The Loan Fee Anomaly: A Short Seller's Best Ideas

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ABSTRACT

We find that equity loan fees are the best predictor of cross-sectional returns. When compared to 102 other anomalies, the loan fee anomaly has the highest monthly long-short return (1.17%), has the highest monthly Sharpe Ratio (0.40), and unlike other anomalies, exhibits strong persistence throughout the sample. We show that 28% of the loan fee anomaly can be explained by its selective exposure to the best performing anomalies, while 72% is due to unique information possessed by short sellers. Our results show that short sellers' willingness to pay prices the cross-section of stocks and these "best ideas" outperform other anomalies.

Keywords: Asset pricing anomalies, equity loan fees, short selling

JEL Classification Numbers: G12, G14

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I. Introduction

It is well-known that short sellers are informed traders.[1] To short a stock, a trader must borrow shares and pay an equity loan fee each day. Thus, stocks with high loan fees represent conviction on the part of short sellers: these are stocks which, by revealed preference, short sellers are willing to pay the most to short. In this paper, we ask a simple question: how good are a short seller's best ideas?

We find that, in modern data, loan fee is arguably the single best predictor of cross-sectional returns. When we compare loan fee to the 102 anomalies in Green, Hand, and Zhang (2017) (hereafter GHZ), loan fee outperforms in a number of dimensions. During our 2006-2019 sample period, it has the highest average long-short return (1.17%), the highest Sharpe Ratio (0.40) and the highest percentage of months with a positive return (68.3%). Before transaction costs, $1 invested in the top percentile or top decile of the aggregate anomaly portfolio, which is formed using the GHZ anomalies, would have finished with $15.07 or $3.01 dollars, respectively, by the end of our sample. The same dollar invested in the top percentile or top decile of the loan-fee anomaly portfolio would have finished with $286.28 or $6.51 dollars respectively.

The loan fee anomaly is not only unique in its performance but also unique in its persistence. While most anomalies fade over time (McLean and Pontiff (2016)), the loan fee anomaly remains strong throughout the sample. Moreover, when we sort all anomalies based on their past performance, the future performance of the best GHZ anomalies is statistically indistinguishable from the worst. In contrast, the loan fee anomaly persists in its superior performance, outperforming the best GHZ anomalies.

[1]Since Seneca (1967), academic studies have found evidence that short sellers' trades predict future returns and short sellers are skilled at processing information (e.g., Boehmer, Jones, and Zhang (2008), Karpoff and Lou (2010), Engelberg, Reed, and Ringgenberg (2012)).

Given the strong performance of loan fee as a return predictor, we next investigate how much of the loan fee anomaly is simply a combination of existing anomalies versus something unique to short sellers. When we project loan fee on each anomaly we find significant, selective exposures: the loan fee anomaly puts more weight on top-performing anomalies than bottom-performing anomalies. In other words, short sellers' best ideas appear to be, in part, a selective re-weighting towards the best performing anomalies.

We then project the loan fee on all 102 GHZ anomalies to decompose it into a fitted and a residual component. The fitted value measures the portion of loan fees that are spanned by the GHZ anomalies, while the residual measures the unique information in loan fees that is distinct from existing anomalies. When we form a long-short trading strategy based on the fitted loan fee, we find that this aggregation of anomalies returns 0.67% per month, which places it among the top 5% of the GHZ anomalies. Furthermore, when we examine the unique information in loan fees, we find that the performance of the residual is 0.71% per month, which makes it the **best** predictor of returns among the GHZ anomalies.

While these differences in performance suggest unique information contained in the loan fee signal, a difference in levels does not tell us how much of the relation between loan fee and returns is explained by each component. Using a regression approach, we find that the fitted loan fee explains 28% of one-month ahead return variation, while the residual explains 72%. The results suggest the most valuable component of a short seller's best ideas are those not spanned by existing anomalies.

While the previous results examine the dependence of the loan fee anomaly on existing anomalies, we also explore the opposite relationship: we find that anomalies almost exclusively live in high loan-fee stocks. For example, among general-collateral (GC) stocks (i.e., those that have low loan-fees) the long-short trading strategy return for an aggregate anomaly portfolio is 0.25% monthly. Among non-GC stocks it is 1.82% monthly. The results show that short sellers have unique information not contained in existing anomalies.

Of course, the literature has already recognized that anomalies tend to live in small and illiquid stocks (Hou, Xue, and Zhang (2017)), but our finding is distinct from this. In fact, when we run a horse race in a E. Fama and MacBeth (1973) regression examining the interaction between our aggregate anomaly variable and size, illiquidity, and loan fee, the loan fee interaction drives out the other two. Put differently, our finding about short sellers' best ideas is distinct from the recognized association between returns either size and liquidity.

Stock loan fees are not only a signal of an informed trader's best ideas, but also a cost that must be paid by short sellers. Thus, a natural question arises, is the loan fee anomaly a profitable trading strategy after adjusting for loan fee? We find the answer is "Yes." For each of the 102 GHZ anomalies we subtract the cost of borrowing the stocks in the short leg of the anomaly portfolio. We do the same for the loan fee anomaly. After this adjustment, we find that the loan fee anomaly continues to outperform almost all of the 102 GHZ anomalies. Specifically, the long-short return for the loan fee anomaly is 0.48% per month compared to -0.02% for the average GHZ anomaly.

In robustness tests, we also examine how our results hold up throughout the cross section. Specifically, we define microcap stocks as those with market capitalization below the 20$^{\text{th}}$ percentile NYSE break-point, as in E. F. Fama and French (2008). We then reexamine our findings when we limit the sample to exclude microcap stocks. All of our conclusions hold – the loan fee anomaly remains the number one anomaly, outperforming all 102 GHZ anomalies.

Our paper makes contributions to several strands of the literature. We contribute to the vast literature on asset pricing anomalies. While this literature began by examining individual anomalies (e.g., Jegadeesh and Titman (1993), E. F. Fama and French (1992), Cooper, Gulen, and Schill (2008)) it has evolved into examining large sets of anomalies (e.g., McLean and Pontiff (2016), Green et al. (2017), Hou et al. (2017), Chen and Velikov (2020)). Our paper's contribution is to identify loan fee as arguably the best cross-sectional predictor among a comprehensive set of anomalies. To date, the best predictor of cross-sectional returns, loan fee, has been left out of the sets examined in this literature (e.g., McLean and Pontiff (2016), Green et al. (2017), Hou et al. (2017), and Chen and Velikov (2020)). We also find that existing anomalies live almost entirely among high loan fee stocks. In the continuing debate about the source of anomalies this represents an important data point: whatever explains anomalies must explain why they almost entirely reside in the domain of high loan-fee stocks.

Our findings are also related to the recent literature on an investor's "best ideas." Most of this work has been done in the mutual find literature which has shown that where a manager's conviction is strongest, these "best ideas" are strongly related to the cross-section of returns (R. Cohen, Polk, and Silli (2010), Jiang, Verbeek, and Wang (2014)). We extend this literature to the domain of short sellers. In so doing, we have two advantages. First, the short selling data covers a wide range of investors, not just mutual fund managers. Second, the investors who choose to short-sell are likely among the best informed market participants. As a result, their best ideas should be included in any discussion of the best of ideas of investors.

The rest of the paper proceeds as follows. Section II discusses the existing literature and motivates our empirical tests. Section III describes our sample and outlines our methodology. Section IV displays our main results. Section V concludes.

II. Literature Review

By showing that the loan fee anomaly is more profitable than other anomalies, we touch on several extant literatures, including the literature on asset pricing anomalies and the literature on short sellers as informed traders.

First, in the area of anomalies, we join a growing body of work. Asset pricing anomalies have been documented since at least Ball and Brown (1968). While the literature initially focused on individual anomalies, increasingly the literature examines large sets of anomalies at the same time in order to draw more general conclusions about asset pricing. McLean and Pontiff (2016) examine 97 anomalies and find that anomalies tend to decrease in profitability after academic papers examining them are first published. Consistent with this, Green et al. (2017) study 102 anomalies and find that anomaly returns appear to be weaker in recent periods. One strand of the anomaly literature (e.g, Harvey, Liu, and Zhu (2016); Hou et al. (2017); Chordia, Goyal, and Saretto (2020)) argues that anomaly findings in the academic literature are largely the result of data mining.[2] However, most data-mining tests are dependent on the set of anomalies considered – if the best performing anomaly was omitted from these tests it is possible that the conclusions from these studies should be changed.

On the other hand, several papers provide evidence that anomalies are not all spurious. Bowles, Reed, Ringgenberg, and Thornock (2020) examine the precise timing of accounting data releases and finds that anomaly returns are strongest in the period immediately following the release of key accounting data. The results suggest anomalies are real and related to delayed information processing. Chen (2020) argues that existing papers that apply multiple

[2]Similarly, both Conrad, Cooper, and Kaul (2003) and Cooper, Gutierrez, and Marcum (2005) make arguments that are consistent with this view.

hypothesis testing adjustments to anomalies are too conservative because they only examine published anomalies; after adjusting for the selective reporting of anomalies, he finds that "at least 80% of published cross-sectional predictors are real." In some sense, our paper supports the idea that anomalies are real. We find that the loan fee anomaly is robust and economically significant throughout our entire sample. We also present evidence that the performance of the anomalies in Green et al. (2017) are robust among the subset of stocks that overlap with the loan fee anomaly.

Second, our work is closely connected to the literature that argues short sellers are informed investors. In particular, papers such as Asquith, Pathak, and Ritter (2005), L. Cohen, Diether, and Malloy (2007), Hong, Li, Ni, Scheinkman, and Yan (2016) and Jones and Lamont (2002), show that future returns are lower when short interest is high. Moreover, several papers document evidence that short sellers are informed investors who are skilled at processing information (Boehmer et al. (2008), Karpoff and Lou (2010), Engelberg et al. (2012)). Although the existing literature largely focuses on the relation between short interest and stock returns, Kolasinski, Reed, and Ringgenberg (2012) shows that equity loan fees are related to short interest in equilibrium. Yet, to date, there is relatively little work examining loan fees as a predictor of returns.

A number of papers have connected short selling to various trading strategies. Dechow, Hutton, Meulbroek, and Sloan (2001) show that firms with low ratios of fundamentals to market values (such as earnings and book values) have increased short interest. Similarly, Geczy, Musto, and Reed (2002) suggest that short selling can be driven by well-accepted patterns in stock prices, including size, book to market, and momentum effects. Using larger sets of anomalies, Stambaugh, Yu, and Yuan (2012) argues that much of the profitability of anomalies comes from the short side and Drechsler and Drechsler (2016) finds that loan fees are an indication of profitability within anomaly strategies. To the best of our knowledge, our paper is the first to argue that loan fee is, itself, an asset pricing anomaly. Our paper is also the first and only paper to consider the relative profitability of the loan fee anomaly.

III. Data, Methodology and Summary Statistics

To examine short seller's best ideas, we combine data from Compustat, the Center for Research in Security Prices (CRSP), and equity lending data from Markit.

A. Data and Sample Construction

While there is a growing list of papers that examine large sets of anomalies, we use the 102 anomalies in Green et al. (2017) not only because their list includes the most widely cited anomalies (e.g., momentum (Jegadeesh & Titman, 1993), asset growth (Cooper et al., 2008), book-to-market ratio (Rosenberg, Reid, & Lanstein, 1985), etc.) but also because Jeremiah Green provides the code used to construct each anomaly on his website.[3] The public availability of the underlying data for 102 anomalies enables both replication of our results and additional exploration of anomaly findings.

From Compustat, we get a number of accounting data items that are necessary to compute asset pricing anomalies. From CRSP, we get data on monthly returns including dividends, trading volume, share price, and shares outstanding for all common U.S. equities (i.e., assets with CRSP share codes of 10 or 11). We exclude stocks with a share price below $5 per share, since margin requirements for short selling change below $5. We filter our sample to exclude extremely small stocks – those below the 5th percentile of the NYSE market

[3] https://sites.google.com/site/jeremiahrgreenacctg/home

capitalization break-points using data provided on Kenneth French's website.[4] In robustness checks, discussed in Section IV.E, we show that our main conclusions are unchanged if we exclude all stocks below the 20^{th} percentile of NYSE size breakpoints, following E. F. Fama and French (2008).

