-2013 sample period. For each anomaly, we sort all stocks into ten portfolios based on the corresponding anomaly characteristic. We order the deciles so that the first decile contains the stocks in the long leg

[4] We do not include the so-called size anomaly because it is *not* associated with a substantial spread in returns in either our short or long samples.

(value stocks, winner stocks, low idiosyncratic volatility stocks, etc...) and the tenth decile contains the stocks in the short leg. The top portion of Panel A reports the average returns of these deciles, while the bottom portion analyzes the corresponding long-short (decile one minus decile ten) portfolios.

The first row in the bottom portion of Panel A shows the average gross return of the long-short portfolios. With the exception of momentum, the average gross returns are large. However, due to the fairly short sample, only three of these average raw return spreads are statistically significant.[5]

The next row in the bottom portion of Panel A reports the net returns of these long-short portfolios. The net long-short returns are all less than the gross returns, reflecting the higher average shorting fees of the stocks in the short leg of the portfolio. The reduction in average returns from gross to net returns is meaningful for all the portfolios, with a high of 23 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 netting out shorting fees. This finding may not be surprising at this point, given that we have already seen that sorting on shorting fees themselves produces a large spread in net returns.

The following row in Panel A shows the FF4 alphas of the long-short gross returns.[6] The alphas are mostly larger than the average returns, in several cases significantly so. With the exception of momentum, the alphas are also all highly statistically significant despite the short sample. This shows that exposures to the conventional risk factors does not explain the large long-short anomaly returns.

The last row in Panel A shows the alphas of the long-short returns relative to the asset pricing model suggested by our shorting premium theory. This model includes the CME return as an additional risk factor. Although we defer the main analysis of this model until further below, we report the alphas for it here for completeness. The table shows that the inclusion of this CME factor leads to a very large reduction in the alphas of all the anomalies except value-growth. Indeed, with this exception, the long-short FF4+CME

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

[6]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 gross and net average returns. Hence, looking at either gross or net alphas gives a very similar picture.

alphas all decrease and become insignificant. For instance, the alpha of the idiosyncratic volatility portfolio decreases from a highly significant FF4 value of 1.20% per month to an insignificant 0.08% per month. Similarly, the FF4 alphas of net share issuance and gross profitability decrease from highly significant values of 0.70% and 1.07% per month, respectively, to an insignificant 0.03% and 0.40% per month. These reductions demonstrate that exposure to shorting risk can explain a large proportion of the average returns earned by these anomalies.

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

4.2 Returns Conditional on Shorting Fees

Next, we examine the interaction between shorting fees and average anomaly returns. We do so by examining the returns to each anomaly conditional on 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 anomaly returns within each of the buckets.

We create the low fee bucket from the cheap-to-short stocks, the stocks in the top eight shorting-fee deciles. 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 these low-fee bucket stocks into deciles based on each of the anomaly characteristics (just as in the full sample of stocks), and examine the corresponding anomaly long-short returns.

We sort the more expensive to short stocks (the ninth and tenth deciles by shorting fee) into three equal size buckets based on shorting fee. This gives us two intermediate fee buckets (labeled $F1$ and $F2$) and a 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 in 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. Hence, this procedure gives us one anomaly long-short portfolio in each of the four shorting fee buckets, for a total of 32 anomaly portfolios.

This sequential sort provides us with a robust, non-parametric 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 large anomaly returns.

Panel A of Table 5 shows the average gross monthly long-short returns for each of the anomalies in each of the buckets. These are reported in the first four rows of the panel. The fifth row of 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 difference allows us to assess whether there is a difference in the size of the average anomaly returns between low- and high-short-fee stocks.

The results exhibit several striking patterns. First, except for gross profitability all of the average long-short returns in the low-fee bucket ($F0$) are small and statistically insignificant, and only the average return of gross profitability exceeds 20 bps per month in absolute value. This is in stark contrast to the unconditional long-short returns, which are much larger. Indeed, for most of the anomalies, the difference relative to the unconditional return is quite remarkable. For example, idiosyncratic volatility (*ivol*) has an unconditional return of 70 bps per month and an average low-fee bucket return of -14 bps! Similarly, the average low-fee momentum return is also negative, at -15 bps per month.

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

The second pattern that emerges is that the average anomaly returns increase strongly with the level of shorting fees. The average long-short return in the $F1$ bucket is generally higher than that in the low fee bucket. The average anomaly return in the $F2$ bucket is larger still and of similar magnitude to the unconditional anomaly returns. Finally, the average returns in the high fee $F3$ bucket are very large across all the anomalies. For example, the average idiosyncratic volatility return is 1.56% per month and highly statistically significant. Indeed, despite the short sample most of the average returns in the $F3$ bucket are highly statistically significant. Even the average return on momentum is sizeable, despite being negligible 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 all sizeable and statistically significant or close to it in four of the eight cases.

To summarize, Panel A shows that there is little evidence of anomaly returns within the eighty percent of stocks that have low shorting fees. Instead, the anomalies are concentrated among stocks with significant fees, especially the highest short-fee stocks, where the average anomaly returns are very large. Indeed, even momentum, which exhibits a negligible return spread unconditionally, is sizable among the high-fee stocks.

The fee buckets are rebalanced monthly. To help understand the migration of stocks across these bucket, Figure 3 plots their transition matrix for periods of one, three, six, and twelve months. The transition matrix shows that although stocks do migrate 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 also in this bucket twelve months later, while about 20% have transitioned into the low-fee bucket. Hence, the return patterns we document do **not** depend on rebalancing the portfolios at a high frequency.

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 but are more pronounced. The alphas for the low-fee anomaly returns are all much smaller than the unconditional alphas, and are statistically insignificant in five of the eight cases. Hence, there is not much evidence of mispricing associated with these anomalies among low fee stocks, which constitute 80% of all stocks and an even greater fraction of total market capitalization.

The FF4 alphas increase in the intermediate fee buckets, and generally increase again as we move up to the $F2$ bucket. Moreover, despite the short sample, the $F2$ alphas are statistically significant in all cases except momentum. Moving to the high fee ($F3$) bucket, the alphas are now all large, including momentum. With the exception of momentum they are also now highly statistically significant despite the short sample. For example, the FF4 alpha of idiosyncratic volatility is 1.79% per month, with a t-statistic of 4.10.

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

4.3 The FF4 + CME Model

We now examine whether the large average returns and positive alphas we find among stocks with significant fees can be explained by exposure to shorting risk. As discussed above, if investors holding concentrated short positions in high-fee stocks are marginal in setting these stocks prices, then the covariance of a stock with the high-fee stock portfolio will represent a systematic priced risk. As explained above, we proxy for this risk using the return on the CME portfolio and create a FF4 + CME model by augmenting the four conventional risk factors with the CME shorting-risk factor.

Panel C of Table 5 reports the alphas of the anomaly portfolios based on the FF4 + CME factor model. The table shows that the alphas in the low-fee bucket $F0$ are close to zero and also now all insignificant. The main difference relative to the FF4 alphas is that even the composite equity issuance and gross profitability alphas are insignificant, due to a reduction in their magnitude from 40 bps and 64 bps per month to 11 bps and 29 bps, respectively. Hence, among 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 an even larger fraction of the total market capitalization.

Turning to the intermediate fee $F1$ and $F2$ buckets, the FF4 + CME alphas are far smaller than their FF4 counterparts and are insignificant for fifteen out of the sixteen anomaly portfolios. In contrast, all the anomalies except momentum had $F2$-bucket FF4 alphas that were significant. Hence, the FF4 + CME model clearly does a much better job in capturing these average returns.

The most striking results are for the stocks in the high-fee bucket ($F3$). Here the FF4 + CME alphas tend to be far smaller than their FF4 counterparts. Seven of the eight alphas 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, whereas the high-fee idiosyncratic volatility portfolio has a FF4 alpha of 1.79% per month (t-stat of 4.14), its FF4 + CME model alpha is only 0.23% per month (t-stat 0.52).

Overall, the FF4 + CME alphas are insignificant for 30 out of the 32 anomaly portfolios across the four shorting-fee buckets. The main exception is the value-growth return in the high-fee bucket, where the 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 anomaly returns between the high- and low-fee buckets. In contrast to the differences in average returns and FF4 alphas, the differences in FF4 + CME alphas are all insignificant except for value-growth, which is due to its high alpha in the high-fee bucket. This shows that accounting for exposure to shorting risk equalizes risk-adjusted average returns between low- and high-fee stocks by capturing high-fee stocks' large anomaly returns.

Figure 4 plots a comparison of predicted versus realized average returns for the FF4 and FF4 + CME models. Each anomaly is plotted separately. Within each plot the points are the extreme characteristic-sorted portfolios for each of the four fee-sorted buckets. Hence, each plot shows eight different portfolios for each of the two models: the decile one and ten portfolios from the $F0$ bucket and the first and third tercile portfolios from the $F1$, $F2$, and $F3$ buckets.

The figure shows that the FF4 + CME model has a much superior fit. This is particularly the case for the portfolios that have low returns, which for the FF4 model generally lie significantly below the forty-five degree line. The FF4 model is unable to account for these low, and sometimes negative, average returns. For the higher return portfolios the fit of the FF4 model is reasonable. In contrast, the fit of the FF4 + CME model is quite good. The model 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 hypotheses that are related. First, the absence of significant anomaly returns and FF4 alphas in the low fee stocks supports the view that market frictions (limited risk sharing in the case of our theory), and not just aggregate risk, are responsible for large anomaly returns. This view is further supported by the strong interaction between short fees and average anomaly returns. Second, the success of the FF4 + CME model in explaining anomaly returns and their interaction with short fees supports the theory that these phenomena are in large part driven by exposure to shorting risk.

Finally, we note another implication of the results in Table 5. In a well-known critique of the risk-factor model of Fama and French (1993), Daniel and Titman (1997) argue that stocks' average returns may be better captured by their (anomaly) characteristics than by their factor covariances. The findings in Table 5 show that this is not the case for the short fee characteristic. The reason is that the long-short anomaly portfolios are created within buckets that control for short fees. Since the short fees are equal between the long and short legs of the anomaly portfolios, they cannot explain the large difference in their average returns. In contrast, the two legs have very different exposures to the CME portfolio, as evidenced by the large decreases in alphas between Panels B and Panel C.

