The Predictability of Short Selling Loan Fees

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ABSTRACT

Using a novel equity lending dataset, this paper is the first to show that expected returns strongly and negatively predict short selling loan fees, both in the time series and cross section, suggesting that short sellers trade based on rational expectations of returns. In light of the importance of loan fees to short seller profitability, a loan fee forecasting exercise demonstrates that a) loan fees are highly predictable out-of-sample, and b) expected returns can improve the out-of-sample predictability of loan fees. Loan fee predictability has implications for future loan demand and price efficiency, suggesting that short sellers are drawn to short stocks with historically predictable fees in order to mitigate against the risk of unexpected loan fee increases. I present evidence that loan demand is the primary channel through which expected returns improve fee predictability.

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1 Introduction

Short selling is risky and potentially very costly. In order to initiate a short sale, an investor must borrow shares in the equity lending market and pay a loan fee (an overnight borrow cost) to the broker dealer as long as the short position is open. Generally, short selling loan fees are low (around 30-50 basis points, annualized), but they can rise to much higher levels, becoming an economically significant cost for short sellers to bear (see Andrews, Lundblad, and Reed (2022)). Not only are short sellers exposed to the price risk associated with the securities they borrow, but they are also exposed to the risk of stock loans becoming expensive while their positions are open (see Engelberg, Reed, and Ringgenberg (2018)).

My main result is that loan fees are predictable out-of-sample through two key channels. First, since loan fees are stable for many stocks, I find that lagged loan fees are good predictors of future loan fees, especially for short horizons. Second, since loan fees are determined in equilibrium by the supply and demand of lendable shares, I find that a stock's expected return predicts future loan fees beyond the current stock loan fee.[1] Intuitively, if a stock's forecasted expected return declines, then the demand for shorting it increases and the loan supply decreases, leading to a higher loan fee in the future.

The predictability of loan fees is a consequential topic to academics and practitioners alike. Given that loan fees represent an important limit to arbitrage, it is not surprising that several academic papers have explored the determinants of loan fee movements (see Section 1.1 for a literature review). It is surprising, however, that this prior literature has largely ignored the predictability of loan

[1] I derive expected return forecasts from Lewellen (2014)'s method, which is further described in Section 3. The extent to which this result is surprising depends on one's prior belief about how informed short sellers are. If the prior belief is that short sellers are naive and unsophisticated, then one may expect that short seller trading would not be linked to a rational estimation of expected returns. However, if the prior belief is that they are sophisticated and informed traders, then it will not be as surprising that short sellers would target stocks with low expected returns and impact their equilibrium loan fees.

fees, which is critical to understanding the formation of loan fees and the determination of short seller profits. This topic is also relevant to practitioners, as the ability to predict future loan fees could inform a short seller's intertemporal decision of whether to short today or tomorrow. Stocks with predictable loan fees would be attractive targets for short sellers, as fee predictability decreases the risk of unexpected loan fee changes while short positions are open. Moreover, loan fee forecasting could improve equity lender estimations of future profits.[2]

To uncover these empirical patterns on the predictability of loan fees and link the expected return channel to the demand for short selling, I rely on a novel dataset that allows me to directly observe the supply and demand of lendable shares. I begin by establishing that forecasted expected returns strongly and negatively predict loan fees, both in the time series and cross section. When investors expect a stock to perform poorly in the future, they are more likely to short the stock, which drives up the stock's future loan fee. This result sheds new light on the sophistication of short sellers, suggesting that short sellers form rational expectations of returns and adjust their short portfolios based on variation in those expectations.

Using this result and controlling for several variables that the literature has shown to relate to loan fees, I conduct an out-of-sample forecasting exercise to determine how predictable loan fees are at horizons up to 1 year. I find that future loan fees are highly predictable out-of-sample, with an average 1-month ahead out-of-sample R^2 (henceforth, R^2_{OS}) of 73%. Although diminishing for longer-term horizons, the out-of-sample predictability of loan fees remains at horizons up to 1 year; in fact, I find an average 1-year ahead loan fee R^2_{OS} of 26%.

In order to provide a benchmark for comparing the predictability of loan fees, I also forecast loan fee changes and compare their predictability with

[2]Further demonstrating the importance of this topic in the current economic environment, short selling activity is frequently on the forefront of the news. See, for example, news regarding short sellers targeting oil and consumer stocks, Tesla and Netflix, and "meme" stocks.

that of stock returns. I find that loan fee changes are much more predictable out-of-sample than stock returns, as evidenced by an R^2_{OS} of 8% in predicting 1-month ahead loan fee changes, compared to an R^2_{OS} of only around 1% among stock returns.[3]

I perform an R^2 decomposition to determine the relative contribution of each variable in predicting future loan fee levels, and I find that loan fees are predictable primarily through two channels. First, loan fees are predictable due to the autoregressive nature of loan fees; in other words, the lagged loan fee has strong predictive power on future loan fees. Second, loan fees are predictable through the expected return channel. After the lagged loan fee, expected returns are the second strongest predictor of future loan fees for stocks with low expected returns. For stocks in the bottom tercile of forecasted expected returns, the expected return forecast itself strongly contributes to loan fee predictability, since investors are likely to short stocks that they expect to perform poorly.

To explore the implications of loan fee predictability on trading, I construct a measure of loan fee predictability and find that it is highly correlated with future loan demand and price efficiency. In particular, I find that an increase in loan fee predictability tends to predict higher short interest and lower price delay (based on Hou & Moskowitz (2005)) in the following quarter. These results suggest that short sellers may incorporate loan fee predictability in their decision to short. Highly predictable loan fees would be an attractive feature for a short target, as fee predictability decreases the risk of unexpected loan fee increases while short positions are open.