Finally, we add securities lending data from Markit to our database. Specifically, we add the daily cost of borrowing score ($DCBS$), Markit's normalized measure of the cost of borrowing a share. $DCBS$ ranges from 1 to 10, where 1 indicates that a stock has the lowest equity lending fees (i.e. easiest to borrow/short-sell) and 10 indicates a stock has the highest equity lending fees. The scores are not based on equal-sized bins, so there are significantly more stocks with a score of 1 than a score of 10. While some studies have received data on equity loan fees directly, allowing them to measure loan fees using a continuous variable, this information is no longer distributed by Markit. However, Blocher and Whaley (2015) examine both DCBS and the continuous measure of equity loan fees and their Table III provides a mapping between the two variables. They show that stocks with a DCBS of 1 have a mean (median) loan fee of 36 bps (27 bps) while stocks with a DCBS of 10 have a mean (median) loan fee of 5,278 bps (4,451 bps). We use the mean loan fee in their Table III as our measure of the equity loan fee in each DCBS category for each stock and date.

B. Methodology

While we discuss our methodology in greater detail in the results section below, we here introduce two key dimensions of our methodology. First, in all of our analyses, we compare the loan fee anomaly to: (i) the set of 102 anomalies individually and (ii) an aggregate of these anomalies which we call the 'GHZ Net' anomaly (as in Engelberg, McLean, and Pontiff

[4] https://mba.tuck.dartmouth.edu/pages/faculty/ken.french/data_library.html

(2018)). The GHZ Net anomaly variable aggregates the signals for all of the anomalies compiled by Green et al. (2017) in the following way: for each stock-month observation, we calculate the number of long-side (Long) and short-side (Short) anomaly portfolios that a given firm belongs to and then calculate the difference between the Long and Short variables. For example, a stock that is in 17 Long portfolios and 13 Short portfolios will have a Net = 17 - 13 = 4. In general, stocks that are in many long (short) anomaly portfolios will have a 'Net' anomaly value that is large and positive (negative).

Second, because the performance of any anomaly depends on how the long and short sides of the anomaly are defined (e.g. top and bottom percentile, decile, ventile, etc.), we report our results across four different definitions of the anomaly portfolios. Specifically, we present results from calculating anomalies using:

1. Top and bottom 1% (percentiles),
2. Top and bottom 2% (quinquagintiles),
3. Top and bottom 5% (ventiles), and
4. Top and bottom 10% (deciles).

Our results are consistent across all of these bin methodologies – in every case, we find that loan fee is arguably the best known cross-sectional predictor of stock returns.

Because we test whether high loan fee stocks represent short sellers best ideas, we are most interested in how stocks with the most extreme loan fees perform. The extreme loan fees are best captured by the top/bottom 1% sample. However, the top/bottom 1% sample naturally relies on relatively few stocks to form each leg of the long/short portfolio and differs from the standard top/bottom 10% that is typically used in the literature. As such, we also present all of our results using the top/bottom 10%. We report results using the top/bottom 2% and top/bottom 5% as further evidence of the robustness of our result to how we define the long/short portfolios. Our results are not sensitive to these definitions.

C. Summary Statistics

Table I presents summary statistics for our sample which covers the period 2006 through 2019. Panel A presents summary statistics for our key short selling variables and demonstrates that short selling variables exhibit large variation. The median *loan fee* is only 36 basis points per annum, yet the mean *loan fee* is 103 basis points per annum and the 99^{th} percentile is 1,367 basis points per annum. The data show that short sellers are, at times, willing to pay a large fee to act on their beliefs. The data on short interest as a percent of shares outstanding (*SIR*) and days-to-cover (DTC) exhibit a similar pattern. In both cases, the mean is significantly higher than the median. Panel B provides summary statistics for the GHZ Net variable. We also provide summary statistics for the 102 anomalies in the GHZ dataset in Table A1 in the Appendix. As discussed above, because our database includes only $DCBS$ and not the loan fee, we use the mapping provided by Blocher and Whaley (2015) to impute the loan fee. Panel C reports the average number and fraction of stocks in each $DCBS$ bin and the corresponding average loan fee.

IV. Results

In this section, we examine loan fee as a cross-sectional predictor of returns. We start by comparing the performance of the loan fee anomaly to the performance of the 102 stock return anomalies compiled and analyzed in Green et al. (2017).

A. Loan Fee Anomaly Performance

We first examine the time-series performance of the loan fee anomaly. To provide a simple comparison of the performance of the long-short loan fee anomaly relative to the GHZ Net anomaly, Figure 1 plots the growth of $1 invested in both portfolios. The four panels of the figure compare this compound growth across our four different definitions of the long/short portfolios. In Panel A, which focuses on the most narrow definition (i.e., the long-short portfolio is formed on stocks in the top and bottom 1% of loan fee), we see that over the sample period a dollar invested in the loan fee anomaly grows to $286.28, while a dollar invested in the GHZ net anomaly grows to only $15.07. In the other three panels, the results are similar. As we repeat the analysis with the alternate bin methodologies (i.e., top and bottom 2%, top and bottom 5%, and top and bottom 10%), the performance difference shrinks, but in every case the loan fee anomaly generates significantly higher profits than the GHZ Net anomaly variable.

In Table II, we formally compare the loan fee anomaly to the GHZ set of anomalies. To further explore the loan fee anomaly, we also include two other variables that measure short-selling. Specifically, we include Days to Cover (e.g., Hong et al. (2016)) and Short Interest (e.g., Asquith et al. (2005)). For each one of the anomalies considered, the table displays the average 1-month return (shown in Panel A) and the percentage of 1-month returns that are positive (shown in Panel B) as well as the Sharpe Ratio (shown in Panel C). For Loan Fee, Days to Cover, Short Interest, and GHZ Net the table displays the average value ('Value') and the rank across all 102 anomalies ('Rank'). The last column provides statistics for the distribution of returns across all 102 of the GHZ anomalies (it shows the mean return, the 95^{th} percentile, and the maximum return).

Across all four bin methodologies, it is clear that the loan fee anomaly is the top performer. In Panel A, the long-short loan fee anomaly is ranked number one in every case. Loan fee ranks first for average 1-month return, percentage of 1-month returns that are positive and average monthly Sharpe ratio. Across the four different percentile definitions of the long/short portfolios, we see that the average return of loan fee ranges between 3.63% and 1.17% while the average for the GHZ set of anomalies ranges between 0.24% and 0.13% and the maximum return across those anomalies ranges between 1.87% and 0.77%. Of the two alternative short-selling measures, short interest performs well, ranking between second and third for average returns, but the long-short loan fee portfolio outperforms the short interest portfolio by between 1.72% and 0.49%.

In Table III we report the top 20 anomalies by long-short performance across our four long-short portfolio percentile definitions, including not only the average long-short performance, but also the performance of the long and short legs and the short-leg rank separately. Separating the performance of the two legs shows that the outperformance of the loan fee anomaly is driven by the short side of the anomaly. The performance of the short leg ranks first across all four definitions and the performance of the long leg appears to be average compared to other anomalies in the top twenty. Examining the list of other anomalies across the four definitions does not identify a clear set of 'superior' anomalies. Across the four long-short portfolio definitions, thirty-four different anomalies appear and only eight anomalies are consistently ranked in the top twenty across all four definitions.[5] Given the clear outperformance of loan fee relative to the two alternative short-selling measures in Tables II and III, we focus on the GHZ set of anomalies as the point of comparison for the remainder of our analysis.

Table IV and Figures 2 and 3 examine the performance of the loan fee anomaly over

[5]Accrual volatility, Cash flow volatility, Dispersion in forecasted EPS, both Financial statement scores, Return volatility, Sales to cash, and Sales to price

time. In Table IV, the average 12-month rolling performance rank of the long-short loan fee portfolio relative to the rest of the GHZ anomaly set is reported. The loan fee anomaly is consistently in the top twenty, and remains first over a number of multi-month periods. Figure 2 plots the rolling 12-month average performance of the long-short loan fee and GHZ Net portfolios and long and short legs of those portfolios separately in Figure 3. Figure 2 confirms this overall outperformance of the loan fee anomaly relative to the aggregation of all GHZ anomalies via the GHZ Net portfolio. Across the four different long/short percentile definitions, loan fee outperforms between 74% and 87% of months.

Table IV shows three time periods when the loan fee anomaly exhibits closer to average performance: the global financial crisis in late 2008/early 2009, late 2013/early 2014, and late 2018/early 2019. While both the global financial crisis and the late 2018/early 2019 periods coincided with large negative market returns and relatively large increases in volatility, the late 2013/early 2014 period appeared relatively normal both in terms of market performance and volatility. Figure 2 shows for all three periods the performance of both the loan fee and the GHZ net portfolios declined and generated near zero returns. In contrast to the comparison with individual GHZ anomalies, Figure 2 shows that the loan fee long-short portfolio outperformed the GHZ net portfolio in 2018 and 2019 over three of the long-short percentile definitions.

It is also instructive to look at the long and short portfolio performance separately in Figure 3. We see that for both the 2008/2009 and 2013/2014 periods the long-short spread for both the loan fee and GHZ net portfolios shrinks to zero as the short portfolio for both experiences a strong positive shock. Also confirmatory of the short side outperformance of loan fees from Table III, the outperformance of the loan fee anomaly over time is driven largely by the short-side of the portfolio, as both loan fee and GHZ net long portfolios exhibit similar performance. This is especially pronounced for the top/bottom percentile portfolio definition (Top/Bottom 1%) in the last two years of the sample when there is an increasing gap between loan fee and GHZ net.

Figure 4 depicts the persistence of the loan fee anomaly as compared to the set of GHZ anomalies. To construct these figures, we calculate the average return for each anomaly over the previous four years and then form deciles based on this past performance. We then evaluate the performance of each decile over the following three years. We also show the loan fee anomaly by itself. For reference, the loan fee anomaly would always be in the top decile of anomalies in this setting.

Comparing the average GHZ anomaly which lands in the top decile to the loan fee anomaly in the top decile, the returns going forward are very different. While the average top-decile GHZ anomaly mean reverts and, after three years, is statistically indistinguishable from the performance of the average bottom-decile anomaly, the loan fee anomaly persists in its superior performance, outperforming the average GHZ anomaly across all deciles after three years.[6] In other words, the high-performing GHZ anomaly today is unlikely to be a high-performing GHZ anomaly in three years, but the loan fee anomaly is consistently a top performer.

Another way of looking at this idea is in Figure 6, where we examine anomaly performance today conditional on being in the top decile of performers over the prior 4-years. In other words, we take the top performing decile of anomalies over the prior 4-years, and we examine the likelihood of *remaining* in the top decile over the next year. The top-left panel (1% Top/Bottom) says that among the GHZ anomalies, a top-decile performer over the past 4

[6] We conduct a t-test for a difference in means of the one-month return for the top decile and bottom decile. We find the difference in means is statistically insignificant at the 10% level using Newey and West (1987) standard errors.

years has a 12% chance of being a top decile performer over the next 1 year and a 10% chance of being a bottom decile performer. Looking across all the decile bins in the four figures, the distribution is relatively flat suggesting that conditioning on relatively strong past performance has little predictability for future performance among the GHZ anomalies.

On the other hand, when look at the distribution of the loan fee anomaly into future performance deciles, we see a striking difference: the loan fee anomaly has an 82% chance of remaining in the top decile. Furthermore, there is a steep decline in probability of moving into lower deciles, and there is a 0% chance of moving into the bottom half of the decile bins. Overall, this contrasts strongly with the top-performing GHZ anomalies indicating that there is significantly more performance persistence in the loan fee anomaly than the average top-performing GHZ anomaly.

B. Double Sorts: Loan Fee and GHZ Net

To better understand the intersection of the loan fee anomaly and the GHZ net anomaly portfolios, we examine the long-short performance of the two independently in Table V and then consider a double sort of the two in Table VI.

Panel A of Table V shows the simplest sort of the loan fee anomaly, separating stocks into 'General Collateral' (hereafter GC) or easy to borrow stocks versus on 'Special' stocks, which are more costly to borrow, consistent with higher demand by short sellers and/or lower supply by equity lenders. Consistent with the literature on equity lending, on special stocks constitute just over 10% of our equity universe. Yet, stocks that are on special underperform GC stocks by 0.91% per month. In Panel B, sorting stocks by their GHZ net score into deciles also results in a return spread. Stocks with the lowest GHZ net score, those that with the strongest aggregate short signal (Decile 1) across the GHZ anomalies, underperform those with the strongest aggregate long signal (Decile 10) by 0.68% monthly.

In Panel A of Table VI we sort stocks independently into GC and special portfolios and separately by decile of the GHZ net score. In Panel B, we first sort stocks into GC and special portfolios, and then within those two portfolios sort stocks into deciles by their GHZ net score. Either double sort procedure generates the same takeaway: while there is no statistically significant difference in performance between the top and bottom GHZ deciles amongst GC stocks, there is a statistically and economically significant difference of 1.80% or 2.24% difference, depending on the double sort method, between the top and bottom GHZ net deciles only among the high loan fee stocks. This suggests that the informative component of the aggregate GHZ net anomaly signal resides largely within the on-special stocks.