4.3.1 Fees and Comovement

An interesting question is what accounts for the high level of co-movement among the high-fee ("E") portfolio stocks. Is this co-movement associated with these stocks being in the E portfolio, or was it already present beforehand. Daniel and Titman (1997) ask a similar question in the context of their study. For instance, it is possible that a group of highly covarying stocks receive a common shock that raises their short fees, which then shows up as high-fee stocks covarying. Note that in either case, covariation with the CME factor represents a source of risk. However, the former case suggests that becoming high fee is associated with an increase in covariation among stocks, whereas the latter case implies that this covariance structure was already present beforehand.

To distinguish between these two cases we follow Daniel and Titman (1997) and track the return volatility of the portfolio of E stocks from sixty months before the date on which they become the E portfolio (the pre-formation period) until sixty months afterwards (the post-formation period). Specifically, for each date t and number of months N, $-60 \leq N \leq 60$, we calculate the one month return of the equally-weighted portfolio of all stocks that belong to the decile ten portfolio on date $t - N$ and have a valid return observation for t to $t + 1$. We then calculate the standard deviation of the return series for each value of N.

Figure 5 shows the results. The upper plot shows the pre-formation standard deviations, while the lower plot shows the post-formation standard deviations. For each plot we calculate the series for all N using one set of calendar dates, so that all points in the cross-section are exposed to the same events in calendar time. Due to the relatively short available sample, we separate the calculation of the pre- and post-formation periods in order to maintain a sufficient number of data points for each.[7]

The upper plot shows that the volatility of the E portfolio *increases* markedly over the pre-formation period. The portfolio's volatility rises from approximately 5.1% per month 60 months prior to portfolio formation to roughly 6.2% per month by formation time. Similarly, in the post-formation period the portfolio's volatility decreases steadily, from a value of 7.2% at formation to roughly 6.4% sixty months later.

This evidence shows that covariation among the group of stocks increases as they enter into the E portfolio. This suggests that they become exposed to an additional source of covariation as they enter this portfolio, which is not present beforehand or afterwards.

4.4 Can Size or Liquidity Account for the Returns?

Table 2 shows that high-fee stocks are generally smaller than average. The average size of a firm in the highest short-fee decile during the sample period is \$1.22 Billion, making it a small mid-cap stock. Hong, Lim, and Stein (2000) find that momentum returns decrease sharply with firm size. This raises the possibility that the large anomaly returns we find among high-fee firms may be related to their small average size rather than their high short fees. Similarly, because smaller firms are generally less liquid, one may wonder if the large anomaly returns are associated with low liquidity rather than high fees.

One piece of evidence against these alternatives is that we see that anomaly returns increase strongly from the intermediate-fee bucket $F1$ to the high-fee bucket $F3$ in Table 5. This already suggests that it is actually high short fees, not size or liquidity, that accounts

[7]In the long-sample analysis below the sample is sufficiently long that we can use a single common sample for both the pre- and post-formation periods, and hence produce a single plot that contains both.

for the large anomaly returns. Nevertheless, we would like a more direct of this hypothesis.[8]

To do so, we create 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 $F1$ to $F3$, 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. The matched long-short return is then the difference between the returns of the matched long and short leg portfolios.

We compare the average returns and alphas of the matched anomaly portfolios to their high-fee counterparts from Table 5. If the large returns we find in Table 5 are actually due to firm size rather than high fees, then we should find that the matched anomaly portfolios exhibit 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. We use the same analysis on portfolios matched to liquidity and anomaly characteristics to assess the possibility that liquidity accounts for our findings.

We create matching portfolios by applying the approach of Daniel, Grinblatt, Titman, and Wermers (1997) within 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 gives the matched anomaly 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

[8]Note that many of our findings continue to hold regardless. These include the finding that anomaly returns are concentrated in a small subgroup of stocks and that the FF4+CME-based factor model is able to capture these anomaly returns. Nevertheless, the interpretation of these results is affected by the answer to this question.

to separate the effect of size and high short fees on the magnitude of the anomaly returns. Using Amihud's (2002) measure of liquidity, we follow the same procedure 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 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 the matching anomaly returns do not increase from the $F1$ to the $F3$ bucket, in sharp contrast to Table 5. 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 they are on average if high-fee firms are excluded. This is an interesting finding by itself and it may explain why some studies (e.g., Hong, Lim, and Stein (2000)) find that anomaly returns are only large outside 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. With the exception of value-growth, the FF4+CME alphas are even smaller than the already small FF4 alphas, consistent with earlier findings. Notably, 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) mirror the raw returns and closely resemble those of the low-fee bucket. Hence, Table 7 shows that liquidity cannot account for the large anomaly returns we find in the sample of high-fee firms.

5 Long Sample Analysis

We now conduct a similar analysis on a longer sample using a proxy for shorting fees. Our proxy is the variable SIR_{IO}, short interest relative to shares owned by institutions. Although our sample of shorting fee data is, to the best of our knowledge, the longest and broadest that has been studied, its time series is still relatively short in comparison to many studies of the cross-section of expected returns. While our results show that the length of this time series provides sufficient power to document significant anomaly alphas, it remains interesting to extend the sample backwards and obtain greater overlap with the samples used in previous cross-sectional studies. However, doing so requires the use of a proxy for short fee that may introduce substantial noise into the analysis.

The use of SIR_{IO} as a proxy allows us to extend the sample back to April 1980, so that our long sample covers April 1980 to December 2013. Table 8 undertakes a similar analysis as 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 of Table 8. The rows again report equal-weighted averages of returns and characteristics for the stocks in the decile portfolios over the long sample.

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 fairly low average SIR_{IO} values. This is consistent with our earlier finding that shorting fees are low for most stocks. Similar to shorting fees, SIR_{IO} rises strongly in the ninth and especially tenth deciles. The effectiveness of SIR_{IO} as a proxy is corroborated by column four, which reports the average short fee for each decile in the period 2004 to 2013, the sample where this data is available. In particular, short fees are by far the highest in the tenth decile, with an average fee of 401 bps per annum. The second highest fees are clearly in the ninth decile, with an average fee (74 bps) that is very similar to that of decile nine in Table 2. Finally, there is comparatively little variation in average fee across the top eight deciles, similar to the case in Table 2.

While SIR_{IO} is an effective proxy, it is not perfect. In particular, the table shows that short fees actually decrease moderately in SIR_{IO} in the first few deciles, producing a J-shaped relationship in the average short fee.[9] This outcome reflects noise in institutional ownership as a proxy for supply in the lending market. For some stocks, supply may be significantly lower (i.e., their supply curve is steeper) than indicated by their institutional ownership, so that even small amounts of shorting–and hence low SIR_{IO}–can induce significant short fees.

Despite the noise in SIR_{IO} as a short-fee proxy, the patterns in Table 8 are quite similar to those in Table 2. Importantly, the relationship between decile numbers and average returns 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 very low. Consequently, the difference in average returns between the first and tenth SIR_{IO} deciles is very large and highly statistically significant, at 1.42% per month (t-stat 5.83).

The table further shows that the difference in average returns across the deciles is not captured by corresponding differences in their loadings on conventional risk factors. The Fama-French four factor (FF4) alpha (labeled "FF4α") of the high SIR_{IO} portfolio is -1.05% per month, whereas the alpha of the CME portfolio is a highly significant 1.51% per month! Note that this FF4 alpha is larger than that of any of the well-known anomalies we study over the long-sample period, 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 higher half of stocks in the decile 10 portfolio based on SIR_{IO} value. The average SIR_{IO} value for these stocks is a tremendous 81.0%, so these are stocks where the amount of shorting is very large relative

[9] D'Avolio (2002) finds a similar relationship.

to the potential total supply. The average raw return on the 10b portfolio is −0.34% per month, resulting in an average monthly return on the 1-minus-10b portfolio of 1.82%. The FF4 alpha is again even larger, at 1.92% per month (t-stat 9.93).

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 again similar to those of the shorting-fee deciles in Table 2. 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.

The relationship between characteristics and decile rankings always strengths at the high deciles. A difference with 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 The E Factor

In keeping with our existing terminology, we refer to the stocks in the tenth SIR_{IO} decile as expensive to short, and to the portfolio of these stocks as the "E" portfolio. As highlighted in the discussion of Table 8 above, the use of the SIR_{IO} proxy does not, however, allow us to readily identify the decile of cheapest-to-short stocks. Therefore, we create the long-sample proxy for shorting risk using only the return on the E portfolio, rather than using the difference between the returns on this portfolio and a corresponding C portfolio, as we did in the short sample.

Specifically, our shorting risk factor for the long sample analysis is the return on a zero-cost portfolio that is long the risk-free asset (1-month treasury bills) and short the E portfolio. We refer to this factor as the E factor. We view this approach to constructing the shorting risk factor in the long sample as conservative relative to the conventional approach of creating a spread portfolio. It circumvents the need to identify the cheap-to-short portfolio and hence avoids introducing noise into its returns due to errors in this identification. However, it comes at a potential cost in terms of maximizing the model's fit.[10] Similar to Section 4, we refer to the cross-sectional pricing model which combines the E factor with the conventional four risk factors as the FF4 + E model.

5.3 Unconditional Anomaly Returns

Table 9 documents the returns to the eight anomalies over the long sample period, April 1980 to December 2013. The structure of the table is the same as in Table 4. The top row in the bottom portion of Panel A reports the average return for each of the anomaly long-short portfolios. As the table shows, all of the average anomaly returns are large and statistically significant. The next row reports the FF4 alphas of the anomalies. 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 anomaly returns cannot be explained by their exposures to the conventional four risk factors.

The last row in the bottom portion of Panel A reports the alphas of the anomaly returns relative to the FF4 + E model. Including the E factor leads to a large reduction in the magnitudes of the alphas of all the anomalies except for the already small momentum alpha. While most of the remaining alphas remain statistically significant, they all decrease by roughly 50% or more from their FF4 values. The largest reductions in alphas are for distress,

[10] If the C portfolio is well-diversified then its return should be well captured by the four conventional risk factors, for which we already control, and hence the loss in model fit should be small. We note that in the short fee sample replacing the CME portfolio with the analogous E factor does not materially change any of our findings.

idiosyncratic volatility and max return, where the alphas are each reduced by at least 93 bps per month. This striking reduction in alphas is consistent with our short-sample results and shows that exposure to shorting risk goes very far towards explaining the average returns to these eight well-known anomalies.