Finally, I explore the channel through which forecasted expected returns impact loan fee predictability. Two potential channels emerge. First, if expected returns impact fee predictability through the demand channel, then stocks with low forecasted expected returns attract shorting demand, which significantly

[3]See, for example, Haddad, Kozak, & Santosh (2020).

drives up loan fees. Second, if the supply channel is true, then stocks with low forecasted expected returns will likely end up being held by relatively unsophisticated investors, who are unlikely to lend out their shares. If this is the case, then stocks with low forecasted expected returns will likely experience low supply of lendable shares, which will result in higher loan fees. After splitting my sample between high/low loan demand/supply stocks, I find evidence that loan demand is the primary channel through which forecasted expected returns improve loan fee predictability, demonstrated by the fact that expected returns do not seem to contribute as much to loan fee predictability for stocks with low loan supply.

1.1 Literature Review

First, this paper contributes to the short selling literature, especially adding to the discussion on determinants and movements of loan fees. Geczy, Musto, & Reed (2002) show that idiosyncratic episodes such as mergers, acquisitions, and IPO's are important in driving loan fees. A more recent paper by Andrews, Lundblad, & Reed (2022) shows that there is actually a high degree of commonality among loan fees and that many loan fees co-move with a common loan fee component. Moreover, Andrews et. al (2022) show that the loan fee common component is highly correlated in the time series with several well-known asset pricing and macro variables, a fact which I incorporate in the loan fee forecasting exercise of Section 4. After decomposing the out-of-sample loan fee R^2, I am able to shed new light on the variables which strongly predict future loan fees out-of-sample, and I find that the lagged loan fee and expected return are the two most powerful predictors. While the aforementioned papers explore the extent to which idiosyncratic episodes and commonality drive loan fee movements over time, this paper is the first to study loan fee predictability, which is critical in understanding how loan fees are determined over time.

Additionally, this paper contributes to the discussion on the relationship between loan fees and returns. Several papers (including Jones & Lamont (2001), Asquith, Pathak, & Ritter (2004), Boehmer, Jones & Zhang (2007), Rapach, Ringgenberg, & Zhou (2016), Kelley & Tetlock (2016), and Drechsler & Drechsler (2021)) show that short selling activity and constraints (proxied by short interest or loan fee levels, depending on the paper) negatively predict future realized returns. Short selling constraints functionally limit arbitrage, which leads to stocks becoming overvalued and thus earning low subsequent realized returns. Moreover, Engelberg, Reed, & Ringgenberg (2018) show that not only do loan fee levels predict low future returns, but loan fee variance does as well.

My paper diverges from these papers in several important ways. First, these papers study short sale constraints or loan fees as a means of predicting stock returns. I assert that loan fees are an economically important variable for short sellers in their own right, independent of their ability to predict realized returns, and thus are worth predicting. The ability to predict loan fees would have significant implications on short sellers' intertemporal decisions of whether to short today or in the future. Moreover, loan fee predictability would have cross-sectional implications on which stocks short sellers would want to short. Stocks with high loan fee predictability would make attractive short targets, as these stocks would mitigate the risk of unexpected loan fee increases while short positions are open. Hence, it is valuable to consider future loan fees as the dependent variable, which differentiates this paper from others in the literature.

A second way in which my paper diverges from the short selling literature is that while other papers study the relationship between loan fees and ex-post realized returns, I am the first to study the relationship between ex-ante forecasted expected returns and loan fees. Expected return forecasts allow me to predict how well a rational investor might believe a stock will perform ex-ante. Thus, linking expected returns to future loan fees provides insight into short sellers' decision-making processes that ex-post realized returns do not. Because of this, I am able to be the first to establish a link between the expected return channel and loan demand, shedding new light on the sophistication of short sellers.

This paper diverges from several recent papers which derive option-implied stock borrowing fees, such as Weitzner (2020) and Muravyev, Pearson, & Pollet (2018, 2021). In forecasting future loan fees, I choose not to use options to derive the implied borrowing costs. Options are not heavily traded for less liquid stocks and for expiration dates in the distant future, so they are not ideal for the forecasting horizons I wish to consider.[4] The regression approach I employ in predicting future loan fees allows the estimation of expected loan fees a) for all stocks and b) at more distant horizons.

Aside from the short selling literature, this paper is also related to a broad array of papers which study forecasting and stock return prediction. Papers such as Fama and MacBeth (1973), Shiller (1981), Fama & French (1988), Jacobs and Levy (1988), Goyal & Welch (2008), Campbell & Thompson (2008), Stambaugh et al. (2012), Lewellen (2014), Martin & Wagner (2019), Haddad, Kozak, & Santosh (2020), Gu, Kelly, & Xiu (2020), and Freyberger, Neuhierl, & Weber (2020) provide useful methodological contributions for predicting stock returns, whether in the aggregate or at the portfolio level. I rely on Lewellen (2014) for the methodology on how to forecast expected returns based on stock characteristics. I modify the R^2_{OS} formula from Campbell & Thompson (2008) (which forecasts the aggregate equity premium) and apply it to loan fees, which vary cross-sectionally.[5] Finally, I reference Haddad, Kozak, & Santosh (2020) for the predictability of portfolio-level stock returns, which is a useful benchmark to which I compare the predictability of loan fee levels and changes.

The remainder of the paper is structured as follows. Section 2 describes my dataset and shows summary statistics. Section 3 describes how I calculate

[4]Hence, using option-implied borrowing costs may introduce a selection issue. The most illiquid stocks are likely to have the most illiquid (or unavailable) options, and stock illiquidity correlates with loan fees.

[5]See Section 4.2 for further details.

forecasted expected returns and how I test their relationship with loan fees. In Section 4, I conduct a loan fee forecasting exercise and explore the channels through which loan fees are predictable. In Section 5, I explore the implications of loan fee predictability on future loan demand, loan fees, and price efficiency. In Section 6, I explore the channel through which expected returns improve loan fee predictability. Finally, in Section 7, I conclude.

2 Data

In this paper, I use a novel equity lending dataset, which has not previously been used in a published academic paper to my knowledge. I obtain equity lending data from S3 Partners, which is an analytics company that has over $3 trillion in assets under advisement on their treasury management platform.[6] This platform is accessible to investors via a subscription on the Bloomberg terminal. Most of S3 Partners' clients are institutional buy and sell side, with some individual investors.