Moreover, this result is not simply a recasting of the well-known relation between anomalies and size or illiquidity (Hou et al. (2017)) which also exists in our data. In fact, in Table VII, we run E. Fama and MacBeth (1973) regressions with loan fee, size, illiquidity, GHZ Net and their interaction terms. When we interact GHZ Net with size (column 6) and with illiquidity (column 7) we find the expected relation from the literature: anomalies perform better among small and illiquid stocks. However, in column 10, when we also include an interaction between GHZ Net and specialness, this interaction drives out the previous two. In other words, we find no statistically detectable relationship between returns and the interaction of size/illiquidity and the aggregate anomaly variable after accounting for its relation with loan fee.

C. The Loan Fee Anomaly and Unique Information

While the results of section B show that the loan fee anomaly largely captures the informative signal contained in the aggregate GHZ net anomaly, it raises a separate question: does the loan fee anomaly contain unique information about future stock returns? As a first step in addressing this question, we identify the short portfolio in each period for both the loan fee and the GHZ net anomalies across our four cutoffs (the bottom 1%, 2%, 5%, and 10%). We then calculate the average performance of those stocks uniquely identified by each anomaly (i.e. 'Only Loan Fee' and 'Only GHZ Net') and the overlapping portfolio ('Both'). The results are plotted in Figure 5.

Looking first at the 1% short portfolio, we see there is only 5% overlap in the stocks identified by the loan fee and GHZ net anomalies. As we increase the cutoff, we find the overlap grows monotonically, maxing out at 15.5% stock overlap for the decile cutoff. Looking at the performance, those stocks included in the short portfolios of both the loan fee and GHZ net anomalies, exhibit the greatest underperformance. Comparing the stocks uniquely identified by both anomalies, we see those included in the 'Only Loan Fee' short portfolio underperform the 'Only GHZ Net' short portfolio by between 1.85% and 0.48% monthly, depending on the cutoff.

This set analysis is suggestive that loan fees contain information unique to short sellers. To better understand both the information contained in loan fees (that represents a selected re-weighting of existing anomalies) versus information that is potentially unique to the loan fee anomaly, we begin by regressing loan fee on each anomaly variable separately and show the strongest and weakest coefficients in VIII.

In the table, we calculate the long/short return for each anomaly using the direction indicated by the anomaly's correlation with loan fee. For example, idiosyncratic return volatility is positively correlated with loan fee. Because the loan fee anomaly goes long low loan fee stocks and short high loan fee stocks, we also go long low idiosyncratic return stocks and short high idiosyncratic return stocks given loan fee's positive correlation with idiosyncratic volatility. We call this the "loan fee indicated direction." As another example, return on assets (ROA) is negatively correlated with the loan fee so we calculate the long/short return in the "loan fee indicated direction" for ROA by constructing a portfolio that is short low ROA stocks and long high ROA stocks.[7]

Table VIII shows that anomalies that have the strongest correlation with loan fee outperform those with the weakest correlation. For example, focusing on the last column of Panel A, we see that the anomalies with the strongest correlation have an average long/short return in the loan fee indicated direction of 0.4% compared to an average return of 0.1% for the weakest correlated anomalies in Panel B and the overall average of 0.1% in Panel C. In other words, the anomaly variables that loan fee is highly correlated with perform better in long-short portfolios than the anomaly variables it has little correlation with. This is evidence that the loan fee anomaly represents selective exposure to the best performing anomalies.

In order to quantify the contribution of this selective exposure to the loan fee anomaly, we next consider a multivariate setting. Put differently, while Table VIII examines the univariate relation between the loan fee anomaly and the GHZ set of anomalies, in Table IX we project loan fee on all of the 102 GHZ anomalies at the same time in order to construct a fitted loan fee and a residual loan fee. The fitted value represents the component of loan fee that is spanned by existing anomalies while the residual measures the component of loan fee that is unique.

[7]In other words, for anomalies that are positively correlated with loan fee we always go long in stocks with a low value of the anomaly variable and short stocks with a high value. For anomalies that are negatively correlated with loan fee we always go long the high value and short the low value.

Table IX shows that long/short portfolios formed based on either the fitted value or the residual perform well relative to the set of GHZ anomalies. Focusing on the decile portfolios (i.e. Top/Bottom 10%), we find that the fitted loan fee has a long/short return of 0.67% and it is ranked third when compared to the GHZ set which confirms our prior conclusion that loan fee is selectively correlated with high-performing anomalies.

The residual performs even better. Among decile portfolios, it has a long/short return of 0.71% and when we replace the fitted value with the residual in the comparative ranking with the GHZ set, we find it is also ranked third. In other words, the unique component of the loan fee anomaly not only outperforms the fitted component but also all but two of the individual GHZ anomalies. This indicates that short sellers have valuable information that is not contained in the existing set of anomalies.

To get a sense of the unique component's relative contribution to the loan fee anomaly, we turn to a regression setting. In Table X, we regress one month ahead monthly returns on predicted loan fee (column 2), residual loan fee (column 3), and both of them simultaneously (column 4). When we look at the R^2s in these regressions, we find that the fitted component explains 28.4% of the total return predictability while the unique component explains 71.6%. This result confirms that, on average, short seller's best ideas come from valuable information that is *not* contained in the existing set of anomalies.

D. Performance Net of Loan Fees

While our loan fee anomaly analysis so far has examined performance gross of borrowing costs, the prior literature has shown that these costs play an important role in determining whether or not arbitrage strategies are profitable. For example, Chen and Velikov (2020) finds that most anomaly strategies earn abnormal returns close to zero after accounting for transaction costs. At the same time, our GHZ anomaly results are also gross of loan fees, so it is not clear, ex ante, how including these costs in the analysis will affect the performance ordering of the strategies. To address this, we repeat the performance comparison of Table II after subtracting borrowing costs and the results are shown in Table XI. While the magnitude of returns is smaller after subtracting transaction costs, it appears the adjustment affects all of the anomalies in almost the same way. As a result, the loan fee anomaly continues to be one of the top performers across all methodologies and metrics. For example, across our four portfolio constructions cutoffs (the bottom 1%, 2%, 5%, and 10%), we find the loan fee anomaly has a Sharpe Ratio that ranks 7^{th}, 2^{nd}, 1^{st}, and 1^{st}, respectively. Similarly, when we examine the average of 1-month returns and the percentage of 1-month returns that are positive, we find the loan fee anomaly ranks no worse than 7^{th}, and is often the 1^{st} or 2^{nd} best amongst all anomalies. Overall, the results show the loan fee anomaly continues to predict returns even after adjusting for the fact that loan fees are a cost that must be paid by short sellers.

E. Robustness

In robustness tests, we also examine how our results hold up throughout the cross section. Specifically, we repeat the analysis of Table II, but first raise the market capitalization NYSE cutoff from the 5^{th} to the 20^{th} percentile. Table A2 in the Appendix reports these results. While the average return of the loan fee anomaly long/short portfolio declines from 1.17% to 0.74% for the top/bottom 10% categorization, it is still the best performing anomaly as measured by average 1-month returns or monthly Sharpe ratio and it has the highest percentage of positive 1-month returns. This top ranking is maintained, in part, because raising the market capitalization cutoff also affects the performance of GHZ Net anomaly. The average 1-month return of the GHZ Net declines from 0.72% to 0.36%. The average return across the GHZ set of anomalies also declines from 0.13% to 0.07%. Overall, excluding the bottom 20% of stocks by market capitalization, does not materially change our performance results.

V. Conclusion

Comprehensive loan fee data is a relatively new addition to finance academia, beginning with D'Avolio (2002). Unlike other well-known anomalies such as momentum or size, we do not have a century's worth of data to analyze. Nevertheless, the time-series of loan fee data is growing, and, in modern data, we find loan fee to be the single best predictor of cross-sectional returns.

Given the evidence that short sellers are informed and that loan fees represent how much those informed traders are willing to pay to hold their position, we view this predictability as evidence of a short seller's best ideas. When short sellers are willing to pay the most to bet against a stock, those stocks predictably have the largest negative future returns.

We also find that these best ideas are unique. Only 28% of the loan fee anomaly can be explained by short sellers selective exposure to existing anomalies; the remaining 72% is unique information held by these informed traders.

Given the uniqueness of loan fee as both an opinion and an impediment, we do not anticipate the loan fee anomaly to disappear like other anomalies have (McLean and Pontiff (2016), Calluzzo, Moneta, and Topaloglu (2019)). When we compare the persistence of the loan-fee anomaly with other high-performing anomalies, we find more evidence of mean reversion among those high-performing anomalies and less evidence with the loan fee anomaly.

Interestingly, in the debate about the robustness of cross-sectional predictors over time after accounting for data mining, the single most effective predictor has been left out of the discussion. Given the newness of these data, this is understandable. We hope this paper encourages future work to examine it.

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Figure 1. Growth of $1 Invested in Anomaly Portfolios

The figure 1 plots the growth of $1 invested in the loan fee anomaly portfolio (black line) and the GHZ Net anomaly portfolio (orange line). The GHZ Net anomaly variable aggregates the signals for all of the anomalies compiled by Green et al. (2017). Panel A displays results when portfolios are formed by sorting stocks on the top and bottom 1% of anomaly variables, while Panels B, C, and D display results when portfolios are formed by sorting stocks on the top and bottom 2%, 5%, and 10%, respectively.

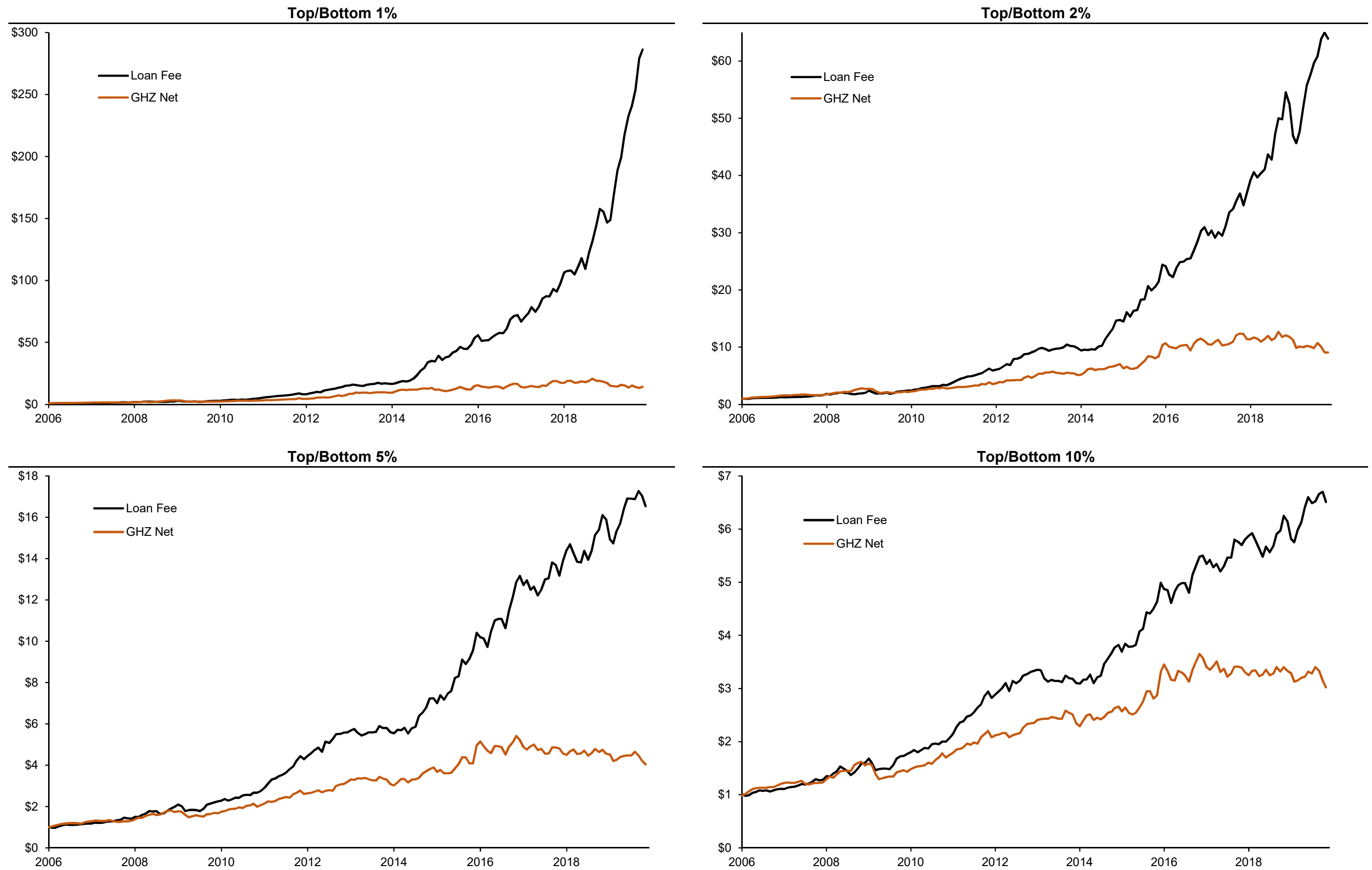

Figure 2. Rolling 12-Month Average of Anomaly Returns

The figure 1 plots the rolling 12-month mean performance of the loan fee anomaly portfolio (black line) and the GHZ Net anomaly portfolio (orange line) over time. The GHZ Net anomaly variable aggregates the signals for all of the anomalies compiled by Green et al. (2017). Panel A displays results when portfolios are formed by sorting stocks on the top and bottom 1% of anomaly variables, while Panels B, C, and D display results when portfolios are formed by sorting stocks on the top and bottom 2%, 5%, and 10%, respectively.