Panel B of Table 9 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. Moreover, 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 even in decile one. These patterns are similar to those for short fees shown in Table 4.

5.4 Returns Conditional on Shorting Fees

Next, we repeat the analysis of Table 5 using SIR_{IO} in place of shorting fee, allowing us to examine the interaction between this short-fee proxy and anomaly returns in the long sample. Table 10 shows the results. The structure mirrors that of Table 5. As in Table 5, the "low fee" bucket ($F0$) consists of the stocks in the top eight SIR_{IO} deciles. The ninth and tenth deciles are again also sorted into the intermediate and high fee buckets ($F1$ through $F3$). In creating the anomaly long-short returns, the low fee bucket is again sorted into ten deciles based on the corresponding anomaly characteristics and each of the high fee buckets is sorted into three terciles. The long-short portfolio returns are given by the difference between the returns of the extreme portfolios within each bucket.

Panel A again shows the average returns in each of the four buckets. As in Table 5, there is a clear pattern of average anomaly long-short returns increasing strongly from the low- to the high-fee buckets. In most cases the average long-short return in the $F1$ bucket is higher than that in the $F0$ bucket, and 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 2.15% per month! Even the smallest average return in $F3$ is a very large 92 bps per month.

The bottom row of panel A reports the difference in average anomaly returns between the low- and high-fee buckets. The differences are large, and with the exception of value-growth and gross profitability, highly statistically significant.

A difference relative to the findings in Table 5 is that the average returns in the low-fee bucket of Table 10 are statistically significant in all but one case. Part of this difference may be due to the use of a proxy for shorting fee in sorting the stocks into buckets. Noise in this proxy will make this sorting imprecise and hence blur the differences in average returns across buckets.

5.4.1 Four Factor Alphas

Panel B of Table 10 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 substantially 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 $F0$). The differences in alphas are 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 our use of a noisy proxy for shorting fee.

5.5 FF4 + E Alphas

We now use the SIR_{IO}-based E factor to proxy for shorting risk in the long sample. Panel C of Table 10 reports the long-sample alphas of the anomaly portfolios relative to the SIR_{IO}-based FF4 + E model. Relative to their FF4 counterparts, the alphas in the $F0$ bucket are generally significantly smaller. For example, the alphas of distress and max return are reduced from 101 bps and 97 bps per month, respectively, under the FF4 model, to 28 bps and 32 bps per month under the FF4 + E model. Except for the momentum alpha, which is insignificant under both models, all the alphas decrease in magnitude. Moreover, four of the eight anomaly alphas are now insignificant at the 5% level. Arguably only the net share issuance alpha (51 bps) and gross profitability alpha (61 bps) remain economically sizable. Hence, among the low fee stocks the evidence for anomalous returns relative to the FF4 + E model is weak.

The FF4 + E alphas of the anomaly returns in the $F1$ and $F2$ buckets are all fairly small and statistically insignificant. Indeed, with one exception the alpha magnitudes are all 50 bps per month or less across the sixteen long-short portfolios. Twelve of the the sixteen are 22 bps or less in magnitude. In comparison, the FF4 alphas are much larger and also generally statistically significant. The dramatic decrease in alphas shows that accounting for shorting risk exposure allows the model to capture most of the expected returns of these portfolios.

Turning to the high fee ($F3$) bucket, across all anomalies there is a striking reduction in alphas from the FF4 model to the FF4 + E model. For example, the alphas of idiosyncratic volatility, composite equity issuance, max return, and distress decrease from 200 bps, 111 bps, 209 bps, and 157 bps per month, respectively, to 100 bps, 57bps, 127 bps, and 48 bps per month. Still, five of the eight anomalies' alphas remain significant at the 5% level (all eight have significant FF4 alphas) as their FF4 alphas are so large that they remain significant despite the large reductions (100 bps, 54 bps, 82 bps, 109 bps respectively).

The bottom row of Panel C again examines the difference in anomaly alphas between the high-fee and low-fee buckets. This difference is only significant for idiosyncratic volatility and max return. The remaining differences are all 27 bps or less. In contrast, the differences in average returns and FF4 alphas were mostly both large significant and large. This finding corroborates that in the short sample, and shows that accounting for exposure to shorting risk helps equalize risk-adjusted returns across the low and high fee stocks.

Figure 6 plots a comparison of realized versus predicted average returns for the FF4 and SIR_{IO}-based FF4 + E models in the long sample. Each anomaly is plotted separately and the points are the extreme characteristic-sorted portfolios within each of the four SIR_{IO}-sorted buckets.

The figure shows that the FF4 + E provides a far superior fit 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 + E model is quite good for both the low- and high- return portfolios, though perhaps the model's fit to some of the very low return portfolios is not as good as was the fee-based version of the model in the short sample. Nevertheless, in all cases the model provides a pretty good fit, and clearly one that is significantly better than the FF4 model.

In summary, the SIR_{IO}-based FF4 + E model is able to capture a substantial part of the average returns of all these anomalies in the long sample, corroborating our findings in the short sample. We again find that average returns and FF4 alphas are strongly increasing in the shorting fee proxy, SIR_{IO}. Much of the difference disappears, and the alphas are substantially reduced, once compensation for exposure to shorting risk exposure is accounted for. These results provide further support for the theory that compensation for shorting risk is a significant component of the expected returns to these anomalies.

5.5.1 Short Interest and Comovement

We again examine whether the high co-movement of stocks in the SIR_{IO}-based E portfolio reflects an increase in co-movement among stocks when they enter this portfolio, or whether this covariance structure was present beforehand. We repeat the procedure used in Section 4.3.1 to calculate the evolution of the return volatility of the portfolio of E stocks from sixty months before the portfolio's formation date to sixty months afterwards.

An advantage of the long sample is that we do not face the same sample length limitations as in Section 4.3.1. The sample is now long enough to use one set of calendar dates for both the pre- and post-formation periods, allowing us to graph the evolution of the portfolio's volatility over both periods within a single plot. Figure 7 shows the result. The pattern shown is similar to that obtained by putting together the top and bottom plots of Figure 5 for the fee-based E portfolio. The volatility of the portfolio rises markedly over the pre-formation period, from approximately 6.8% per month sixty months prior to portfolio formation, to roughly 8.2% per month by the portfolio formation date. During the post-formation period the portfolio's volatility decreases steadily, so that by sixty months after formation it is down to 6.6% per month. Hence, the figure shows that the portfolio's volatility rises and falls in tandem with stocks' entrance into the E portfolio. The covariance structure of the group of stocks is not constant, but instead increases in event time as the E portfolio's formation date is approached. As Daniel and Titman (1997) note, this pattern is consistent with these stocks loading onto an additional source of covariation when they are in the E portfolio.

5.6 Size and Liquidity Matched Portfolios

We repeat the analysis of Section 4.4 in the long sample in order to separate the impact of high SIR on anomaly returns from that of firm size or stock liquidity. Following the procedure used 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 10.

Table 11 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 10. 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 in the $F1$ to $F3$ buckets in Table 10. 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 10. As a consequence, in all cases the high-SIR_{IO} ($F3$) anomaly returns are far larger than their matched returns. The same patterns hold for the FF4 alphas (panel B) of the matched portfolios. Hence, panels A and B of Table 11 show that firm size does *not* account for the highly amplified anomaly returns we find among high-SIR_{IO} firms.

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

Finally, Table 12 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 or large FF4 alphas we find among high-SIR_{IO} firms. Moreover, we again find that the FF4 + E alphas are substantially smaller than their FF4 counterparts. Indeed, all 24 of the matched portfolio FF4+E alphas are 50 bps or less in magnitude.

6 Conclusion

We document the shorting premium and reveal tight relationships between this premium and the returns to eight well-known cross-sectional anomalies. Our analysis establishes four main findings. Short fees are a strong predictor of the cross-section of stock returns, both gross and net of fees. This result is reflected in the large average return and four-factor alpha of the CME portfolio. Two, short fees are substantially higher for stocks designated for selling by anomalies. Three, anomaly returns are highly dependent on short fees: the anomalies largely disappear among the 80% of stocks that have low fees, but are highly amplified among those with high fees. Four, the Fama-French + CME model, which captures exposure to shorting risk, is able to capture most of the anomaly returns among both high- and low-fee stocks.

We provide a joint explanation for these findings. Our theory is that the shorting premium is compensation demanded by arbitrageurs for exposure to undiversifiable risk involved in shorting. We envisage a world where optimistic investors drive up the prices of certain stocks, making them overvalued. Arbitrageurs short these stocks, causing their short fees to increase. Hence, high fees identify stocks that are in arbitrageurs' portfolios. This also implies that for arbitrageurs, a stock's systematic risk includes its covariance with the high-fee portfolio. Because in practice such arbitrageurs represent a small subset of market participants, they end up bearing concentrated amounts of this shorting risk and therefore demand a large risk premium to do so.

The shorting premium implies that prices remain too high from the vantage point of the average investor. The difference with the usual outcome–that risk premia decrease prices–is due to incomplete risk sharing. In the standard setting with full risk sharing, all investors price risk equally at the margin and market clearing implies that they are long every stock. However, if short sellers are marginal then it is their personal risk-return tradeoff that matters for prices. If their risk-bearing capacity is limited, then a large shorting premium can arise and the prices of high-fee stocks will be high from the perspective of the average investor.

Instead of being viewed as exotic, this outcome may be quite prevalent in asset markets. Indeed, the ingredients necessary for this situation to arise–differences of opinion between market participants and limited short seller risk-bearing capacity–are very generic. In many settings it may simply be difficult to identify this situation empirically. In the case of stocks, short fees provide a valuable window for doing so because they provide a price-based proxy for differences of opinion.

The fact that large short fees are prevalent for stocks with substantial aggregate market capitalization shows that such differences of opinion are important. Moreover, our finding that shorting is highly informative about the cross-section of returns and the sources of anomalies indicates that concentration of risk plays an important role in asset pricing even in a market as large and liquid as US stocks. It seems likely that the same forces also play an important role in many other markets.