S3 Partners is set apart from its competitors in the equity lending data market by its unique position in the data capture workflow. Unlike its competitors, S3 directly captures trade details for over 5 million transactions on a daily basis. Since investors enter their trades directly through S3's platform, S3 is able to capture complete and accurate data directly. Competitors in the market for equity lending data rely on clients to optionally send them trade details, casting doubt on the data quality they are able to provide. Because of S3's unique position in this industry, it seems likely that their equity lending data is more complete and accurate than other providers in the space.

The S3 Partners equity lending dataset spans from 2015 through 2021 and allows me to view loan fees, short interest, and loan supply on a daily basis at the

[6]See the S3 Partners website here.

stock level. The equity lending dataset covers all US equities. After checking the coverage of the dataset, I verified that I am able to view loan fee data for all stocks in the current S&P 500 and Russell 2000, indicating that the dataset is exceptional in its coverage of the US equity market.

Aside from S3 Partners equity lending data, I use stock characteristics and accounting data from Compustat and stock return data from CRSP. I obtain the data on the Fama & French (2014) five factors, as well as momentum and the risk-free rate, from Ken French's data library.[7] I obtain data on VIX from FRED. Finally, I obtain the "devil's in the details" DVL and "betting against beta" BAB factors from AQR Capital Management's website.[8] The following table displays summary statistics for many of the variables of interest.

[Table 1]

In Table 1 Panel A, I display monthly summary statistics for the equity lending data. The median loan fee is about 34bp in my sample, which is comparable to the median from other papers which use Markit data. The mean loan fee is 272bp, indicating significant right skewness in the distribution of loan fees. The average short interest ratio (defined as short interest scaled by shares outstanding) is 5%. The average loan supply ratio (defined as loan supply scaled by shares outstanding) is 30%. The average utilization (defined as loan demand scaled by loan supply) is 11%.[9]

The bottom three variables in Table 1 Panel A relate to monthly profit and loss for short sellers.[10] From the variable "Total Monthly Net MTM P&L (millions)", it is apparent that in the average stock-month, short sellers earned

[7] See Ken French's data library here.

[8] See AQR's Betting Against Beta data here or their Devil's in the Details data here.

[9] In order to better understand how several of the firm characteristics in the sample relate to one another in the cross section, I convert the dataset to be fully cross-sectional and calculate pairwise correlations between variables in Table A.1. Notably, in the cross section of stocks, the loan fee variable tends to be highly correlated with utilization, volatility, and turnover, while it tends to be negatively correlated with size.

[10] These variables are only populated for 2021, which explains the smaller sample size.

a -\$6.08 million marked-to-market loss, net of loan fees. They earned a -\$6.01 million marked-to-market loss, gross of fees. The fact that short sellers lost money on average in 2021 is not surprising, given the strong bull market throughout the year. I also calculate the monthly loan fee costs for each stock as the gross minus net profit/loss and report the monthly loan fee costs. For the average stock-month, short sellers paid a total of about \$67,000 in loan fees to borrow stock in that month.

In Table 1 Panel B, I report summary statistics on realized and expected returns. In my sample, the average monthly return is 0.85%, while the median monthly return is 0.55%. The other 3 variables in this panel relate to Lewellen (2014), whose methodology I discuss in detail in Section 3. Regardless of which of the three Lewellen models for forecasting expected returns that I consider, the average forecasted monthly expected return is around 0.4-0.55%, while the median is in the 0.49-0.59% range. The final variable in Panel B is the 1-year ahead forecasted expected return. The average 1-year ahead expected return forecast, based on Lewellen's Model 3, is about 5.7%, while the median is 7.3%.

In Table 1 Panel C, I report summary statistics on each of the firm characteristics that I use to calculate expected return forecasts. Each of these variables is described in detail in Table A.2. Although my sample window is quite different from Lewellen (2014), the averages and standard deviations that I calculate for these variables align closely with those reported in Lewellen (2014).

2.1 Motivating Example

To illustrate the point that loan fees are an economically important quantity for short sellers to consider, I plot the loan fee level and aggregate loan fee expenditures in 2021 for BLNK (Blink Charging Company). BLNK is a company which builds charging stations for electric vehicles.

[Figure 1]

In Figure 1, I plot loan fee levels (in percent per annum) in red with units on the right vertical axis. BLNK experienced highly volatile loan fees throughout 2021, ranging from only a few percent to over 50 percent. In blue with units on the left vertical axis, I plot cumulative loan fee costs across all short sellers who borrowed BLNK across the market. Over the course of the year, short sellers paid almost $60 million to short BLNK. A large portion of these fees were paid in the second quarter of 2021, when loan fee levels were at their highest. Aggregate shorting costs can accumulate rapidly when loan fee levels are high. For short sellers hoping to capitalize on falling stock prices, the loan fee could make the difference between earning a profit and recognizing a loss.[11]

3 Loan Fees and Forecasted Expected Returns

In this section, I study the relationship between loan fees and forecasted expected returns. While the prior literature has explored the relationship between loan fees and subsequent realized returns, I am the first to study the relationship between ex-ante expected returns and loan fees. As such, I am able to study whether short sellers incorporate rational expectations of returns in their short selling decisions. To calculate expected return forecasts, I rely on Lewellen (2014), which provides a methodology for estimating a rational expectation of future returns for a stock given firm characteristics.[12] I will first outline the methodology,

[11] I am unable to observe transaction-level data, so I cannot disentangle individual short seller profits or costs.

[12] I also calculated option-implied expected returns based on Martin & Wagner (2019), but I found that the cross-sectional coverage was much lower. Specifically, I was able to calculate option-implied expected returns for only 852 stocks, while I was able to calculate Lewellen expected returns for 4,909 stocks. Moreover, the Lewellen expected returns match up much closer with realized returns in the cross section. I do not take a stand on whether investors actually expect to receive these expected return estimates. The expected return forecast is purely an empirical version of a rational expectation of returns, given the characteristics that Lewellen (2014) considers. The results of this paper suggest that investors do, to some extent, expect to receive the

and then I will show the results.