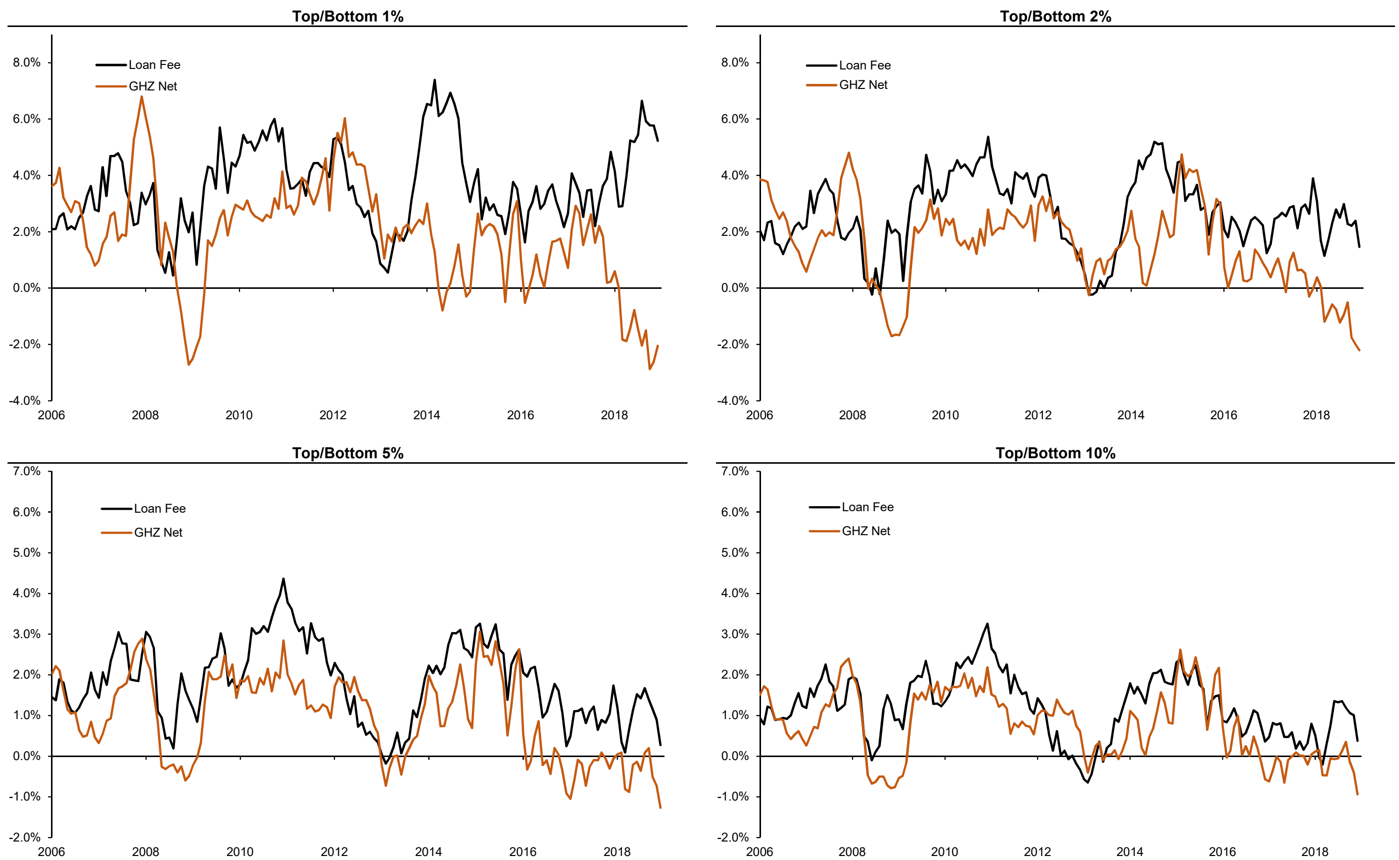

Figure 3. Rolling 12 Month Average of Anomaly Long and Short Returns

The figure 1 plots the rolling 12-month mean performance of the loan fee anomaly portfolio (black line and gray line) and the GHZ Net anomaly portfolio (orange line and light orange line) over time, and it breaks out the performance by long- and short-legs of the portfolios. The GHZ Net anomaly variable aggregates the signals for all of the anomalies compiled by Green et al. (2017). Panel A displays results when portfolios are formed by sorting stocks on the top and bottom 1% of anomaly variables, while Panels B, C, and D display results when portfolios are formed by sorting stocks on the top and bottom 2%, 5%, and 10%, respectively.

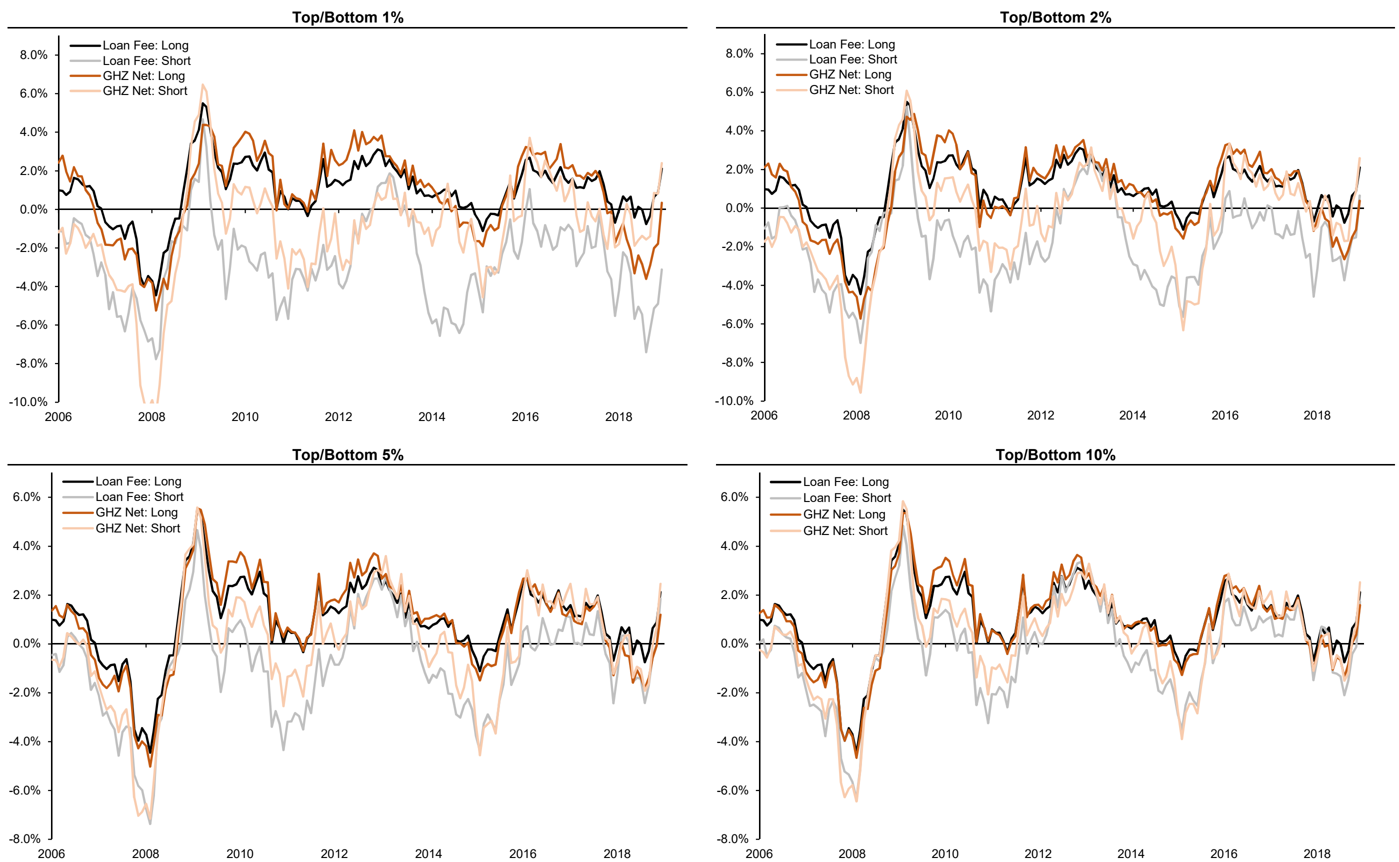

Figure 4. Anomaly Performance Persistence

The figure displays the persistence of the loan fee anomaly relative to the set of GHZ anomalies. Each date, we look back 4 years and take the average return for each anomaly and we form deciles based on these past performance levels. We then plot the mean return of each decile over the next three years (black lines). We also plot the mean return for the loan fee anomaly (blue line). Panel A displays results when portfolios are formed by sorting stocks on the top and bottom 1% of anomaly variables, while Panels B, C, and D display results when portfolios are formed by sorting stocks on the top and bottom 2%, 5%, and 10%, respectively.