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Figure 1: Time Series of Aggregate Short Interest and Average Shorting Fee

The figure plots the monthly time series of aggregate short interest and the average lending (i.e., shorting) fee across all stocks. The shaded area plots the aggregate dollar value of shares shorted across all stocks in billions of dollars, measured in the middle of the month. The solid blue line plots the equal weighted average annual shorting fee across all stocks in basis points. The dashed red line reports the short-interest weighted average annual shorting fee across all stocks in basis points.

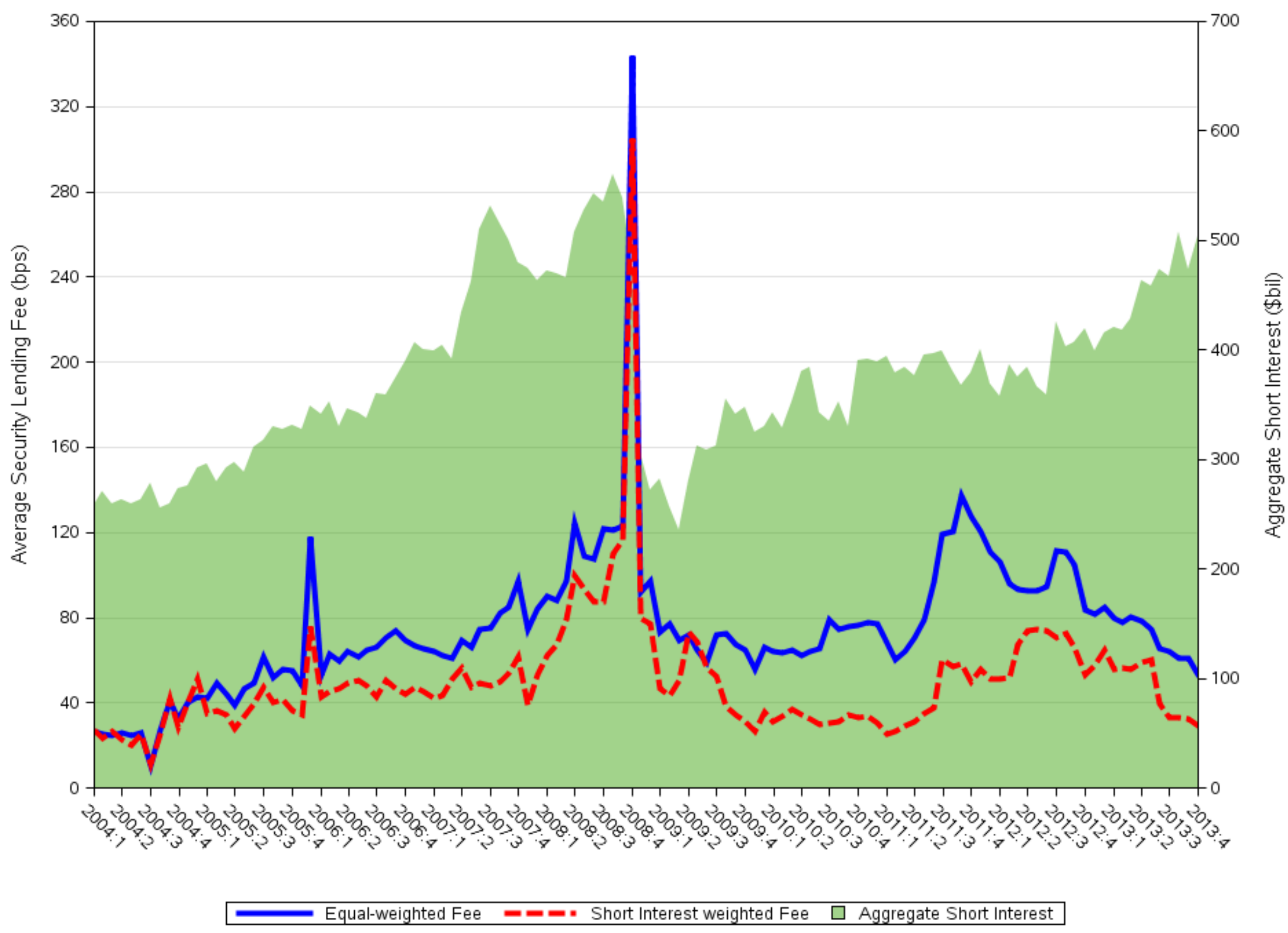


Figure 2: Distribution of Decile 10 Short Fees

The figure plots a histogram of the annual short fees for the expensive-to-short stocks (decile 10 in Table 2). It is calculated for the sample of all short fees for decile-10 stocks from January 2004 to December 2013. The legend reports the distribution's mean, 25-percentile ("P25"), median, and 75th-percentile ("P75") values.

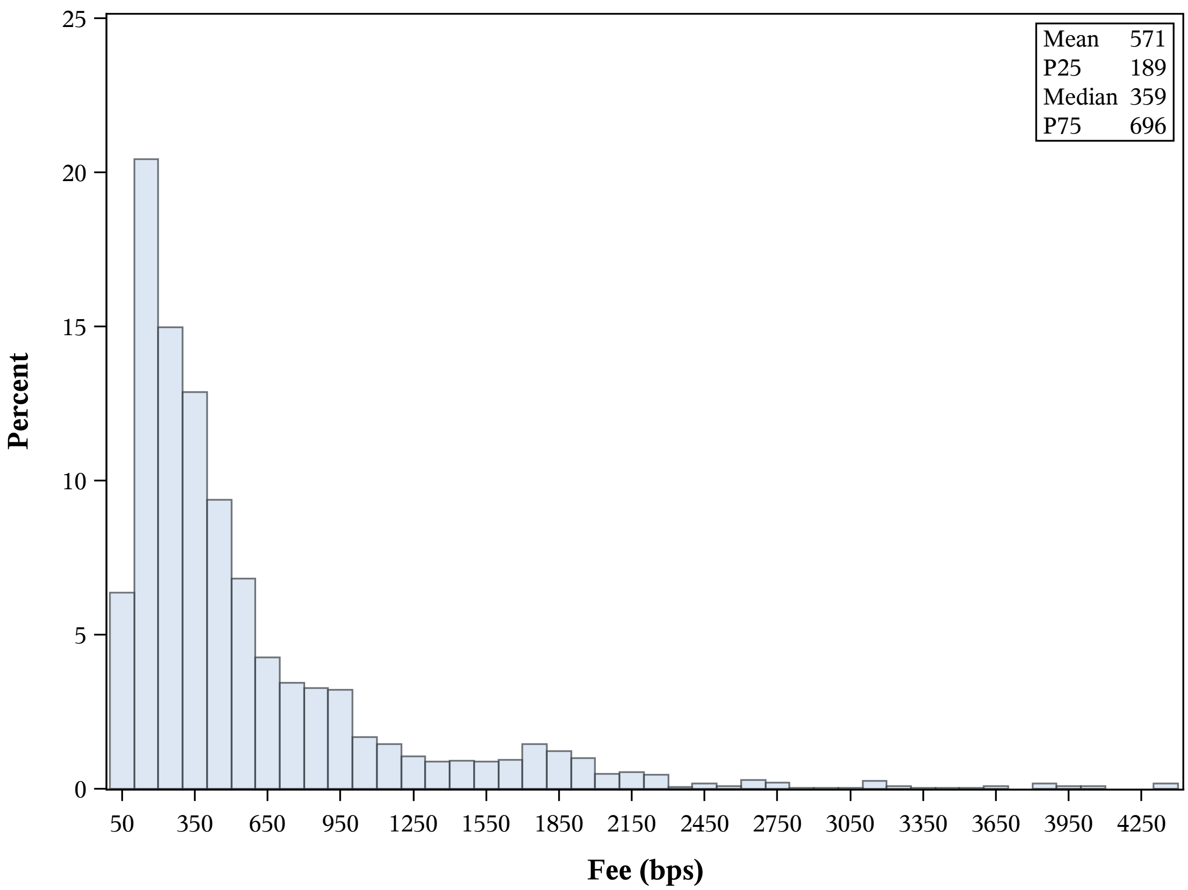


Figure 3: Transition Probabilities of Stocks Based on Shorting Fee

The figure plots the transition probabilities of stocks across the four short-fee-sorted buckets of Table 5 over periods of one, three, six, and twelve months, as indicated in the plot title. For instance, in the plot labeled "1", the row labeled "F0" shows the percentage of stocks in the F0 bucket that ends up in each of the four buckets after 1 month.