3.1 Methodology

Lewellen (2014) studies cross-sectional properties of return forecasts from Fama-MacBeth (1973) regressions of returns on stock and firm characteristics. Using CRSP and Compustat data, I calculate all 15 of the return signals used in Lewellen (2014). For a description of all return signals considered, see Appendix Table A.2.

To estimate expected return forecasts, I run Fama-MacBeth (1973) monthly cross-sectional regressions of realized monthly returns on the lagged Lewellen (2014) signals.[13] I implement Newey-West standard errors with 4 lags. The coefficients are similar in magnitude to those found in Lewellen (2014), even though our sample windows differ. The results from these regressions are found in Table A.3. Note that I consider each of the 3 Lewellen (2014) expected return models; these models differ only in the number of characteristics used in the regressions.

After running monthly Fama-MacBeth regressions of returns on signals, I save the monthly slope coefficients and calculate 10-year rolling average slopes.[14] I then estimate expected return forecasts as linear combinations of rolling-average slope coefficients and firm characteristics. For example, in calculating the 1-month ahead expected return forecast based on Lewellen's Model 1, which is only constructed from 3 firm characteristics, $\hat{R}^{Model1}_{i,t+1|t} = b_0 + b^{size} * LogSize_{i,t} + b^{bm} * LogB/M_{i,t} + b^{return} * Return_{i,t}$, where each b is a 10-year rolling average

forecasted return I rely on, since Subsection 3.2 shows that the expected return forecast negatively predicts shorting demand and loan fees.

[13] I also run Fama-MacBeth regressions of realized 1-year ahead returns on lagged firm characteristics to estimate 1-year ahead expected return forecasts. I test all the main results of the paper using both 1-month ahead and 1-year ahead expected return forecasts.

[14] In order to calculate 10-year rolling average slope coefficients, I use CRSP and Compustat data back to 2005. This ensures I have populated expected return forecasts for the entire span of the equity lending dataset, which is 2015-2021.

slope coefficient estimated through month t from the first stage of the previous Fama-MacBeth regressions.

To validate the expected return forecasts, I run Fama-MacBeth regressions of realized returns on expected return forecasts and display the results in Table A.4. Regardless of the Lewellen expected return model, expected return forecasts are highly and significantly correlated with realized returns in the cross section of stocks. As an additional validation step, I report summary statistics of realized and expected return forecasts in Table 1 Panel B, and it is clear that the median realized return is very close to the median expected return forecast.

At this point, it may be helpful to clarify some of the notation I use in the remainder of the paper to denote expected return forecasts. I utilize 2 expected return forecast measures throughout the paper. Both of these forecast measures are derived from Lewellen (2014)'s Model 3 (which incorporates all 15 stock characteristics). First, I denote $\hat{R}_{i,t+1|t}$, which indicates the forecasted expected 1-month ahead return for stock i in month $t+1$, where the forecast is made in month t. This expected return measure is constructed using the aforementioned procedure by regressing 1-month ahead returns on lagged firm characteristics in the Fama-MacBeth regression step. Second, I denote $\hat{R}_{i,t+1:t+12|t}$ as the forecasted expected 1-year ahead return for stock i from months $t+1$ to $t+12$, where the forecast is made in month t. Unlike the 1-month ahead expected return measure, this one involves regressing cumulative 1-year ahead returns on lagged firm characteristics in the Fama-MacBeth regression step. I test all main results of the paper using both measures of expected return forecasts.

3.2 Time Series Relationship

To establish the relationship between loan fees and expected returns in the time series, I rely on panel regressions with stock fixed effects. In particular, I run the following regression specification:

$$LoanFee_{i,t+1} = \beta_0 + \alpha_i + \beta * \hat{R}_{i,t+1:t+12|t} + \Gamma * Controls_{i,t} + \varepsilon_{i,t+1}, \quad (1)$$

where $Controls_{i,t}$ contains the following variables:

1. $R_{i,t}$: realized stock return
2. $\beta_{i,t}^{MKT}$, $\beta_{i,t}^{SMB}$, $\beta_{i,t}^{HML}$, $\beta_{i,t}^{RMW}$, and $\beta_{i,t}^{CMA}$: 3-year rolling average sensitivity to the Fama & French (2014) 5 factors (market risk premium $Mkt - Rf$, size premium SMB, value premium HML, profitability premium RMW, and investment premium CMA)
3. Lagged dependent variable

The parameter of interest, β, indicates the sensitivity of 1-month ahead loan fees to expected return forecasts made in month t. By controlling for stock fixed effects, I am able to focus on the time series relationship between loan fees and forecasted expected returns.[15] Importantly, I control for the realized stock return in month t to show that the expected return has predictive power on loan fees beyond the contemporaneous realized return. Moreover, controlling for sensitivities to the Fama & French (2014) factors allows me to show that the relationship between expected returns and future loan fees exists independent of standard risk factors.

[Table 2]

From Table 2, columns 1 and 2, it is clear that forecasted expected returns strongly and negatively predict 1-month ahead loan fees. Intuitively, as investors'

[15] Assuming that unobservable factors that might simultaneously affect the LHS and RHS of the regression are time-invariant, then a panel regression with stock fixed effects allows me to focus on within-stock variation and thus establish the time-series relationship between expected return forecasts and loan fees. In Subsection 3.3, I focus on the cross-sectional relationship between expected returns and loan fees.

expectations about the future performance of a stock worsen, they are more likely to short the stock, which drives up the future loan fee. The point estimate of β in column 2, which is much smaller in magnitude than in column 1 due to the fact that I control for the lagged loan fee in column 2, indicates that a 5-percentage point decrease in the 1-year ahead forecasted expected return predicts a 8.5-bp increase in the 1-month ahead loan fee, holding all else equal.

To further explore the economic story behind the sign on β, columns 3-8 test the relationship between forecasted expected returns and lendable share quantities. In columns 3 and 4, the dependent variable is future utilization (the ratio of loan demand to loan supply). Strong, negative coefficients on forecasted expected returns indicate that as expected return forecasts worsen, loan demand increases relative to loan supply. In particular, the point estimate from column 4 indicates that for a 5-percentage point decrease in the 1-year ahead forecasted expected return predicts a 0.26-percentage point increase in loan utilization.