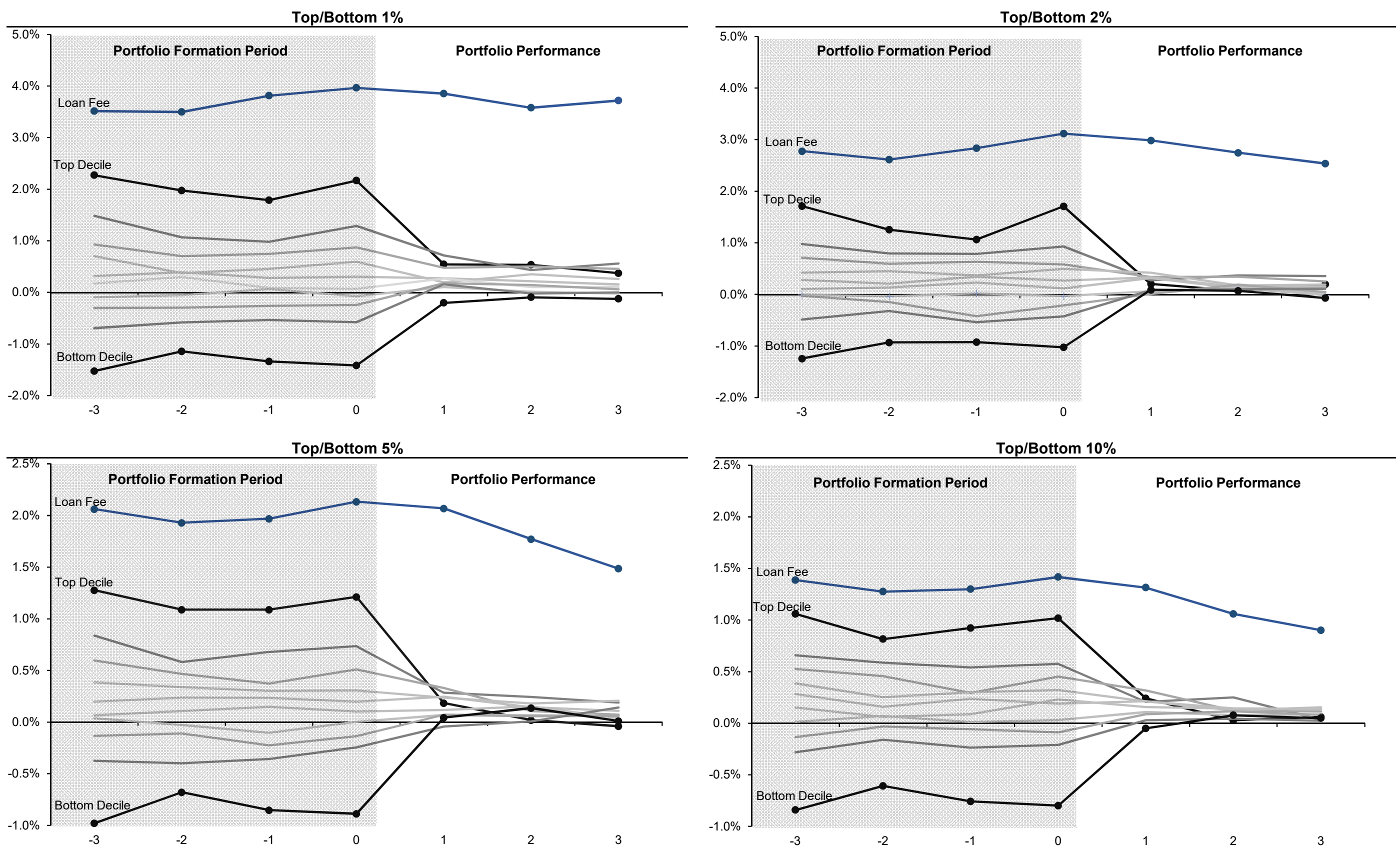

Figure 5. Set Analysis: Performance and Overlap of Loan Fee and GHZ Net Anomaly
The figure displays the performance of the unique components of the loan fee anomaly and the GHZ Net anomaly, as well as the the performance when stocks are in both portfolios at the same time. we identify the short portfolio in each period for both the loan fee and the GHZ net anomalies across our four cutoffs (the bottom 1%, 2%, 5%, and 10%). We then calculate the average performance of those stocks uniquely identified by each anomaly (i.e. 'Only Loan Fee' and 'Only GHZ Net') and the overlapping portfolio ('Both').

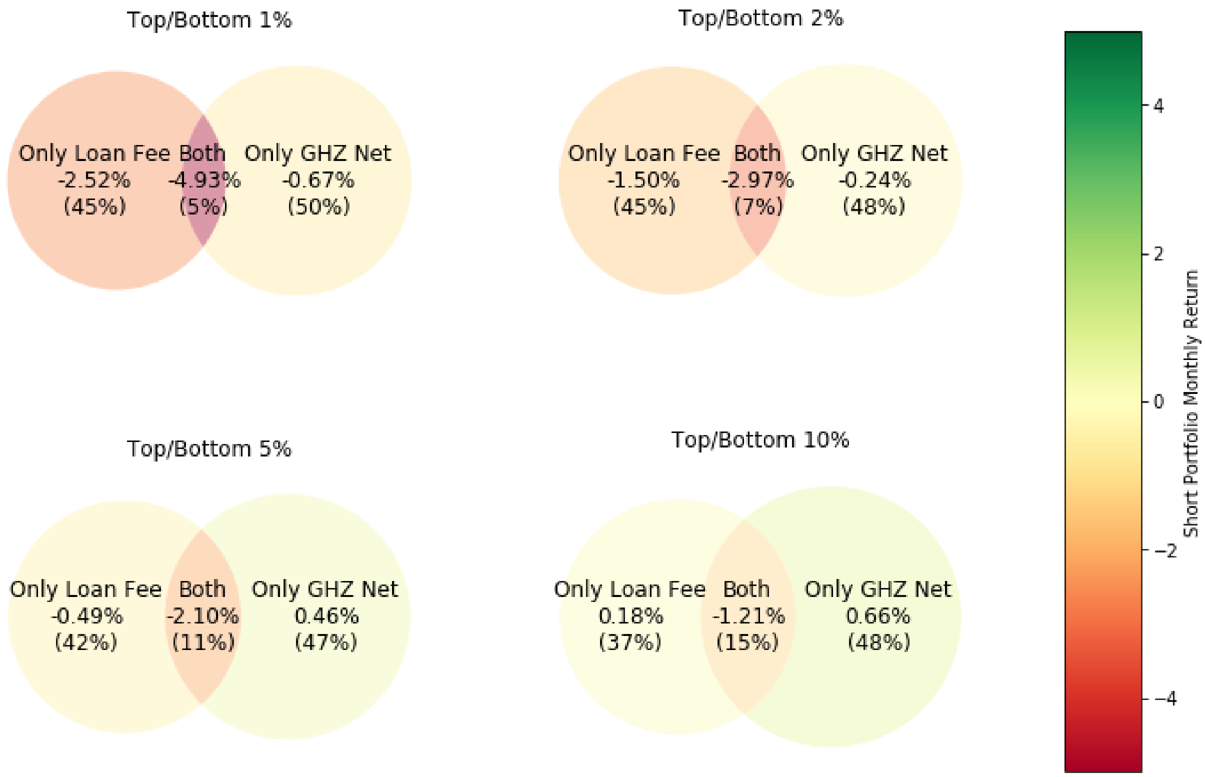

Figure 6. GHZ Decile Portfolio Transition Probabilities

The figure examines anomaly performance today conditional on being in the top decile of performers over the prior 4-years. On each date, we take the top performing decile of anomalies over the prior 4-years and we examine the likelihood of remaining in the top decile over the next year. The figure displays probabilities for remaining in the top decile, or transitioning to the second decile, third decile, etc. Panel A displays results when portfolios are formed by sorting stocks on the top and bottom 1% of anomaly variables, while Panels B, C, and D display results when portfolios are formed by sorting stocks on the top and bottom 2%, 5%, and 10%, respectively.

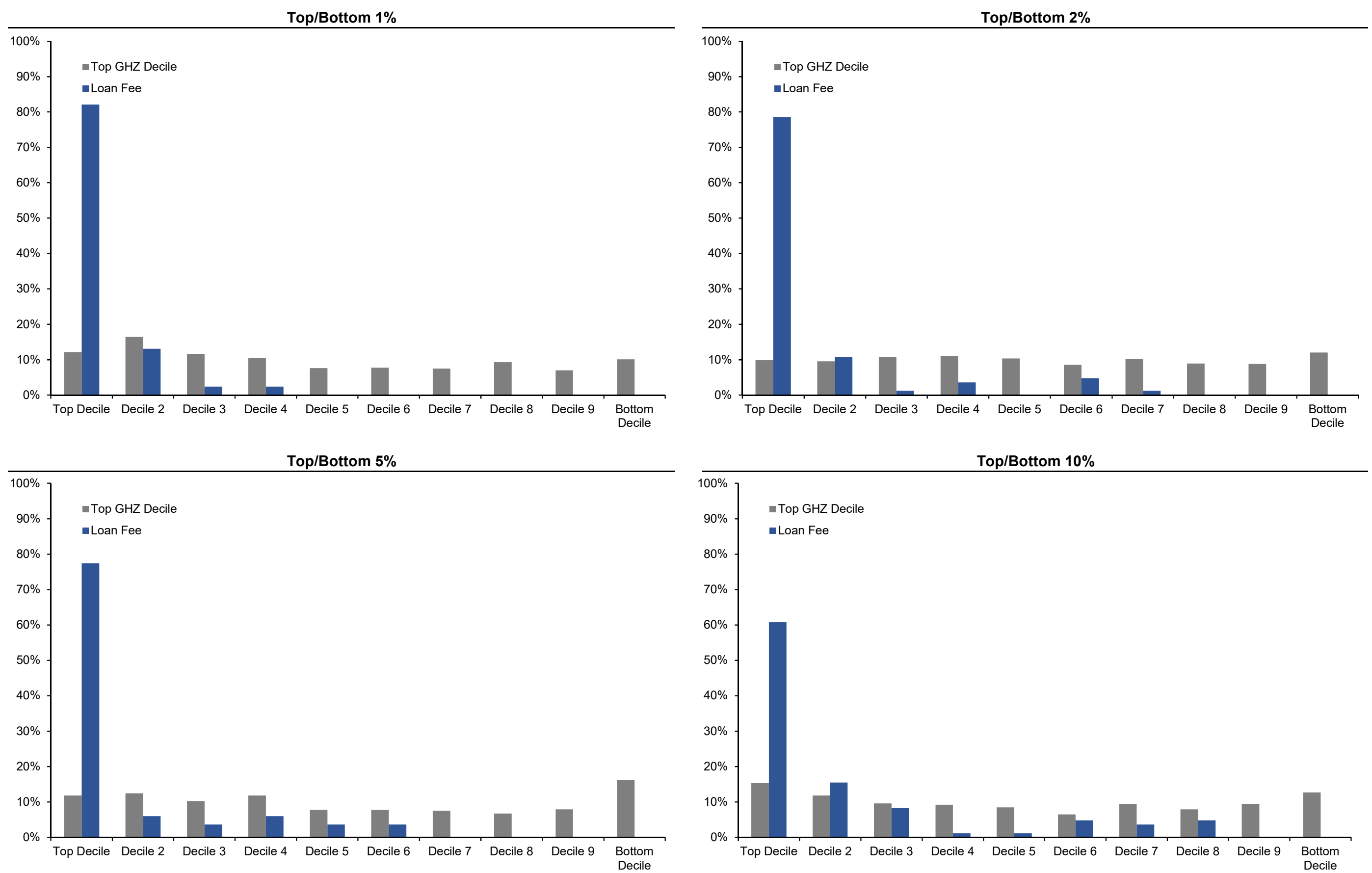

Table I
Summary Statistics

The table reports means, standard deviations, and the 1st, 50th, and 99th percentiles of the anomaly sorting variables we examine. The GHZ Net anomaly variable aggregates the signals for all of the anomalies compiled by Green et al. (2017), see Section III of the text for detailed variable definitions. The sample consist of all US common equities above the 5th percentile NYSE size breakpoint over the period 2006 to 2019.

Anomaly	**Mean**	**Std. Dev.**	**1st %**	**Median**	**99th %**
Panel A: Short Selling Related Anomalies					
Loan Fee	103.0	365.5	36.0	36.0	1367.0
Days to Cover	750.0	2317.2	60.5	551.1	3326.9
Short Interest	6.0	6.1	0.2	4.0	29.4
Panel B: GHZ Anomalies					
GHZ Net	-4.2	6.2	-21.0	-4.0	10.0

Panel C: DCBS Mapping

DCBS	**Avg. # of Stocks**	**Avg. Fraction of Stocks**	**Blocher and Whaley (2014) Average Fee (bps)**
1	2,157	88.6%	36
2	115	4.6%	183
3	53	2.1%	318
4	31	1.3%	488
5	18	0.7%	741
6	14	0.6%	964
7	13	0.5%	1,367
8	7	0.3%	2,040
9	7	0.3%	2,403
10	8	0.3%	5,278

Table II
Performance of Long/Short Portfolio for Short-Selling Related and GHZ Set of Anomalies

The table reports the performance of the loan fee anomaly relative to two other short selling related anomalies and the GHZ anomalies. For each anomaly we construct a long/short portfolio and calculate its return. The performance of each anomaly is evaluated using three metrics: the average 1-month returns (Panel A), the percentage of 1-month returns that are positive (Panel B), and the monthly Sharpe Ratio (Panel C). For each of these, we also rank each anomaly variable relative to the entire set of anomalies. Loan fee is measured by the DCBS on the last trading day of the month. The short interest ratio is the mid-month short interest divided by shares outstanding. Day-to-cover is calculated as the short interest ratio divided by average daily trading volume as a percent of shares outstanding during the same month in which short interest is measured. The GHZ set of anomalies is the set of 102 anomalies studied in Green et al. (2017). In each panel we present results when portfolios are formed by sorting stocks on the top and bottom 1% of anomaly variables ("Top/Bottom 1%"), as well as when portfolios are formed by sorting stocks on the top and bottom 2%,