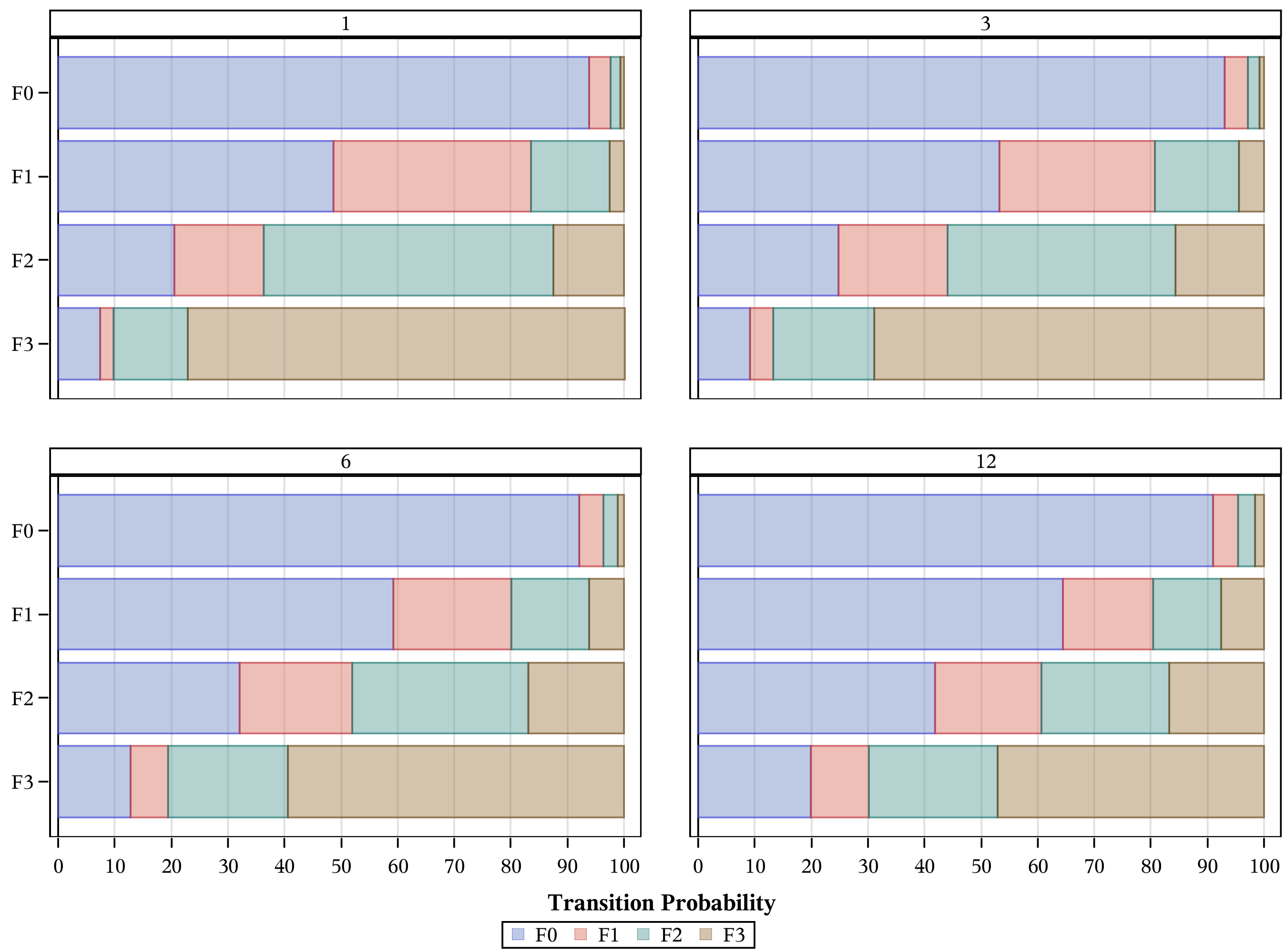
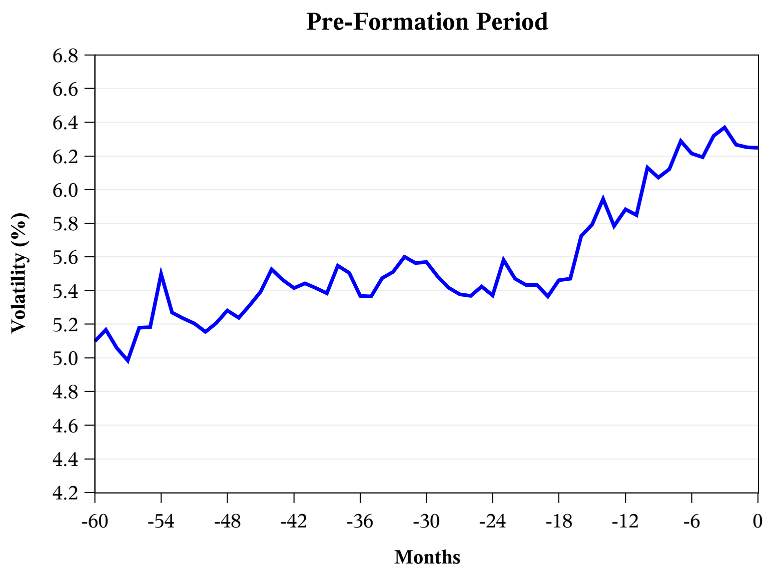


Figure 4: Realized versus Predicted Average Returns

For each anomaly, the figure plots the realized average monthly return versus the predicted average monthly return for each of the extreme characteristic-sorted portfolios in each of the short-fee sorted buckets of Table 5. The blue circles correspond to the Fama-French four-factor (FF4) model, while the red pluses correspond to the FF4 + CME model. The sample period is January 2004 to December 2013.

Figure 5: Pre- and Post-Formation Monthly Return Standard Deviations of the Decile Ten Portfolio (Fee Sorted)

The figure plots the monthly standard deviation of the pre- and post-formation returns of the tenth decile portfolio of stocks sorted by short fee (from Table 2). For each date t and number of months N, we calculate the one month return of the equally-weighted portfolio of all stocks that belong to the decile ten portfolio on date $t - N$ and have a valid return observation for t to $t + 1$. For each N we then calculate the standard deviation of the resulting return series. Within a plot we use the same calendar dates to calculate all the series so that the cross-section is exposed to the same events in calendar time. The upper plot shows the pre-formation standard deviations going back 60 months. The sample used for this plot is January 2004 to December 2008. The lower plot shows the post-formation standard deviations going forwards up to 60 months. The sample used for this plot is January 2009 to December 2013.



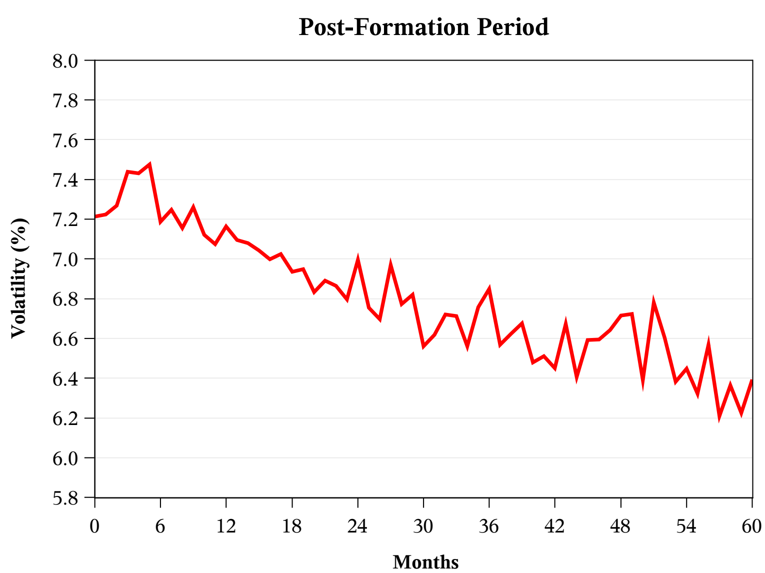


Figure 6: Realized versus Predicted Average Returns (long sample)

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 in each the short-fee sorted buckets of Table 10. The blue circles correspond to the Fama-French four-factor (FF4) model, while the red pluses correspond to the FF4 + E model (based on SIR_{IO}). The sample period is April 1980 to December 2013.

Figure 7: Pre- and Post-Formation Monthly Return Standard Deviations of the Decile Ten Portfolio (SIR_{IO} Sorted)

The figure plots the monthly standard deviation of the pre- and post-formation returns of the tenth decile portfolio of stocks sorted by SIR_{IO} (from Table 8). For each date t and number of months N, we calculate the one month return of the equally-weighted portfolio of all the stocks that belong to the decile ten portfolio on date $t - N$ and have a valid return observation for t to $t + 1$. For each N we then calculate the standard deviation of the resulting return series. We use the same calendar dates to calculate all the series so that the cross-section is exposed to the same events in calendar time. The figure shows pre- and post-formation standard deviations for up to 60 months from portfolio formation. The sample is April 1985 to December 2008.

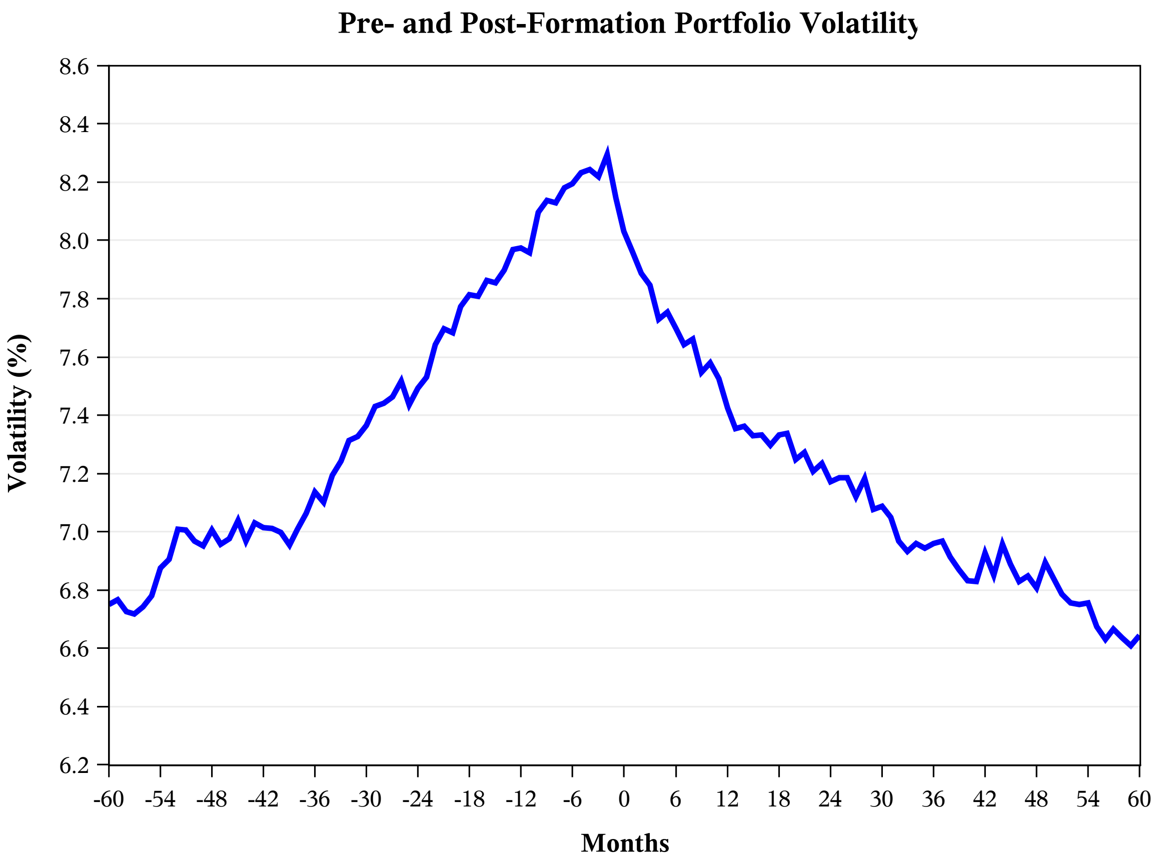


Table 1: **Summary Statistics**

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 Aggregate Short Interest are equal-weighted averages.