In columns 5 and 6, the dependent variable is future short interest ratio (loan demand scaled by shares outstanding). Strong, negative coefficients on forecasted expected returns indicate that as expected return forecasts worsen, loan demand increases. Finally, in columns 7 and 8, the dependent variable is future loan supply ratio (shares available to be lent scaled by shares outstanding). Here, I note a strong positive coefficient on the forecasted expected return, indicating that as expected return forecasts worsen, loan supply declines. The point estimates in columns 6 and 8 suggest that for a 5-percentage point decrease in the 1-year ahead expected return predicts a 0.015-percentage point increase in the short interest ratio and a 0.265-percentage point decrease in the loan supply ratio. The fact that expected returns negatively predict loan demand and positively predict loan supply helps explain why forecasted expected returns have net negative predictive power on future loan fees.

As a robustness check, I test the relationship with 1-month ahead expected return forecasts (see Table A.5), and the result remains: expected returns strongly and negatively predict future loan demand and fees.

This result may shed light on the sophistication of short sellers. The result suggests that short sellers adjust their positions temporally in accordance with variation in a rational expectation of future returns, or at least the firm characteristics that Lewellen (2014) considers, which are correlated with expected returns. Moreover, this result establishes a temporal link between the expected return channel and future loan demand.

3.3 Cross-Sectional Relationship

In the previous subsection, I established that expected return forecasts negatively predict future loan fees in the time series. In this subsection, I seek to study the relationship between expected returns and loan fees in the cross section of stocks. In order to do this, I run monthly Fama-MacBeth regressions of loan fees on forecasted expected returns and several controls.[16]

The regression specification is similar to that used in Subsection 3.2, although now instead of running panel regressions with fixed effects, I am running Fama-MacBeth regressions. There is no lagging here; all variables are contemporaneous. It is worth noting that the expected return forecast is made in month t, which is contemporaneous with the loan fee, although the forecast is projected over months $t+1$ to $t+12$.

$$LoanFee_{i,t} = \beta_0 + \beta * \hat{R}_{i,t+1:t+12|t} + \Gamma * Controls_{i,t} + \varepsilon_{i,t}, \tag{2}$$

[Table 3]

[16]Fama-MacBeth regressions have a different interpretation from the panel regressions with stock fixed effects, which I employed in Subsection 3.2. Fama-MacBeth regressions involve monthly cross-sectional regressions, allowing me to focus on the purely cross-sectional relationship between expected returns and loan fees.

In Table 3, I show that loan fees and expected return forecasts are strongly and negatively correlated on average in the cross section. Contemporaneously, stocks which have high loan fees also tend to be stocks which have low forecasted expected returns. The results from columns 3 through 8 confirm the economic intuition behind this relationship. Stocks with low expected returns also tend to capture high loan utilization, high short interest, and low loan supply. As a robustness check, I test this relationship with 1-month ahead forecasted expected returns in Table A.6.

Taken together with the results from Subsection 3.2, it is clear that expected return forecasts strongly and negatively predict loan fees, both in the time series and the cross section. The negative cross-sectional relationship may shed additional light on the sophistication of short sellers. Not only does it appear that they adjust their trades temporally for variation in expected returns, but it seems that they successfully target stocks in the cross section which have low expected returns. It appears that short sellers incorporate expected returns in both their decisions of which stocks to short and how to adjust their trades temporally.

4 Loan Fee Forecasting

At this point, I have established a strong link between expected returns and loan fees, indicating that short sellers incorporate expectations about firm performance in their shorting decisions. This finding may not be altogether surprising, given that other papers in the literature have shown that loan fees predict subsequent realized returns. In this section, I conduct a loan fee forecasting exercise with the goal of exploring how predictable loan fees are, which is a novel contribution of my paper. If loan fees are, in fact, predictable out-of-sample, then loan fee forecasting could have massive financial implications for short sellers and equity lenders.

I emphasize the out-of-sample forecasting results in the main text, although I also report in-sample forecasting results in the appendix. In addition to exploring the out-of-sample predictability of loan fees, I aim to understand how the predictability compares across different forecasting horizons and determine which variables contribute the most to loan fee predictability.

4.1 Methodology

To estimate loan fee forecasts, I run forecasting regressions over the estimation window and use the results to predict loan fees in the out-of-sample period. I then evaluate both the in- and out-of-sample forecast performance and determine which variables contribute most to loan fee predictability.

Specifically, I begin by running the following regression specification over the first 75% of the sample, fixing the resulting regression coefficients, and using the coefficients to predict loan fees over the last 25% of the sample:[17]

$$LoanFee_{i,t+h} = \alpha + \rho * LoanFee_{i,t} + \beta * \hat{R}_{i,t+1:t+12|t} + \Gamma * Controls_{i,t} + \varepsilon_{i,t+h}, \quad (3)$$

where h represents the forecasting horizon, or the h-month lag between the dependent variable and regressors. $Controls_{i,t}$ contains the following variables, which have been shown in the short selling literature to be related to loan fees:

1. Loan fee volatility[18]

2. Utilization[19]

[17] As robustness checks, I consider modifying the breakpoint between the estimation window and the out-of-sample window to the 50% mark (see Appendix Table A.19) and the 90% mark (see Appendix Table A.20) and ensure that the main results remain. The specific month in which the breakpoint occurs is determined based on data availability for each horizon, so the breakpoint is slightly different when forecasting loan fees at different horizons. Specifically, the breakpoints for each lag (for the 75% breakpoint) are the following: 1 month (7/2019), 3 months (9/2019), 6 months (12/2019), 9 months (3/2020), and 12 months (6/2020).

[18] Estimated using monthly standard deviation of daily loan fees. See Engelberg, Reed, & Ringgenberg (2018).

[19] Defined as short interest scaled by loan supply, a proxy for the ratio of demand to supply.