	Loan Fee		**Days to Cover**		**Short Interest Ratio**		**GHZ Net**		**GHZ Set of Anomalies**		
	Value	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Mean**	**95th Ptile**	**Max.**
Panel A: Average of 1-Month Return											
Top/Bottom 1%	3.63%	1	0.76%	17	1.91%	1	1.83%	2	0.24%	1.43%	1.87%
Top/Bottom 2%	2.64%	1	0.75%	9	1.42%	3	1.47%	2	0.18%	0.84%	1.59%
Top/Bottom 5%	1.76%	1	0.79%	2	0.87%	2	0.92%	1	0.13%	0.67%	0.88%
Top/Bottom 10%	1.17%	1	0.57%	6	0.68%	3	0.72%	2	0.13%	0.52%	0.77%
Panel B: Percentage of 1-Month Returns that are Positive											
Top/Bottom 1%	74.3%	1	62.9%	3	61.1%	6	60.5%	6	51.8%	59.9%	64.7%
Top/Bottom 2%	73.1%	1	59.9%	4	62.9%	1	64.7%	1	52.0%	58.7%	61.7%
Top/Bottom 5%	68.9%	1	62.3%	2	60.5%	3	63.5%	1	51.5%	58.7%	62.9%
Top/Bottom 10%	68.3%	1	60.5%	4.5	57.5%	17	65.3%	1	52.1%	59.3%	63.5%
Panel C: Monthly Sharpe Ratio											
Top/Bottom 1%	0.58	1	0.16	10	0.31	2	0.27	2	0.04	0.21	0.32
Top/Bottom 2%	0.53	1	0.18	3	0.30	1	0.28	1	0.04	0.16	0.21
Top/Bottom 5%	0.48	1	0.22	1	0.20	2	0.23	1	0.04	0.15	0.21
Top/Bottom 10%	0.40	1	0.18	5	0.18	5	0.22	2	0.04	0.17	0.23

Table III
Top 20 Anomalies by Long/Short Portfolio Performance

The table reports the return of the long/short portfolio and the return of each leg of the portfolio for the loan fee and the top 19 GHZ anomalies (so the top 20 overall anomalies are displayed). Anomalies are sorted from highest long/short return to lowest. "Short Rank" reports the rank of the return on the short leg of the portfolio. Since a short position is taken on the short leg of the portfolio, the lowest return has rank 1. Panel A displays results when portfolios are formed by sorting stocks on the top and bottom 1% of anomaly variables, while Panels B, C, and D display results when portfolios are formed by sorting stocks on the top and bottom 2%, 5%, and 10%,

Top/Bottom 1%

Rank	Anomaly	Long Leg	Short Leg	Port. Ret.	Short Rank
1	Loan Fee	0.9%	-2.7%	3.6%	1
2	Sales to price	1.0%	-0.9%	1.9%	6
3	Sales to cash	0.8%	-1.0%	1.8%	5
4	Accrual volatility	0.9%	-0.7%	1.7%	8
5	Financial statement score	0.5%	-1.1%	1.6%	4
6	Ind-adj. change in profit margin	1.6%	0.1%	1.5%	32
7	Dispersion in forecasted EPS	1.4%	-0.1%	1.4%	18
8	Cash flow volatility	1.1%	-0.2%	1.3%	15
9	Bid-ask spread	0.8%	-0.4%	1.2%	9
10	Employee growth rate	0.9%	-0.2%	1.2%	11
11	Change in number of analysts	1.4%	0.4%	1.0%	48
12	Sales to inventory	0.9%	0.0%	0.9%	22
13	Return volatility	0.8%	-0.1%	0.9%	17
14	Depreciation / PP&E	0.8%	-0.1%	0.8%	20
15	Tax income to book income	1.1%	0.3%	0.8%	47
16	Financial statement score	1.2%	0.4%	0.8%	55
17	Absolute accruals	0.7%	-0.1%	0.8%	16
18	Change in forecasted EPS	-0.1%	-0.8%	0.8%	7
19	Long-term net op. asset growth	0.9%	0.1%	0.7%	35
20	Sales to receivables	0.9%	0.2%	0.7%	38

Top/Bottom 2%

Rank	Anomaly	Long Leg	Short Leg	Port. Portfolio	Short Rank
1	Loan Fee	0.9%	-1.7%	2.6%	1
2	Sales to price	0.9%	-0.7%	1.6%	3
3	Sales to cash	0.9%	-0.6%	1.4%	5
4	Dispersion in forecasted EPS	1.3%	0.4%	1.0%	39
5	Cash flow volatility	1.0%	0.1%	0.9%	12
6	Sales to inventory	0.8%	-0.1%	0.9%	8
7	Volatility of liquidity (share turnover)	1.0%	0.1%	0.8%	16
8	Bid-ask spread	0.8%	0.0%	0.8%	11
9	Financial statement score	1.2%	0.4%	0.8%	45
10	Return volatility	0.8%	0.1%	0.7%	14
11	Accrual volatility	0.9%	0.2%	0.7%	19
12	Cash flow to debt	1.0%	0.3%	0.7%	34
13	Maximum daily return	0.8%	0.2%	0.7%	20
14	Real estate holdings	0.7%	0.1%	0.6%	13
15	Change in number of analysts	1.0%	0.4%	0.6%	47
16	Industry adjusted book to market	0.5%	-0.2%	0.6%	7
17	Growth in common shareholder equity	1.0%	0.4%	0.6%	43
18	% change in sales - % change in A/R	0.8%	0.2%	0.5%	27
19	Absolute accruals	0.6%	0.1%	0.5%	15
20	Financial statement score	0.5%	0.0%	0.5%	10

Top/Bottom 5%

Rank	Anomaly	Long Leg	Short Leg	Port. Ret.	Short Rank
1	Loan Fee	0.9%	-0.8%	1.8%	1
2	Industry adjusted book to market	0.7%	-0.2%	0.9%	2
3	Volatility of liquidity (share turnover)	1.0%	0.3%	0.7%	13
4	Cash flow volatility	1.0%	0.3%	0.7%	11
5	Accrual volatility	0.9%	0.2%	0.7%	10
6	Sales to price	1.1%	0.4%	0.7%	17
7	Financial statement score	0.9%	0.2%	0.7%	8
8	Financial statement score	1.2%	0.5%	0.7%	38
9	Dispersion in forecasted EPS	1.2%	0.6%	0.6%	53
10	Organizational capital	0.7%	0.2%	0.5%	9
11	Sales to inventory	0.7%	0.2%	0.5%	7
12	Change in number of analysts	1.1%	0.6%	0.5%	50
13	Idiosyncratic return volatility	0.9%	0.4%	0.5%	28
14	Cash flow to debt	0.9%	0.4%	0.5%	21
15	Gross profitability	0.9%	0.4%	0.5%	23
16	Sales to cash	0.9%	0.4%	0.5%	27
17	Return volatility	0.9%	0.4%	0.5%	26
18	Maximum daily return	0.9%	0.5%	0.4%	31
19	Capital expenditures and inventory	0.7%	0.3%	0.4%	12
20	Industy sales concentration	1.3%	0.9%	0.4%	95

Top/Bottom 10%

Rank	Anomaly	Long Leg	Short Leg	Port. Ret.	Short Rank
1	Loan Fee	0.9%	-0.2%	1.2%	1
2	Accrual volatility	1.0%	0.3%	0.8%	4
3	Cash flow volatility	1.0%	0.3%	0.7%	7
4	Dispersion in forecasted EPS	1.1%	0.5%	0.6%	18
5	Organizational capital	0.9%	0.3%	0.6%	5
6	Financial statement score	1.1%	0.5%	0.6%	21
7	Industry adjusted book to market	0.8%	0.3%	0.5%	2
8	Gross profitability	1.0%	0.5%	0.5%	15
9	Operating profitability	1.0%	0.5%	0.5%	16
10	Sales to price	1.1%	0.6%	0.5%	40
11	Volatility of liquidity (share turnover)	1.0%	0.5%	0.4%	19
12	Bid-ask spread	0.9%	0.5%	0.4%	20
13	Idiosyncratic return volatility	0.9%	0.5%	0.4%	23
14	Sales to receivables	0.9%	0.5%	0.4%	11
15	Unexpected quarterly earnings	0.7%	0.3%	0.4%	3
16	Return volatility	0.9%	0.5%	0.4%	29
17	Ind-adj. cash-flow-to-price ratio	0.7%	0.3%	0.4%	6
18	Number of analysts covering stock	1.2%	0.8%	0.4%	83
19	Financial statement score	0.8%	0.5%	0.4%	14
20	Sales to cash	0.9%	0.6%	0.4%	33

Table IV
12-Month Rolling Rank of Loan Fee Anomaly Among GHZ Set of Anomalies

The table reports the rolling rank of the average long/short return for the loan fee anomaly among the GHZ anomalies. The average long-short return is calculated over the year prior to the date that appears in the table. Color coding indicates the performance of the loan fee anomaly – lighter colors indicate the loan fee anomaly had one of the best rankings, while the color red denotes periods when the loan fee anomaly had a low ranking. We present results when portfolios are formed by sorting stocks on the top and bottom 1% of anomaly variables ("Top/Bottom 1%"), as well as when portfolios are formed by sorting stocks on the top and bottom 2%, 5%, and 10%.

	2006												**2007**												**2008**											
Top/Bottom 1%												13	12	11	7	11	9	14	10	5	5	5	10	7	1	8	1	4	5	5	5	14	22	23	18	18
Top/Bottom 2%												8	14	11	4	10	16	23	14	10	10	11	13	11	3	10	7	6	7	7	4	13	21	27	25	21
Top/Bottom 5%												13	14	12	6	12	15	20	15	13	11	10	13	15	8	15	6	7	6	3	1	12	19	22	11	5
Top/Bottom 10%												19	26	15	13	13	17	16	17	11	8	8	16	12	10	10	10	10	12	10	5	22	22	23	15	11

	2009												**2010**												**2011**											
Top/Bottom 1%	17	8	33	33	49	30	42	21	11	13	15	11	34	21	5	3	4	4	1	3	4	2	2	1	1	1	1	1	1	1	1	1	1	1	1	1
Top/Bottom 2%	22	20	47	47	64	33	58	25	10	11	12	13	41	19	6	4	3	4	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
Top/Bottom 5%	8	6	21	17	37	31	42	17	11	14	15	22	29	19	8	7	6	6	1	1	3	3	6	5	1	1	1	1	1	1	1	1	1	1	1	1
Top/Bottom 10%	12	14	40	42	63	52	42	16	13	18	24	26	31	20	8	8	4	5	1	1	6	11	9	9	4	3	1	2	2	2	1	2	1	2	2	2

	2012												**2013**												**2014**											
Top/Bottom 1%	2	1	2	3	5	3	2	2	1	2	2	1	1	1	1	2	4	3	5	8	5	9	9	31	29	35	18	7	6	13	6	3	2	1	1	1
Top/Bottom 2%	1	1	1	2	2	1	1	2	1	1	1	1	1	1	2	2	2	7	7	10	12	14	19	35	59	61	63	52	56	36	38	8	10	5	3	2
Top/Bottom 5%	1	1	1	1	1	1	1	1	1	1	1	3	2	3	5	9	5	27	19	36	30	38	42	55	60	56	44	21	47	38	33	5	15	7	5	4
Top/Bottom 10%	1	1	1	2	2	1	1	4	1	6	5	3	7	11	30	53	23	61	50	67	60	68	76	80	79	77	60	27	66	35	26	4	9	5	3	4

	2015												**2016**												**2017**											
Top/Bottom 1%	1	1	1	1	1	1	2	2	4	7	6	8	10	20	17	20	18	20	15	15	14	6	7	15	23	7	4	4	6	5	2	3	3	6	10	6
Top/Bottom 2%	1	2	2	3	3	3	2	2	2	1	3	5	8	11	9	9	8	11	8	12	3	8	9	15	15	3	3	6	13	6	5	2	2	4	22	18
Top/Bottom 5%	3	4	4	6	4	4	4	3	3	2	4	6	11	10	6	5	9	9	7	9	3	7	7	7	5	3	1	3	15	10	8	4	5	16	37	29
Top/Bottom 10%	5	4	3	7	5	5	4	6	5	4	8	8	14	14	10	11	13	12	8	17	6	17	20	21	16	9	4	5	23	20	13	6	9	19	27	24

	2018												**2019**										
Top/Bottom 1%	3	2	1	5	2	2	6	3	3	3	1	2	6	4	2	1	1	1	1	1	1	1	2
Top/Bottom 2%	2	2	1	4	2	2	6	3	3	4	2	3	13	15	9	11	4	9	8	14	11	2	11
Top/Bottom 5%	12	4	4	12	6	5	23	19	21	11	7	14	44	43	26	24	11	17	14	20	13	12	31
Top/Bottom 10%	17	13	10	22	22	17	40	29	41	39	13	30	62	59	33	24	9	11	12	22	14	8	22

Table V
Univariate Sorts: 1-Month Return of Loan Fee and GHZ Net Anomaly

The table displays monthly mean returns from univariate sorts formed on the loan fee anomaly portfolio (Panel A) and the GHZ net anomaly portfolio (Panel B). In each panel, **L/S** indicates the long-short return earned from buying the top portfolio and short-selling the bottom portfolio.