Year	No. Stocks	Market Cap. (\$*mil*)	B/M	IOR (%)	SIR (%)	SIR_{IO} (%)	Aggregate Short Interest (\$*bil*)	Short Fee (*bps*)
2004	3,072	3,988	0.58	59.2	4.4	8.0	267	29
2005	3,435	3,919	0.52	60.1	4.4	8.3	312	55
2006	3,529	4,100	0.52	62.2	5.2	9.0	362	65
2007	3,653	4,384	0.51	64.5	6.2	9.9	464	75
2008	3,568	3,803	0.60	64.9	7.3	11.3	473	126
2009	3,358	3,014	1.00	60.6	4.9	8.4	307	68
2010	3,283	3,792	0.85	60.1	5.0	9.4	360	70
2011	3,195	4,500	0.70	63.2	5.0	8.7	385	98
2012	3,113	4,811	0.77	63.0	5.0	9.0	392	96
2013	3,036	5,853	0.73	62.6	4.7	8.2	472	67

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

At the end of each month from January 2004 to December 2013 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. Fee is the annualized short 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 (usual) raw return without accounting for shorting fees; *Net Ret* is the return net of shorting fees. $FF4\,\alpha$ is the Fama-French 4-factor alpha. Returns are monthly and in percent. Panel B further splits the stocks in decile 10 by their shorting fee.

Fee Decile	No. Stocks	*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)	332	3	4.5	16.05	0.62	9.93	1.65	0.04	-8.36	4.63	0.02	0.98	0.99	0.12
2	332	8	5.9	6.51	0.64	10.12	1.82	0.06	-8.37	5.08	0.02	1.04	1.05	0.14
3	333	10	6.6	3.69	0.64	9.94	1.92	0.08	-8.33	5.29	0.03	1.11	1.12	0.17
4	332	12	6.6	2.34	0.66	9.92	2.01	0.09	-8.33	5.52	0.03	1.03	1.04	0.11
5	332	13	6.3	1.99	0.69	9.63	2.11	0.09	-8.25	5.72	0.03	1.14	1.15	0.18
6	333	15	6.2	1.82	0.72	9.14	2.20	0.09	-8.26	5.92	0.03	1.11	1.12	0.18
7	333	18	7.0	2.55	0.73	10.08	2.26	0.10	-8.22	6.11	0.04	1.20	1.21	0.24
8	332	29	8.9	2.91	0.72	10.48	2.41	0.14	-8.05	6.44	0.05	1.11	1.13	0.16
9	333	71	12.5	3.11	0.69	10.33	2.67	0.21	-7.78	6.98	0.07	0.83	0.88	-0.10
10 (Expensive)	332	571	26.7	1.22	0.66	12.62	3.41	0.44	-3.24	8.76	0.12	-0.33	0.21	-1.33
$1-10$ Return												1.31	0.78	1.44
(t-stat)												(5.00)	(3.01)	(6.87)
Panel B: Highest Fee Decile														
$10a$ (Expensive)	166	223	18.6	1.56	0.68	10.47	3.11	0.33	-7.48	8.00	0.10	0.32	0.49	-0.63
$10b$ (Expensive)	166	921	34.7	0.88	0.64	14.73	3.72	0.57	1.16	9.52	0.15	-0.99	-0.08	-2.02
$1-10b$ Return												1.97	1.07	2.14
(t-stat)												(5.95)	(3.28)	(7.85)

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

Summary statistics for the monthly return of the CME (cheap-minus-expensive) portfolio. Panel A reports moments of the CME return. Panel B gives the correlation matrix for the returns of the CME portfolio and the four Fama-French factors, $MKTRF$, SMB, HML, and UMD. The sample is January 2004 to December 2013.

Panel A: Moments					
N	Mean(%)	Std. Dev.(%)	Skewness	Kurtosis	AC(1)
120	1.31	2.87	-0.38	1.51	0.26
Panel B: Correlations					
	CME	$MKTRF$	SMB	HML	UMD
CME	1.00	-0.36	-0.47	-0.28	0.46
$MKTRF$		1.00	0.46	0.34	-0.33
SMB			1.00	0.18	-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 eight anomalies. For each anomaly, we sort stocks 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 annualized 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 ($maxret$), net share issuance (nsi), and gross profitability ($gprof$). The sample is January 2004 to December 2013.

Anomaly	Anomalies							
Rank	B/M	mom	$ivol$	cei	$distress$	$maxret$	nsi	$gprof$
Panel A: Anomaly Strategy Returns (%)								
1 (Long)	1.15	1.15	0.92	0.99	1.09	0.93	0.95	1.24
2	1.03	0.94	1.06	0.93	1.08	1.01	0.94	1.09
3	0.96	0.94	1.03	1.08	1.08	1.09	0.91	1.13
4	1.05	1.05	0.95	1.09	1.07	1.06	0.92	1.11
5	0.87	0.97	1.06	1.09	1.13	1.08	1.13	1.18
6	1.03	1.01	1.10	1.24	1.11	0.97	1.12	1.03
7	0.91	1.07	1.00	1.07	1.14	0.96	1.11	0.97
8	0.85	1.01	1.05	1.08	1.16	0.89	1.05	0.82
9	0.75	0.92	0.81	0.86	1.00	0.81	0.75	0.41
10 (Short)	0.64	1.00	0.22	0.48	0.47	0.39	0.40	0.28
L-S Return	0.51	0.15	0.70	0.51	0.62	0.54	0.55	0.96
(t-stat)	(1.52)	(0.25)	(1.49)	(1.92)	(1.19)	(1.20)	(2.26)	(3.46)
L-S Net Fee Return	0.44	0.07	0.47	0.40	0.44	0.37	0.41	0.84
(t-stat)	(1.29)	(0.11)	(1.00)	(1.51)	(0.84)	(0.83)	(1.69)	(3.05)
L-S FF4 α	0.45	0.19	1.20	0.78	0.98	1.05	0.70	1.07
(t-stat)	(2.24)	(0.64)	(4.30)	(3.42)	(3.87)	(4.09)	(3.34)	(3.55)
L-S FF4+CME α	0.65	0.16	0.08	0.14	0.48	0.25	0.03	0.40
(t-stat)	(2.68)	(0.44)	(0.29)	(0.56)	(1.61)	(0.89)	(0.13)	(1.14)
Panel B: Average Annual Shorting Fee (bps)								
1 (Long)	80	104	26	46	47	37	45	80
2	52	56	26	44	32	37	42	54
3	52	48	31	37	34	40	62	49
4	51	46	38	39	37	47	73	51
5	51	46	47	37	41	54	58	55
6	54	49	56	39	46	60	55	49
7	60	56	72	41	59	75	50	68
8	64	65	95	53	75	93	62	71
9	83	89	135	79	112	123	114	83
10 (Short)	151	169	228	148	220	187	169	189

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

We divide the short-fee deciles from Table 2 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 divided into three equal-sized buckets, $F1$ to $F3$, based on shorting fee, with $F3$ containing the highest 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 of the extreme portfolios. Due to the larger number of stocks in the $F0$ bucket, we sort it 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 anomaly and bucket. Panel B reports the corresponding FF4 alphas. Panel C reports the FF4 + CME alphas. The sample period is January 2004 to December 2013.

Fee Bucket	Anomalies B/M	mom	$ivol$	cei	$distress$	$maxret$	nsi	$gprof$
Panel A: Monthly Returns (%)								
$F0$	0.19	-0.15	-0.14	0.19	-0.07	-0.10	0.17	0.65
(t-stat)	(0.60)	(0.25)	(0.32)	(0.87)	(0.13)	(0.23)	(0.82)	(2.51)
$F1$	0.26	0.22	0.69	0.17	0.22	0.41	-0.21	0.68
(t-stat)	(0.79)	(0.47)	(1.98)	(0.49)	(0.45)	(1.09)	(0.64)	(2.17)
$F2$	0.59	0.11	0.65	0.41	0.71	0.62	0.50	0.74
(t-stat)	(1.56)	(0.20)	(1.61)	(0.98)	(1.26)	(1.53)	(1.46)	(2.36)
$F3$	0.67	0.56	1.56	1.00	1.22	1.26	0.49	1.06
(t-stat)	(1.48)	(1.09)	(3.40)	(1.88)	(2.03)	(2.73)	(1.28)	(2.63)
$F3 - F0$	0.48	0.71	1.70	0.80	1.29	1.36	0.33	0.41
(t-stat)	(1.33)	(1.13)	(3.62)	(1.74)	(2.46)	(3.31)	(1.00)	(1.26)
Panel B: Fama-French 4-Factor Alphas (%)								
$F0$	0.11	0.05	0.32	0.40	0.34	0.35	0.38	0.64
(t-stat)	(0.73)	(0.18)	(1.42)	(2.38)	(1.50)	(1.69)	(2.32)	(2.63)
$F1$	0.30	0.37	1.06	0.38	0.56	0.79	0.03	0.62
(t-stat)	(1.09)	(1.14)	(4.06)	(1.24)	(1.96)	(2.81)	(0.11)	(2.04)
$F2$	0.72	0.22	1.00	0.71	1.13	0.98	0.79	0.72
(t-stat)	(2.32)	(0.58)	(3.23)	(2.01)	(3.07)	(3.35)	(2.90)	(2.26)
$F3$	0.74	0.54	1.79	1.21	1.41	1.51	0.70	1.03
(t-stat)	(2.12)	(1.12)	(4.10)	(2.42)	(2.62)	(3.54)	(2.12)	(2.56)
$F3 - F0$	0.63	0.49	1.48	0.81	1.07	1.17	0.32	0.40
(t-stat)	(1.80)	(0.90)	(3.60)	(1.74)	(2.13)	(3.06)	(1.07)	(1.19)
Panel C: Fama-French 4-Factor + CME Alphas (%)								
$F0$	0.30	0.18	-0.18	0.11	0.19	0.09	0.10	0.29
(t-stat)	(1.70)	(0.50)	(0.72)	(0.56)	(0.72)	(0.38)	(0.53)	(1.04)
$F1$	0.48	0.48	0.71	0.12	0.49	0.56	-0.32	0.42
(t-stat)	(1.48)	(1.26)	(2.31)	(0.34)	(1.45)	(1.68)	(0.99)	(1.16)
$F2$	0.48	-0.21	-0.07	-0.07	0.59	0.17	0.08	0.69
(t-stat)	(1.30)	(0.46)	(0.22)	(0.17)	(1.37)	(0.52)	(0.26)	(1.81)
$F3$	1.10	0.69	0.23	0.67	0.12	0.20	-0.01	0.37
(t-stat)	(2.66)	(1.19)	(0.52)	(1.14)	(0.20)	(0.44)	(0.01)	(0.79)
$F3 - F0$	0.80	0.52	0.42	0.57	-0.08	0.11	-0.11	0.08
(t-stat)	(1.90)	(0.80)	(0.92)	(1.02)	(0.14)	(0.26)	(0.30)	(0.19)

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 then 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 anomaly returns for each bucket. Panel B reports the corresponding FF4 alphas. Panel C reports the FF4 + CME alphas. The sample period is January 2004 to December 2013.