3. Short interest ratio
4. Turnover
5. Past average return[20]
6. Return volatility[21]
7. Various asset pricing and macro factors ($Mkt - Rf$, SMB, HML, RMW, CMA, MOM, Rf, BAB, DVL, VIX)[22]

I estimate the above forecasting regressions using the full cross section of stocks via OLS. Given my relatively short sample, utilizing the cross section provides more power and much better forecast estimates than if I were to forecast loan fees on a stock-by-stock basis.[23] I also estimate these regressions separately for different portfolios of stocks (portfolios based on $\hat{R}$ tercile, loan fee tercile, or utilization tercile), which allows for a comparison of loan fee predictability across portfolios of stocks with different characteristics.

The remainder of this section is structured as follows. Since I view my primary forecasting contribution to be the out-of-sample results, I will first report the out-of-sample R^2_{OS} when forecasting loan fee levels in Subsection 4.2. In Subsection 4.3, I report the out-of-sample R^2_{OS} when forecasting future loan fee changes, rather than levels. I then decompose R^2_{OS} from predicting loan fee levels to determine the out-of-sample contribution of each variable in Subsection 4.4.

[20]Estimated by calculating the average of daily returns during the past month.
[21]Estimated by calculating the standard deviation of daily returns during the past month.
[22]See Andrews, Lundblad, & Reed (2022).
[23]I tried forecasting loan fees on a stock-by-stock basis, but the lack of power due to the short sample provided noisy betas and inconsistent results across the sample. Forecasting stock loan fees at the portfolio level is likely also a more relevant exercise for most short sellers in the market, who are mostly large institutional investors who have portfolios of short positions.

4.2 Out-of-Sample R^2 for Loan Fee Levels

In this subsection, I calculate the out-of-sample R^2 to determine the predictability of future loan fee levels out-of-sample. To do this, I modify the Campbell & Thompson (2008) R^2_{OS} formula, which they apply to forecasting the equity premium, which does not vary cross-sectionally. By simply modifying the formula for a cross-sectionally varying variable as follows, I can calculate R^2_{OS} for loan fees:

$$R^2_{OS} = 1 - \frac{\Sigma_i \Sigma_{t=1}^{T} (LF_{i,t} - \widehat{LF_{i,t}})^2}{\Sigma_i \Sigma_{t=1}^{T} (LF_{i,t} - \overline{LF_i})^2} \tag{4}$$

In the above formula, $\widehat{LF_{i,t}}$ represents the fitted loan fee value from a predictive regression and $\overline{LF_i}$ represents the historical average loan fee for stock i estimated over the in-sample period. Hence, the numerator of the fraction represents a sum of squared forecasting errors over the out-of-sample period, while the denominator represents the variance of loan fees relative to the historical stock-specific mean calculated over the out-of-sample period.

[Table 4]

Table 4 displays the out-of-sample R^2 from predicting loan fee levels over horizons ranging from 1-month to 1-year ahead. The first column shows the portfolio of stocks over which I run the forecasting regressions and calculate the R^2_{OS}.

The first row of this table indicates that when I run forecasting regressions and calculate R^2_{OS} over the full sample, the 1-month ahead R^2_{OS} of loan fee levels is 73%. This is an extremely high degree of out-of-sample predictability, and the predictability remains (though declines to some extent) up until the 1-year horizon, at which point the R^2_{OS} is 26%.

When I predict loan fees separately for three expected return ($\hat{R}$) portfolios, I note that loan fees belonging to high $\hat{R}$ stocks tend to be more predictable out-of-sample (93% R^2_{OS} at the 1-month horizon, 43% at the 1-year horizon) compared to low $\hat{R}$ stocks (71% R^2_{OS} at the 1-month horizon, while -17% at the 1-year horizon).[24] This is largely because stocks with high forecasted expected returns tend to have much more persistent loan fees. It is also worth noting that the out-of-sample predictability strongly fades away for stocks with low or average forecasted expected returns at distant horizons.

When predicting loan fees separately for three loan fee portfolios, I note that the low loan fee tercile has extremely predictable loan fees out-of-sample. This is due to the fact that a large portion of stocks in the sample have a loan fee that is very sticky around 30 basis points. Most of the loan fees in the low-loan fee portfolio have almost no variation in the loan fee variable at short horizons, which explains the 98% 1-month R^2_{OS} and the 59% 1-year R^2_{OS}. The portfolio of stocks with high loan fees, on the other hand, has much more volatile (and less predictable) loan fees. However, the 1-month ahead predictability is still quite high, with an R^2_{OS} of 71%.

When predicting loan fees separately for three utilization portfolios, I do not find very large differences in loan fee predictability.

Table 4 indicates that loan fee levels are highly predictable out-of-sample for short-term horizons, regardless of the portfolio over which coefficients are estimated or how R^2_{OS} is calculated. It also shows that loan fee levels are quite highly predictable at horizons up to 1 year for many portfolios of stocks, with the exception of stocks with low expected returns. As a robustness test for this section, I also use the 1-month expected return forecast (see Table A.15) and find that the results remain largely the same.

Many papers have focused on return predictability (see the literature review in Subsection 1.1), so a natural benchmark for comparing the predictability of loan

[24] A negative out-of-sample R^2 indicates that one would do a better job predicting loan fees for the low and mid $\hat{R}$ stocks at the 9- or 12-month horizon by simply guessing the historical stock-specific mean loan fee.

fees would be returns. However, comparing the predictability of loan fee levels with stock returns may not be a fair comparison. In Subsections 4.3 and A.4, I explore the predictability of loan fee changes and stock returns, respectively, using my forecasting model.

4.3 Out-of-Sample R^2 for Loan Fee Changes

In Table 4, I established that loan fee levels are highly predictable out-of-sample. In Table 5, I report the out-of-sample R^2 when forecasting loan fee changes, rather than levels. Forecasting loan fee changes rather than levels allows me to test if loan fee predictability remains after negating some of the predictive power of the lagged loan fee. In this analysis, I define $\Delta LoanFee_{i,t+h} = LoanFee_{i,t+h} - LoanFee_{i,t}$ and forecast $\Delta LoanFee_{i,t+h}$. Specifically, I run the regression:

$$\Delta LoanFee_{i,t+h} = \alpha + \rho * LoanFee_{i,t} + \beta * \hat{R}_{i,t+1:t+12|t} + \Gamma * Controls_{i,t} + \varepsilon_{i,t+h}, \quad (5)$$

where $Controls_{i,t}$ contains the same regressors as in Equation 3.