	Mean # of Stocks in Portfolio	**Mean Return**
Panel A: Loan Fee		
General Collateral	2,175	0.94%
Special	273	0.03%
L/S	–	0.91%
Panel B: GHZ Net		
1	242	0.26%
2	244	0.62%
3	239	0.81%
4	257	0.90%
5	241	0.92%
6	245	1.01%
7	255	0.94%
8	233	1.07%
9	253	1.01%
10	240	0.95%
L/S	–	0.68%

Table VI
Double Sorts: 1-Month Return of Loan Fee and GHZ Net Anomaly

The table displays monthly mean returns from dual-sorts formed on the loan fee anomaly portfolio (Panel A) and the GHZ net anomaly portfolio (Panel B). In panel A, we independently sort stocks into GC and special portfolios and we sort by decile of the GHZ net score. In Panel B, we first sort stocks into GC and special portfolios and then within each of these groups we sort by decile of the GHZ net score. In both panels, **L/S** indicates the long-short return earned from buying the top portfolio and short-selling the bottom portfolio.

	General Collateral		**Special**		
Decile	**Mean # of Stocks in Portfolio**	**Mean Return**	**Mean # of Stocks in Portfolio**	**Mean Return**	**Return on GC minus Special**
	Panel A: Independent Double Sort				
1	168	0.72%	74	-0.97%	1.69%
2	206	0.71%	37	-0.05%	0.75%
3	212	0.89%	27	-0.18%	1.06%
4	233	0.94%	24	0.71%	0.23%
5	221	0.94%	20	1.02%	-0.08%
6	225	1.03%	20	0.48%	0.55%
7	238	0.93%	17	0.54%	0.39%
8	216	1.08%	17	0.93%	0.14%
9	235	1.02%	18	0.60%	0.43%
10	221	0.97%	20	0.85%	0.12%
L/S	–	**0.25%**	–	**1.82%**	–
	Panel B: Conditional Double Sort				
1	218	0.72%	27	-1.66%	2.38%
2	219	0.77%	28	-0.56%	1.32%
3	208	0.96%	28	-0.58%	1.54%
4	229	0.91%	28	0.05%	0.86%
5	213	0.98%	26	-0.52%	1.50%
6	207	1.02%	28	0.71%	0.31%
7	234	0.94%	27	0.36%	0.58%
8	213	1.07%	28	0.65%	0.42%
9	216	1.01%	28	1.04%	-0.02%
10	217	0.96%	27	0.61%	0.35%
L/S	–	**0.24%**	–	**2.27%**	–

Table VII
Loan Fee Anomaly and GHZ Net: Fama-MacBeth Regressions (Quantiles)

The table reports results from (E. Fama & MacBeth, 1973) cross-sectional regressions of one month ahead stock returns on the indicated independent variable. “Special” is an indicator variable that takes a value of one if the stock has a DCBS greater than one and zero otherwise. Quantiles are used for each of the remaining independent variables (GHZ Net, Size, and Bid-Ask Spread). The quantiles are calculated within the month and are shifted so that the median within the month has value zero. T-statistics are calculated using Newey West standard errors. Significant at * 10%, ** 5%, and *** 1%. Note that the coefficient on the ”Special” indicator variable in column 1 is not directly comparable to the coefficient in column 5, 8, 9, and 10. The coefficient in column 1 reports the average effect of specialness on returns, while the other columns report the average effect of specialness on returns conditional on the stock having a median GHZ Net score. The average effect of specialness on returns is -0.87%, -0.86%, -0.81%, and -0.82% for columns 5, 8, 9, and 10 respectively.

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Special	-0.91%***				-0.62%***			-0.62%***	-0.57%***	-0.58%***
	-4.24				-3.31			-3.83	-3.72	-3.93
GHZ Net		0.62%***			0.30%*	0.56%***	0.53%***	0.28%*	0.32%**	0.29%**
		3.45			1.88	3.19	3.98	1.70	2.41	2.29
Size			0.13%			0.09%		-0.11%		-0.15%
			0.38			0.27		-0.34		-0.51
Bid-Ask Spread				-0.36%			-0.25%		-0.05%	-0.10%
				-0.67			-0.47		-0.09	-0.18
Special*GHZ Net					1.77%***			1.72%***	1.64%***	1.63%***
					5.16			5.06	4.91	4.84
Size*GHZ Net						-1.30%***		-0.56%*		-0.46%
						-4.16		-1.83		-1.32
Bid-Ask Spread*GHZ Net							1.27%***		0.45%	0.22%
							2.72		1.01	0.41

Table VIII
Univariate Projection of Loan Fee on GHZ Set of Anomalies

The table displays coefficient estimates and t-statistics for univariate regressions of loan fee on individual anomaly sorting variables. Panel A shows results for the anomalies that are most strongly related to loan fee, as given by the t-statistic on the univariate regression, while Panel B shows results for the anomalies that are most weakly related to loan fee, as given by the t-statistic on the univariate regression. Panel C displays results using all of the GHZ anomalies. In the four rightmost columns, we then show long-short returns to each anomaly using our four different sorting cutoffs (1%, 2%, 5%, and 10%). At the bottom of each panel, "Mean" and "Median" display the mean and median return for each panel.

				Long/Short Return for Loan Fee Indicated Direction			
					Top/Bottom		
Rank	**Anomaly**	**Coef.**	**t-stat**	**1%**	**2%**	**5%**	**10%**
Panel A: Anomalies that are strongly correlated with loan fee							
1	Idiosyncratic return volatility	97.5	23.5	0.4%	0.5%	0.5%	0.4%
2	Bid-ask spread	96.7	21.4	1.2%	0.8%	0.4%	0.4%
3	Return volatility	79.7	21.2	0.9%	0.7%	0.5%	0.4%
4	Earnings volatility	69.6	20.7	0.5%	0.5%	0.1%	0.1%
5	Return on assets	-68.9	-19.0	0.2%	0.3%	0.3%	0.3%
6	R&D to sales	67.4	12.8	1.7%	1.2%	1.1%	1.0%
7	Maximum daily return	65.6	19.7	0.7%	0.7%	0.4%	0.3%
8	Scaled earnings forecast	-64.7	-13.5	0.7%	0.5%	0.1%	0.0%
9	Accrual volatility	58.7	17.9	1.7%	0.7%	0.7%	0.8%
10	Earning to price	-58.2	-18.0	0.2%	0.3%	0.2%	0.2%
	Mean			0.8%	0.6%	0.4%	0.4%
	Median			0.7%	0.6%	0.4%	0.4%
Panel B: Anomalies that are weakly correlated with loan fee							
1	Corporate investment	-0.6	-0.2	0.8%	0.2%	0.1%	0.0%
2	Sin stocks	-0.7	-0.8	0.3%	0.3%	0.3%	0.3%
3	Industry sales concentration	0.8	0.8	-0.2%	-0.1%	0.4%	0.3%
4	Real estate holdings	0.8	0.3	-0.5%	-0.6%	-0.3%	-0.2%
5	Change in 6-month momentum	0.8	0.3	-0.2%	-0.3%	-0.2%	0.0%
6	Sales to inventory	-0.9	-0.9	0.9%	0.9%	0.5%	0.3%
7	Change in tax expense	1.2	0.8	0.5%	0.4%	0.2%	0.1%
8	Abnormal earnings announce. vol.	-1.7	-1.3	0.1%	0.0%	0.1%	0.1%
9	1-month momentum	-2.3	-1.3	-0.3%	0.0%	0.0%	0.0%
10	Secured debt indicator	2.3	2.9	0.0%	0.0%	0.0%	0.0%
	Mean			0.1%	0.1%	0.1%	0.1%
	Median			0.0%	0.0%	0.1%	0.0%
Panel C: Summary statistics for 102 GHZ anomalies							
	Mean			0.2%	0.2%	0.1%	0.1%
	Median			0.1%	0.1%	0.1%	0.1%

Table IX
Performance of the Unique versus Common Information in Loan Fee Anomaly

The table shows monthly long-short returns and corresponding ranks from portfolios formed on the loan fee anomaly, GHZ Net, and all GHZ anomalies, as well as the fitted loan fee and residual loan fee. The the fitted loan fee and residual loan fee are constructed by projecting loan fee on all of the 102 GHZ anomalies at the same time and we then examine the performance of the fitted value ("fitted loan fee") and residual ("residual loan fee") from this regression. Panel A displays the average of 1-month returns, Panel B displays the percentage of 1-month returns that are positive, and Panel C displays the monthly Sharpe Ratio. In each panel we present results when portfolios are formed by sorting stocks on the top and bottom 1% of anomaly variables ("Top/Bottom 1%"), as well as when portfolios are formed by sorting stocks on the top and bottom 2%, 5%, and 10%.

	Loan Fee		**Fitted Loan Fee**		**Residual Loan Fee**		**GHZ Net**		**GHZ Set of Anomalies**		
	Value	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Value**	**Rank**	**Mean**	**95th Ptile**	**Max.**
Panel A: Average of 1-Month Return											
Top/Bottom 1%	3.63%	1	1.41%	7	2.85%	1	1.83%	2	0.24%	1.43%	1.87%
Top/Bottom 2%	2.64%	1	1.48%	2	2.37%	1	1.47%	2	0.18%	0.84%	1.59%
Top/Bottom 5%	1.76%	1	0.99%	1	1.33%	1	0.92%	1	0.13%	0.67%	0.88%
Top/Bottom 10%	1.17%	1	0.67%	3	0.71%	3	0.72%	2	0.13%	0.52%	0.77%
Panel B: Percentage of 1-Month Returns that are Positive											
Top/Bottom 1%	74.3%	1	59.9%	7	65.3%	1	60.5%	6	51.8%	59.9%	64.7%
Top/Bottom 2%	73.1%	1	61.7%	1.5	67.1%	1	64.7%	1	52.0%	58.7%	61.7%
Top/Bottom 5%	68.9%	1	59.9%	4	64.1%	1	63.5%	1	51.5%	58.7%	62.9%
Top/Bottom 10%	68.3%	1	59.3%	6	57.5%	17	65.3%	1	52.1%	59.3%	63.5%
Panel C: Monthly Sharpe Ratio											
Top/Bottom 1%	0.58	1	0.15	10	0.38	1	0.27	2	0.04	0.21	0.32
Top/Bottom 2%	0.53	1	0.21	2	0.39	1	0.28	1	0.04	0.16	0.21
Top/Bottom 5%	0.48	1	0.18	4	0.30	1	0.23	1	0.04	0.15	0.21
Top/Bottom 10%	0.40	1	0.14	15	0.20	2	0.22	2	0.04	0.17	0.23

Table X
Loan Fee R^2 Decomposition

The table displays results from regressions of one-month ahead monthly returns on loan fee (column 1), the predicted loan fee (column 2) derived from the regression in Table IX, the residual loan fee (column 3) derived from the regression in Table IX, and both of them simultaneously (column 4). In each column, we display the coefficient estimate with t-statistics shown below in parenthesis. In the second to last row of the table we display the the within R^2 for each regression. In the last row we display the within R^2 for each model as a percent of the R^2 in column 4.

	(1)	(2)	(3)	(4)
Loan Fee	-0.41%			
	(-7.80)			
Predicted Loan Fee		-0.57%		-0.57%
		(-1.73)		(-1.73)
Residual Loan Fee			-0.38%	-0.38%
			(-7.55)	(-7.52)
Time Fixed Effects	Yes	Yes	Yes	Yes
Observations	412,147	412,147	412,147	412,147
Within R-Squared	0.126%	0.037%	0.092%	0.129%
As Fraction of (4)	97.4%	28.4%	71.6%	100.0%

Table XI
Performance of Long/Short Portfolio Net of Short Selling Costs

The table examines the performance of the loan fee anomaly and the GHZ anomalies after subtracting short selling costs. For each anomaly we construct a long/short portfolio and calculate its return. The performance of each anomaly is evaluated using three metrics: the average 1-month returns (Panel A), the percentage of 1-month returns that are positive (Panel B), and the monthly Sharpe Ratio (Panel C). For each of these, we also rank each anomaly variable relative to the entire set of anomalies. The GHZ set of anomalies is the set of 102 anomalies studied in Green et al. (2017). In each panel we present results when portfolios are formed by sorting stocks on the top and bottom 1% of anomaly variables ("Top/Bottom 1%"), as well as when portfolios are formed by sorting stocks on the top and bottom 2%, 5%, and 10%.