Fee Bucket	Anomalies B/M	mom	$ivol$	cei	$distress$	$maxret$	nsi	$gprof$
Panel A: Monthly Returns (%)								
$F1$	0.21	-0.12	-0.11	0.09	-0.01	0.01	-0.02	0.54
(t-stat)	(0.88)	(0.33)	(0.38)	(0.45)	(0.02)	(0.04)	(0.13)	(2.39)
$F2$	0.25	-0.16	0.00	0.08	0.05	0.09	0.09	0.63
(t-stat)	(0.97)	(0.42)	(0.01)	(0.36)	(0.12)	(0.31)	(0.52)	(2.63)
$F3$	0.13	-0.13	0.04	0.14	-0.02	0.04	0.17	0.56
(t-stat)	(0.51)	(0.29)	(0.15)	(0.58)	(0.05)	(0.15)	(0.90)	(2.27)
Panel B: Fama-French 4-Factor Alphas (%)								
$F1$	0.23	0.02	0.15	0.27	0.29	0.29	0.15	0.41
(t-stat)	(1.80)	(0.12)	(0.81)	(1.90)	(1.79)	(1.72)	(1.29)	(2.18)
$F2$	0.30	0.00	0.24	0.26	0.38	0.36	0.28	0.52
(t-stat)	(2.12)	(0.02)	(1.20)	(1.66)	(1.91)	(2.09)	(2.10)	(2.47)
$F3$	0.19	0.05	0.22	0.32	0.29	0.24	0.35	0.48
(t-stat)	(1.21)	(0.21)	(1.00)	(1.66)	(1.26)	(1.22)	(2.48)	(2.06)
Panel C: Fama-French 4-Factor + CME Alphas (%)								
$F1$	0.47	0.10	-0.26	0.10	0.16	0.05	-0.03	0.19
(t-stat)	(3.23)	(0.40)	(1.22)	(0.58)	(0.84)	(0.27)	(0.22)	(0.84)
$F2$	0.54	0.04	-0.18	0.04	0.18	0.13	0.12	0.30
(t-stat)	(3.32)	(0.16)	(0.79)	(0.20)	(0.77)	(0.62)	(0.79)	(1.19)
$F3$	0.33	0.11	-0.17	0.07	0.02	-0.07	0.20	0.24
(t-stat)	(1.79)	(0.40)	(0.70)	(0.30)	(0.09)	(0.29)	(1.17)	(0.89)

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 then 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 FF4 + CME alphas. The sample period is January 2004 to December 2013.

Fee Bucket	Anomalies B/M	mom	$ivol$	cei	$distress$	$maxret$	nsi	$gprof$
Panel A: Monthly Returns (%)								
$F1$	0.26	-0.11	-0.09	0.08	0.03	0.02	0.01	0.57
(t-stat)	(1.10)	(0.29)	(0.31)	(0.38)	(0.06)	(0.07)	(0.04)	(2.55)
$F2$	0.26	-0.08	0.08	0.04	0.06	0.07	0.09	0.60
(t-stat)	(1.03)	(0.20)	(0.25)	(0.19)	(0.13)	(0.24)	(0.55)	(2.57)
$F3$	0.15	-0.10	0.15	0.13	0.05	0.06	0.19	0.54
(t-stat)	(0.58)	(0.24)	(0.52)	(0.57)	(0.12)	(0.22)	(1.11)	(2.27)
Panel B: Fama-French 4-Factor Alphas (%)								
$F1$	0.28	0.04	0.17	0.27	0.35	0.30	0.18	0.45
(t-stat)	(2.20)	(0.21)	(0.85)	(1.86)	(2.12)	(1.72)	(1.51)	(2.43)
$F2$	0.31	0.09	0.31	0.23	0.39	0.33	0.27	0.48
(t-stat)	(2.27)	(0.44)	(1.50)	(1.45)	(1.96)	(1.90)	(2.14)	(2.38)
$F3$	0.20	0.07	0.32	0.31	0.37	0.26	0.37	0.45
(t-stat)	(1.32)	(0.28)	(1.46)	(1.70)	(1.70)	(1.37)	(2.71)	(2.04)
Panel C: Fama-French 4-Factor + CME Alphas (%)								
$F1$	0.50	0.13	-0.27	0.10	0.23	0.05	-0.02	0.28
(t-stat)	(3.37)	(0.53)	(1.23)	(0.61)	(1.20)	(0.25)	(0.12)	(1.27)
$F2$	0.53	0.10	-0.12	0.02	0.16	0.11	0.06	0.26
(t-stat)	(3.31)	(0.39)	(0.52)	(0.13)	(0.69)	(0.52)	(0.39)	(1.10)
$F3$	0.33	0.08	-0.12	0.03	0.16	-0.07	0.14	0.15
(t-stat)	(1.84)	(0.29)	(0.48)	(0.14)	(0.62)	(0.34)	(0.89)	(0.58)

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

At the end of each month from April 1980 to December 2013, 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}, while decile 10 the stocks with the highest SIR_{IO}. Fee_{04-13} is shorting fee, available only for the years 2004 to 2013; *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. Returns are in percent. Panel B further splits the stocks in decile 10 by SIR_{IO}.

SIR_{IO} Decile	No. Stocks	SIR_{IO} (%)	$Fee_{(04-13)}$ (*bps*)	*mktcap* (\$ *bil*)	B/M	*mom* (%)	*ivol* (%)	*cei*	*distress*	*maxret* (%)	*nsi*	*gprof*	*Ret* (%)	$FF4\,\alpha$ (%)
Panel A: Portfolio Characteristics and Returns by Decile														
1 (Low)	342	0.1	56	0.46	1.01	8.02	2.65	0.01	-8.10	6.27	0.03	30.36	1.47	0.47
2	343	0.5	39	4.30	0.91	9.38	2.54	0.02	-8.15	6.16	0.03	32.26	1.48	0.39
3	343	0.9	29	3.88	0.85	9.59	2.43	0.02	-8.17	6.00	0.03	33.28	1.40	0.25
4	342	1.5	25	3.18	0.83	10.08	2.38	0.03	-8.19	5.96	0.03	33.75	1.45	0.25
5	342	2.1	24	2.98	0.81	10.61	2.38	0.04	-8.20	6.00	0.03	34.20	1.37	0.16
6	343	2.9	24	2.46	0.79	11.07	2.44	0.06	-8.16	6.19	0.04	33.71	1.33	0.12
7	343	4.1	30	1.87	0.78	11.29	2.56	0.10	-8.06	6.51	0.05	33.17	1.18	0.02
8	342	6.2	40	1.39	0.77	11.77	2.74	0.14	-7.95	6.94	0.06	32.65	1.03	-0.14
9	343	11.1	74	0.92	0.74	12.00	2.98	0.19	-7.76	7.56	0.06	31.27	0.84	-0.27
10 (High)	342	51.6	401	0.50	0.68	13.17	3.69	0.33	-6.26	9.31	0.09	26.72	0.05	-1.05
$1-10$ Return													1.42	1.51
(t-stat)													(5.83)	(8.97)
Panel B: Highest SIR_{IO} Decile														
10*a*	171	22.4	178	0.55	0.69	11.55	3.38	0.27	-6.77	8.53	0.08	30.35	0.45	-0.64
10*b*	171	81.0	634	0.46	0.67	14.77	4.01	0.41	-5.72	10.10	0.11	22.94	-0.34	-1.46
$1-10b$ Return													1.82	1.92
(t-stat)													(6.94)	(9.93)

Table 9: **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 + E model using the SIR_{IO}-based E factor. Panel B reports the average SIR_{IO} for the stocks in each anomaly decile. The sample is April 1980 to December 2013.