[Table 5]

Table 5 reveals that loan fee changes are also predictable out-of-sample. Focusing on the first row, I note that when forecasting loan fee changes using the full sample, 1-month ahead loan fee changes are predictable with an R^2_{OS} of 8%. The out-of-sample predictability improves for longer horizons, increasing up to 64% at the 1-year horizon. Because I control for the lagged loan fee level, which increases in predictive power for more distant horizons, the overall R^2_{OS} actually increases as the horizon increases.

The out-of-sample predictability for loan fee changes is comparable among the three $\hat{R}$ portfolios. Focusing on the low expected return portfolio ($\hat{R}$ Low), 1-month ahead loan fee changes are predictable with an R^2_{OS} of 8%, while 1-year ahead loan fee changes are much more predictable with an R^2_{OS} of 65%. The high expected return portfolio shows even more predictable loan fee changes, with a 1-month R^2_{OS} of 13% and a 1-year R^2_{OS} of 70%. Predictability is comparable across the loan fee and utilization portfolios.

This section demonstrates that not only are loan fee levels predictable, but loan fee changes are also predictable out-of-sample. Indeed, while forecasting loan fee changes produces an average R^2_{OS} of 8% at the 1-month horizon, papers in the return forecasting literature find an average R^2 of around 1% for portfolios of stock returns. In Appendix A.4, I verify that my forecasting model does not outperform these papers in forecasting returns out-of-sample.

4.4 Out-of-Sample R^2 Decomposition

In this subsection, I decompose the out-of-sample loan fee R^2_{OS} to determine the relative strength of each variable in predicting future loan fee levels out-of-sample. I use the following formula:

$$R^2_j = \beta_j * \frac{cov(x_j, LF + \varepsilon)}{var(LF)} \tag{6}$$

In this equation, R^2_j represents the fraction of variation in future loan fee levels explained by regressor j. β_j is the regression coefficient estimated in Equation 3 and displayed later, in Subsection A.1. The numerator represents the covariance between regressor j and the loan fee plus the forecasting error ε, estimated over the out-of-sample period. The denominator denotes the variance of loan fees over the out-of-sample period. See Appendix B for the derivation of this formula.

[Table 6]

In Table 6, I display the out-of-sample R^2 decomposition when predicting loan fee levels for low forecasted expected return stocks (stocks in the bottom $\hat{R}$ tercile).[25] Note that the percentages in this table are not percentages of the total explainable variation contributed by each regressor, but rather the fraction of total loan fee variation explained by each regressor (hence, the columns do not sum to 100%).[26]

I first note that the lagged loan fee level explains more out-of-sample variation than any of the other considered variables across all horizons. Hence, a large part of the reason loan fees are predictable is due to the strong persistence of loan fees, which is a fact that has not been documented in the prior literature to my knowledge. After the lagged loan fee level, however, it is apparent that the forecasted expected return is the strongest out-of-sample predictor of future loan fees. At the 1-month ahead horizon, for example, the forecasted expected return explains 1.1% of the out-of-sample loan fee variation, which is more than any other variable. However, the out-of-sample predictive power of forecasted expected returns increases for longer horizons. The forecasted expected return explains 4.4% of the variation at the 1-year horizon, while the next strongest out-of-sample predictor is the short interest ratio, contributing only 2.0%. Therefore, the expected return contributes to loan fee predictability beyond the lagged loan fee, especially for longer-term horizons.

From the out-of-sample R^2 decomposition, it is apparent that loan fee predictability arises primarily through two channels, both of which are novel to the literature. First, loan fees are predictable due to the persistence of loan fees themselves. Second, loan fees are predictable because of the link between expected returns and loan demand.

[25]Regression coefficients are estimated for just the low expected return stocks to highlight that expected returns contribute to loan fee predictability for stocks most likely to be shorted.

[26]The values also do not sum to be the total R^2_{OS} displayed in Table 4 due to the denominators of the two equations being slightly different. Specifically, the denominator in Equation 6 is the variance of loan fees relative to the historical mean loan fee (calculated over the full cross section), whereas the denominator in Equation 4 is the variance of loan fees relative to the stock-specific historical mean loan fee.

It is striking that out of all of the variables which I have included in the forecasting regression (aside from the lagged loan fee), the expected return is the strongest out-of-sample predictor for low $\hat{R}$ stocks. This fact suggests that for stocks expected to perform poorly, short sellers trade based on rational forecasts of future returns, which significantly impacts equilibrium loan fees.

Another interesting result from this analysis is the predictive power of loan fee volatility. When I decompose the in-sample R^2 in Appendix Table A.12, it is apparent that loan fee volatility is one of the strongest predictors of future loan fees in-sample. However, in Table 6, I show that past loan fee volatility has a negative R^2 contribution out-of-sample. This is likely evidence of an unstable coefficient on loan fee volatility. The true sensitivity of future loan fees to past loan fee volatility in the out-of-sample period must be quite different from the estimation window.

It is also worth noting that I display the R^2_{OS} decomposition here for low $\hat{R}$ stocks, as my intuition is that shorting demand will only be driven by expected returns for stocks expected to perform poorly. Coinciding with this intuition, I find that an R^2_{OS} decomposition for other portfolios does not reveal the forecasted expected return as one of the strongest loan fee predictors. It is the portfolio of stocks with low expected returns which displays the link between expected returns and loan fee predictability.

As a robustness check, I perform the same R^2_{OS} decomposition using 1-month ahead forecasted returns (see Table A.17) and I find largely similar results.

In Appendix A, I report further details on the forecasting exercise. In Appendix A.1, I discuss the betas from the forecasting regressions (in other words, the coefficients from Equation 3). In Appendix A.2, I decompose the in-sample R^2 to evaluate which variables are the strongest in-sample predictors of future loan fees. I report the median absolute forecasting errors for each portfolio and horizon in Appendix A.3. Finally, to provide a benchmark for comparison, I predict future returns using my forecasting model in Appendix A.4.