	Loan Fee		**GHZ Net**		**GHZ Set of Anomalies**		
	Value	**Rank**	**Value**	**Rank**	**Mean**	**95th Ptile**	**Max.**
Panel A: Average of 1-Month Return							
Top/Bottom 1%	0.97%	7	1.40%	2	0.01%	1.20%	1.55%
Top/Bottom 2%	0.82%	4	1.07%	2	-0.03%	0.52%	1.15%
Top/Bottom 5%	0.69%	2	0.61%	2	-0.04%	0.42%	0.76%
Top/Bottom 10%	0.48%	2	0.47%	4	-0.02%	0.40%	0.51%
Panel B: Percentage of 1-Month Returns that are Positive							
Top/Bottom 1%	58.7%	5	58.1%	5.5	50.1%	57.5%	64.1%
Top/Bottom 2%	58.7%	3	60.5%	1	49.9%	57.5%	59.9%
Top/Bottom 5%	59.3%	1	59.9%	1	49.3%	56.9%	58.1%
Top/Bottom 10%	61.7%	1	61.1%	1	49.6%	56.9%	59.3%
Panel C: Monthly Sharpe Ratio							
Top/Bottom 1%	0.16	7	0.21	3	0.00	0.17	0.31
Top/Bottom 2%	0.16	2	0.20	1	-0.01	0.12	0.19
Top/Bottom 5%	0.19	1	0.15	3	-0.01	0.11	0.18
Top/Bottom 10%	0.16	1	0.14	1	-0.01	0.12	0.14

Online Appendix for
"The Loan Fee Anomaly: A Short Seller's Best Ideas"[1]

This appendix provides additional empirical evidence to supplement the main text.

1. Table A1 displays summary statistics for each of the GHZ anomalies.
2. Table A2 repeats the analysis of Table II in the main paper, but it raises the market capitalization NYSE breakpoint from the 5^{th} to the 20^{th} percentile.

[1]Citation format: Joseph E. Engelberg, Richard B. Evans, Greg Leonard, Adam V. Reed, and Matthew C. Ringgenberg, Online Appendix for "The Loan Fee Anomaly: A short seller's Best Ideas," 2020, Working Paper.

Table A1
GHZ Anomaly Summary Statistics

The table reports means, standard deviations, and the 1st, 50th, and 99th percentiles for each of the 102 anomaly variables in Green, et al. (2017). The sample consist of all US common equities above the 5th percentile NYSE size breakpoint over the period 2006 to 2019.

Anomaly	**Mean**	**Std. Dev.**	**1st %**	**Median**	**99th %**
Absolute accruals	0.1	0.1	0.0	0.1	0.4
Working capital accruals	-0.1	0.1	-0.4	0.0	0.2
Abnormal earnings announcement volume	0.9	1.3	-0.6	0.6	6.1
# of years since first Compustat coverage	19.0	12.2	1.0	17.0	43.0
Asset growth	0.1	0.4	-0.4	0.1	1.8
Bid-ask spread	0.0	0.0	0.0	0.0	0.1
Beta	1.2	0.5	0.2	1.2	2.7
Beta squared	1.8	1.6	0.1	1.3	7.5
Book-to-market	0.5	0.5	-0.3	0.4	2.0
Indust-adj. book to market	-5.0	62.2	-344.2	0.1	126.5
Cash holdings	0.2	0.2	0.0	0.1	0.9
Cash flow to debt	0.1	0.9	-3.6	0.1	1.6
Cash productivity	3.0	36.7	-111.7	1.5	167.5
Cash-flow-to-priceratio	0.1	0.2	-0.4	0.1	0.6
Indust-adj. cash-flow-to-price ratio	-1.3	12.8	-42.8	0.0	14.3
Indust-adj. change in asset turnover	0.0	0.2	-0.7	0.0	0.6
Change in shares outstanding	0.1	0.2	-0.2	0.0	1.1
Indust-adj. change in employees	-0.2	1.1	-2.8	-0.1	1.1
Change in forecasted EPS	0.0	0.4	-1.0	0.0	1.0
Change in inventory	0.0	0.0	-0.1	0.0	0.1
Change in 6-month momentum	0.0	0.5	-1.3	0.0	1.4
Change in number of analysts	-0.1	2.3	-7.0	0.0	6.0
Indust-adj. change in profit margin	0.5	25.7	-29.0	0.0	44.0
Change in tax expense	0.0	0.0	0.0	0.0	0.0
Corporate investment	0.0	3.9	-2.7	0.0	2.7
Convertible debt indicator	0.1	0.3	0.0	0.0	1.0
Current ratio	3.5	5.9	0.5	1.9	37.6
Depreciation / PP&E	0.3	0.5	0.0	0.2	2.7
Dispersion in forecasted EPS	0.1	0.4	0.0	0.0	2.2
Dividend initiation	0.0	0.2	0.0	0.0	1.0
Dividend omission	0.0	0.2	0.0	0.0	1.0
Dollar trading volume	14.6	2.0	10.1	14.6	18.6
Dividend to price	0.0	0.0	0.0	0.0	0.1
Earning announcement return	0.0	0.1	-0.2	0.0	0.2
Growth in common shareholder equity	0.1	0.6	-1.8	0.1	3.2
Earning to price	0.0	0.3	-0.9	0.0	0.2
Forecasted growth in 5-year EPS	14.1	9.9	-8.5	12.5	50.0
Gross profitability	0.3	0.3	-0.5	0.3	1.3
Growth in capital expenditures	0.7	2.8	-1.0	0.2	13.1

Continued on next page

Table A1 – continued from previous page

Anomaly	Mean	Std. Dev.	1st %	Median	99th %
Growth in long-term net operating assets	0.1	0.2	-0.3	0.1	0.7
Industry sales concentration	0.1	0.1	0.0	0.0	0.4
Employee growth rate	0.1	0.2	-0.4	0.0	1.2
Idiosyncratic return volatility	0.1	0.0	0.0	0.0	0.1
Illiquidity	0.0	0.0	0.0	0.0	0.0
Industry momentum	0.1	0.3	-0.5	0.1	1.0
Capital expenditures and inventory	0.1	0.1	-0.2	0.0	0.6
New equity issue	0.0	0.2	0.0	0.0	1.0
Leverage	1.6	3.5	0.0	0.5	14.8
Growth in long-term debt	0.2	0.6	-0.5	0.1	3.4
Maximum daily return	0.1	0.1	0.0	0.0	0.3
12-month momentum	0.1	0.5	-0.7	0.1	1.8
1-month momentum	0.0	0.1	-0.3	0.0	0.4
36-month momentum	0.4	0.8	-0.8	0.2	3.5
6-month momentum	0.1	0.3	-0.6	0.0	1.0
Financial statement score	4.5	1.6	1.0	5.0	7.0
Size	14.2	1.6	11.7	14.0	18.2
Indust-adj. size	1403.9	13971.8	-12727.7	-1583.1	66489.4
Number of analysts covering stock	8.8	7.5	0.0	7.0	32.0
Number of earnings increases	0.9	1.2	0.0	1.0	6.0
Operating profitability	0.7	1.3	-3.4	0.6	6.4
Organizational capital	0.0	0.0	0.0	0.0	0.0
Indust-adj. % change in capital expenditures	10.9	110.0	-28.1	-0.5	633.7
% change in current ratio	0.1	0.4	-0.7	0.0	2.1
% change in depreciation	0.1	0.4	-0.7	0.0	1.7
% change in gross margin - % change in sales	0.0	0.7	-3.8	0.0	1.8
% change in quick ratio	0.1	0.5	-0.7	0.0	2.4
% change in sales - % change in inventory	-0.1	0.8	-3.5	0.0	1.2
% change in sales - % change in A/R	0.0	0.5	-2.4	0.0	1.2
% change in sales - % change in SG&A	0.0	0.2	-0.6	0.0	0.9
% change sales-to-inventory	0.1	0.7	-0.8	0.0	3.6
Percent accruals	-2.1	5.7	-35.9	-0.7	3.9
Price delay	0.0	0.4	-0.9	0.0	1.0
Financial statement score	5.0	1.5	1.0	5.0	8.0
Quick ratio	2.9	5.2	0.3	1.4	33.0
R&D increase	0.1	0.3	0.0	0.0	1.0
R&D to market capitalization	0.1	0.1	0.0	0.0	0.4
R&D to sales	1.1	10.4	0.0	0.0	23.9
Real estate holdings	0.3	0.2	0.0	0.3	0.7
Return volatility	0.0	0.0	0.0	0.0	0.1
Return on assets	0.0	0.1	-0.2	0.0	0.1
Earnings volatility	0.0	0.1	0.0	0.0	0.3
Return on equity	0.0	0.2	-0.7	0.0	0.5
Return on invested capital	-0.1	1.3	-6.9	0.1	0.7
Revenue surprise	0.0	0.1	-0.3	0.0	0.3

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Table A1 – continued from previous page

Anomaly	Mean	Std. Dev.	1st %	Median	99th %
Sales to cash	30.5	95.0	0.0	5.4	573.4
Sales to inventory	35.7	84.0	0.5	9.9	492.8
Sales to receivables	12.2	23.1	0.1	6.2	146.5
Secured debt	0.4	0.5	0.0	0.3	1.3
Secured debt indicator	0.5	0.5	0.0	0.0	1.0
Scaled earnings forecast	-0.1	1.8	-1.6	0.1	0.5
Sales growth	0.1	0.4	-0.6	0.1	2.2
Sin stocks	0.0	0.1	0.0	0.0	0.0
Sales to price	1.1	1.9	0.0	0.6	9.0
Volatility of liquidity (dollar trading volume)	0.5	0.2	0.2	0.4	1.1
Volatility of liquidity (share turnover)	5.6	7.6	0.3	3.3	40.8
Accrual volatility	7.0	49.0	0.0	0.1	282.8
Cash flow volatility	19.4	135.7	0.0	0.1	729.9
Unexpected quarterly earnings	0.0	0.1	-0.2	0.0	0.1
Debt capacity/firm tangibility	0.5	0.2	0.1	0.5	1.0
Tax income to book income	0.0	1.5	-3.7	0.0	5.6
Share turnover	2.1	1.7	0.1	1.6	9.2
Zero trading days	0.0	0.3	0.0	0.0	0.0

Table A2
Performance of Long/Short Portfolio - Market Cap. $\geq 20^{th}$ Percentile

The table reports the performance of the loan fee anomaly relative to the GHZ anomalies when we limit the sample to include only stocks above the 5th percentile of NYSE size breakpoints. For each anomaly we construct a long/short portfolio and calculate its return. The performance of each anomaly is evaluated using three metrics: the average 1-month returns, the percentage of 1-month returns that are positive, and the monthly Sharpe Ratio. For each of these, we also rank each anomaly variable relative to the entire set of anomalies. Loan fee is measured by the DCBS on the last trading day of the month. The short interest ratio is the mid-month short interest divided by shares outstanding. Day-to-cover is calculated as the short interest ratio divided by average daily trading volume as a percent of shares outstanding during the same month in which short interest is measured. The GHZ set of anomalies is the set of 102 anomalies studied in Green et al. (2017). We present results when portfolios are formed by sorting stocks on the top and bottom 1% of anomaly variables ("Top/Bottom 1%"), as well as when portfolios are formed by sorting stocks on the top and bottom 2%, 5%, and 10%.

	Loan Fee		**GHZ Net**		**GHZ Set of Anomalies**		
	Value	**Rank**	**Value**	**Rank**	**Mean**	**95th Ptile**	**Max.**
Average of 1-Month Return							
Top/Bottom 1%	2.04%	1	0.92%	7	0.18%	1.05%	1.42%
Top/Bottom 2%	1.73%	1	0.84%	4	0.11%	0.73%	1.03%
Top/Bottom 5%	1.06%	1	0.61%	3	0.09%	0.51%	0.76%
Top/Bottom 10%	0.74%	1	0.36%	12	0.07%	0.39%	0.59%
Percentage of 1-Month Returns that are Positive							
Top/Bottom 1%	66.5%	1	55.1%	26.5	51.6%	60.5%	64.7%
Top/Bottom 2%	65.9%	1	56.3%	18	51.4%	59.3%	63.5%
Top/Bottom 5%	65.9%	1	56.9%	12	51.3%	58.7%	62.9%
Top/Bottom 10%	64.1%	1	59.3%	1	51.0%	57.5%	58.7%
Monthly Sharpe Ratio							
Top/Bottom 1%	0.28	1	0.12	15	0.03	0.18	0.28
Top/Bottom 2%	0.34	1	0.17	6	0.02	0.17	0.25
Top/Bottom 5%	0.30	1	0.16	4	0.03	0.15	0.24
Top/Bottom 10%	0.25	1	0.12	8	0.03	0.12	0.20