Anomaly Rank	Anomalies *B/M*	*mom*	*ivol*	*cei*	*distress*	*maxret*	*nsi*	*gprof*
Panel A: Anomaly Strategy Returns (%)								
1 (Long)	1.51	1.71	1.25	1.50	1.82	1.39	1.54	1.72
2	1.45	1.35	1.39	1.44	1.47	1.43	1.32	1.50
3	1.33	1.27	1.41	1.44	1.46	1.46	1.26	1.38
4	1.37	1.18	1.41	1.39	1.41	1.41	1.22	1.28
5	1.27	1.21	1.46	1.42	1.34	1.44	1.34	1.30
6	1.13	1.14	1.45	1.43	1.24	1.29	1.37	1.07
7	1.09	1.06	1.26	1.34	1.20	1.28	1.30	1.02
8	1.05	0.97	1.17	1.23	1.05	1.07	1.18	1.02
9	0.83	0.78	0.80	1.05	0.86	0.80	0.84	1.06
10 (Short)	0.55	0.78	-0.04	0.60	0.24	0.01	0.48	0.59
L-S Ret	0.96	0.94	1.29	0.90	1.58	1.38	1.06	1.12
(t-stat)	(3.76)	(2.44)	(3.65)	(4.54)	(4.96)	(4.27)	(5.95)	(6.16)
L-S FF4 α	0.64	0.17	1.31	0.92	1.38	1.48	1.07	1.12
(t-stat)	(4.59)	(0.70)	(6.26)	(7.37)	(6.43)	(7.33)	(8.54)	(6.05)
L-S FF4+E α	0.34	-0.39	0.27	0.45	0.35	0.55	0.59	0.66
(t-stat)	(2.39)	(1.60)	(1.68)	(3.99)	(2.09)	(3.37)	(5.26)	(3.59)
Panel B: Average SIR_{IO} (%)								
1	5.94	12.10	3.93	4.77	4.74	4.13	5.56	7.70
2	5.03	7.62	4.07	3.95	4.58	4.55	5.46	6.55
3	5.17	6.63	4.77	4.19	4.90	5.14	6.78	6.50
4	5.43	6.02	5.55	4.25	5.27	5.98	6.81	6.64
5	5.93	6.14	6.60	5.06	5.81	6.75	6.38	6.87
6	6.28	6.26	7.74	6.20	6.62	7.79	6.60	7.57
7	6.78	6.76	9.05	7.12	7.60	8.91	7.22	8.11
8	8.55	7.84	10.68	8.34	9.05	10.44	9.10	7.60
9	10.51	9.84	12.83	9.78	11.72	12.10	11.12	6.56
10	18.24	15.06	16.36	13.48	16.46	15.56	14.04	14.55

Table 10: **Anomaly Returns Conditional on SIR_{IO} (long sample)**

We divide the SIR_{IO}-sorted deciles from Table 9 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 + E alphas. The sample is April 1980 to December 2013.

SIR_{IO} Group	Anomalies B/M	mom	$ivol$	cei	$distress$	$maxret$	nsi	$gprof$
Panel A: Monthly Returns (%)								
$F0$	0.64	0.63	0.60	0.53	1.14	0.83	0.69	0.77
(t-stat)	(2.80)	(1.79)	(1.86)	(3.08)	(4.07)	(2.78)	(4.70)	(5.27)
$F1$	0.45	0.89	1.02	0.54	1.11	0.90	0.58	0.89
(t-stat)	(1.67)	(2.95)	(3.33)	(2.43)	(3.69)	(3.15)	(2.90)	(4.63)
$F2$	0.51	1.01	1.07	0.53	1.39	1.02	0.62	0.72
(t-stat)	(1.91)	(3.08)	(3.58)	(2.11)	(4.72)	(3.67)	(2.99)	(3.82)
$F3$	0.92	1.25	2.15	1.25	1.81	2.11	1.14	1.16
(t-stat)	(3.41)	(3.55)	(7.32)	(4.32)	(5.61)	(7.42)	(4.73)	(5.08)
$F3 - F0$	0.27	0.62	1.55	0.72	0.66	1.28	0.44	0.40
(t-stat)	(1.22)	(2.39)	(6.49)	(3.01)	(2.60)	(5.36)	(2.16)	(1.87)
Panel B: Fama-French 4-Factor Alphas (%)								
$F0$	0.39	-0.04	0.67	0.57	1.01	0.97	0.73	0.80
(t-stat)	(3.12)	(0.20)	(3.54)	(5.10)	(5.39)	(5.37)	(6.91)	(5.33)
$F1$	0.18	0.32	0.84	0.42	0.88	0.84	0.56	0.89
(t-stat)	(0.98)	(1.38)	(3.86)	(2.51)	(3.76)	(3.96)	(3.24)	(4.72)
$F2$	0.24	0.39	0.91	0.46	1.19	0.94	0.42	0.79
(t-stat)	(1.28)	(1.53)	(4.03)	(2.32)	(4.98)	(4.21)	(2.34)	(4.07)
$F3$	0.59	0.56	2.00	1.11	1.57	2.09	1.03	1.14
(t-stat)	(2.61)	(1.95)	(7.98)	(4.36)	(5.36)	(8.21)	(4.72)	(4.78)
$F3 - F0$	0.18	0.61	1.33	0.54	0.57	1.12	0.30	0.34
(t-stat)	(0.77)	(2.33)	(5.94)	(2.20)	(2.20)	(4.90)	(1.41)	(1.53)
Panel C: Fama-French 4-Factor + E Alphas (%)								
$F0$	0.33	-0.36	-0.12	0.30	0.28	0.32	0.51	0.61
(t-stat)	(2.43)	(1.59)	(0.74)	(2.67)	(1.69)	(1.92)	(4.77)	(3.89)
$F1$	-0.07	-0.12	0.07	0.20	0.22	0.14	0.34	0.72
(t-stat)	(0.37)	(0.49)	(0.36)	(1.13)	(0.97)	(0.70)	(1.86)	(3.60)
$F2$	-0.02	-0.06	-0.00	0.03	0.41	0.13	0.18	0.50
(t-stat)	(0.12)	(0.24)	(0.02)	(0.14)	(1.83)	(0.65)	(0.97)	(2.48)
$F3$	0.27	-0.17	1.00	0.57	0.48	1.27	0.57	0.75
(t-stat)	(1.15)	(0.61)	(4.53)	(2.20)	(1.80)	(5.28)	(2.57)	(3.03)
$F3 - F0$	-0.07	0.18	1.12	0.27	0.20	0.96	0.05	0.13
(t-stat)	(0.31)	(0.69)	(4.75)	(1.05)	(0.74)	(3.95)	(0.24)	(0.58)

Table 11: **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 10, 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 + E alphas. The sample is April 1980 to December 2013.

SIR_{IO} Group	Anomalies B/M	mom	$ivol$	cei	$distress$	$maxret$	nsi	$gprof$
Panel A: Monthly Returns (%)								
$F1$	0.56	0.43	0.45	0.35	0.64	0.58	0.34	0.56
(t-stat)	(2.90)	(1.57)	(1.83)	(2.44)	(2.79)	(2.56)	(2.68)	(4.97)
$F2$	0.55	0.39	0.59	0.51	0.75	0.69	0.36	0.59
(t-stat)	(2.68)	(1.35)	(2.48)	(3.65)	(3.25)	(3.18)	(2.89)	(5.09)
$F3$	0.55	0.63	0.90	0.57	0.99	0.97	0.44	0.66
(t-stat)	(2.68)	(2.12)	(4.07)	(4.17)	(4.29)	(4.75)	(3.33)	(4.99)
Panel B: Fama-French 4-Factor Alphas (%)								
$F1$	0.37	-0.10	0.38	0.39	0.45	0.56	0.33	0.58
(t-stat)	(3.36)	(0.54)	(2.50)	(4.35)	(3.06)	(3.94)	(3.77)	(5.83)
$F2$	0.34	-0.19	0.51	0.57	0.61	0.69	0.35	0.59
(t-stat)	(2.83)	(1.01)	(3.32)	(6.06)	(3.89)	(4.80)	(4.02)	(5.32)
$F3$	0.37	0.07	0.79	0.59	0.87	0.95	0.42	0.61
(t-stat)	(2.85)	(0.35)	(4.71)	(5.46)	(4.99)	(6.22)	(4.41)	(4.53)
Panel C: Fama-French 4-Factor + E Alphas (%)								
$F1$	0.16	-0.34	-0.21	0.18	-0.06	0.10	0.21	0.51
(t-stat)	(1.41)	(1.82)	(1.59)	(2.00)	(0.41)	(0.71)	(2.29)	(4.87)
$F2$	0.12	-0.54	-0.08	0.38	0.05	0.20	0.20	0.48
(t-stat)	(0.93)	(2.75)	(0.57)	(3.92)	(0.33)	(1.50)	(2.23)	(4.09)
$F3$	0.06	-0.27	0.16	0.36	0.26	0.44	0.26	0.42
(t-stat)	(0.42)	(1.36)	(1.06)	(3.26)	(1.60)	(3.09)	(2.61)	(2.99)

Table 12: **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 10, 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 + E alphas. The sample is April 1980 to December 2013.

SIR_{IO}	Anomalies							
Group	B/M	mom	$ivol$	cei	$distress$	$maxret$	nsi	$gprof$
Panel A: Monthly Returns (%)								
$F1$	0.51	0.37	0.40	0.33	0.49	0.54	0.30	0.51
(t-stat)	(2.74)	(1.29)	(1.58)	(2.41)	(2.11)	(2.27)	(2.33)	(4.52)
$F2$	0.48	0.34	0.55	0.50	0.63	0.59	0.38	0.56
(t-stat)	(2.48)	(1.18)	(2.24)	(3.72)	(2.68)	(2.58)	(3.19)	(4.77)
$F3$	0.52	0.52	0.82	0.53	0.78	0.83	0.44	0.58
(t-stat)	(2.63)	(1.76)	(3.57)	(4.04)	(3.28)	(3.85)	(3.55)	(4.41)
Panel B: Fama-French 4-Factor Alphas (%)								
$F1$	0.31	-0.18	0.34	0.39	0.33	0.53	0.29	0.54
(t-stat)	(3.05)	(0.98)	(2.23)	(4.56)	(2.27)	(3.61)	(3.31)	(5.41)
$F2$	0.29	-0.22	0.49	0.57	0.50	0.61	0.40	0.58
(t-stat)	(2.60)	(1.15)	(3.07)	(6.22)	(3.21)	(4.07)	(4.75)	(5.08)
$F3$	0.35	-0.03	0.72	0.57	0.68	0.82	0.45	0.57
(t-stat)	(2.82)	(0.15)	(4.22)	(5.86)	(3.97)	(5.20)	(5.23)	(4.19)
Panel C: Fama-French 4-Factor + E Alphas (%)								
$F1$	0.15	-0.39	-0.22	0.18	-0.17	0.08	0.18	0.43
(t-stat)	(1.38)	(2.04)	(1.63)	(2.14)	(1.25)	(0.57)	(1.93)	(4.14)
$F2$	0.08	-0.50	-0.10	0.39	-0.07	0.12	0.29	0.43
(t-stat)	(0.68)	(2.56)	(0.71)	(4.15)	(0.47)	(0.87)	(3.32)	(3.63)
$F3$	0.10	-0.33	0.09	0.40	0.08	0.29	0.33	0.37
(t-stat)	(0.76)	(1.65)	(0.55)	(3.97)	(0.51)	(2.00)	(3.67)	(2.62)