5 Implications of Loan Fee Predictability

In this section, I explore the implications of loan fee predictability on trading. In Subsection 5.1, I discuss the methodology. In Subsection 5.2, I show and discuss the results.

5.1 Methodology

Now that the predictability of loan fees has been established, it is natural to question whether short sellers trade based on fee predictability. I hypothesize that a stock with predictable loan fees would be an attractive short target, holding all else equal, since it is unlikely that this stock's loan fee would become unexpectedly high while a short position is open.

To explore two implications of loan fee predictability, I first need a time-varying measure of loan fee predictability. For each stock, I calculate $LoanFeeR^2_{i,t}$ as the R^2 when forecasting 1-quarter ahead loan fees over 36-month rolling windows, using the forecasting regressions from Equation 3. $LoanFeeR^2_{i,t}$ provides a time-varying proxy for how predictable the 1-quarter ahead loan fee has been over the past 3 years.

I aim to test the relationship between $LoanFeeR^2_{i,t}$ and two consequential variables: namely, the future short interest ratio and price efficiency. If past loan fee predictability predicts these variables in the future, then this would be the first evidence that short sellers trade at least in part based on loan fee predictability.

In Table 7, I regress 1-quarter ahead short interest ratio (in Panel A) and Hou & Moskowitz (2005) D1 Price Delay (in Panel B) on several stock characteristics. Specifically, I run the following panel regressions with stock fixed effects:

$$SIR_{i,t+3} = \beta_0 + \alpha_i + \beta LoanFeeR^2_{i,t} + \rho SIR_{i,t} + \Gamma Controls_{i,t} + \varepsilon_{i,t+3} \tag{7}$$

$$PriceDelay_{i,t+3} = \beta_0 + \alpha_i + \beta LoanFeeR^2_{i,t} + \lambda LoanFee_{i,t} + \Gamma Controls_{i,t} + \varepsilon_{i,t+3} \tag{8}$$

In these regressions, the $Controls_{i,t}$ matrix contains either the 1-month ahead forecasted expected return ($\hat{R}_{i,t+1|t}$) or all the signals from Lewellen (2014) (see Table A.2).

For the measure of price delay (price inefficiency), I rely on Hou & Moskowitz (2005). I first regress (within each stock-quarter, using weekly returns):

$$R_{i,t} = \alpha + \Sigma_{j=0}^{4}\beta_j R_{mkt,t-j} + \Sigma_{k=1}^{4}\lambda_k R_{i,t-k} + \varepsilon_{i,t},$$

saving the resulting R^2 as R^2_{Full}, which represents the fraction of variation in stock returns which is explained by contemporaneous and lagged stock and market returns. Next, I regress

$$R_{i,t} = \alpha + \beta_1 R_{mkt,t} + \varepsilon_{i,t},$$

saving R^2 as R^2_{Rest}, which represents the fraction of variation in stock returns which is explained solely by the contemporaneous market return. Finally, I define $PriceDelay = 1 - \frac{R^2_{Rest}}{R^2_{Full}}$. Hence, $PriceDelay$ is a measure of price inefficiency.

5.2 Implications on Loan Demand and Price Efficiency

Table 7 displays the relationship between past loan fee predictability and future loan demand and price inefficiency.

[Table 7]

The dependent variable in Panel A is the 1-quarter ahead short interest ratio. In columns 1-4, I run the regression over the full sample. In columns 5-8, I run the regression over the subsample of low $\hat{R}$ stocks (bottom tercile of forecasted expected returns).

In all 8 columns, I observe a strong, positive relationship between loan fee predictability and future shorting demand, even when controlling for the contemporaneous short interest ratio, forecasted expected return, or Lewellen (2014) return signals. This result suggests that short sellers are drawn to increase their short positions in stocks that have historically predictable loan fees, as loan fee predictability helps mitigate the risk of varying loan fees over the life of the stock loan.

In Table 7 Panel B, the dependent variable is the 1-quarter ahead measure of price inefficiency. It is clear that past loan fee predictability negatively (positively) predicts price inefficiency (efficiency). This result fits the intuition from Panel A. Short sellers respond to loan fee predictability by shorting more, which improves the price efficiency of the underlying stock.

Overall, the results from this analysis suggest that loan fee predictability has important implications for future shorting demand and price efficiency, providing the first evidence to suggest that short sellers incorporate loan fee predictability in their shorting decisions.

As robustness checks, I recreate these tables in this section using 1-year ahead forecasted expected returns. The results can be found in Appendix Tables A.21 and A.22.

6 Supply or Demand Channel

In Section 4, I showed that the forecasted expected return is a strong predictor for loan fees out-of-sample for stocks expected to perform poorly. The goal of this section is to explore the channel through which expected returns impact loan fee predictability. In Subsection 6.1, I discuss my methodology. In Subsections 6.2 and 6.3, I test whether the forecasted expected return is a strong out-of-sample predictor of future loan fees for stocks with different levels of loan supply and short interest ratios, respectively.

6.1 Methodology

There are two possible channels through which forecasted expected returns may impact loan fee predictability. First is through loan supply. Low $\hat{R}$ stocks are likely to be owned by less sophisticated investors who are unlikely to lend their shares. The resulting low loan supply may drive up loan fees. The second possible channel is loan demand. Low $\hat{R}$ stocks are likely to be shorted by investors looking to profit off the poor future performance, which drives up loan demand and thus loan fees.

To test the channel, I re-run the loan fee forecasting exercise for portfolios of stocks with a) high (above-median) loan supply ratio, b) low (below-median) loan supply ratio, c) high (above-median) short interest ratio, and d) low (below-median) short interest ratio. Afterwards, I decompose the R^2_{OS} to determine the relative predictive power of $\hat{R}$. If $\hat{R}$ has particularly low predictive ability of future loan fees for any of these exercises, it would allow us to rule out one of the potential channels.

6.2 Supply Channel Test

In Table 8, I decompose the R^2_{OS} for 2 portfolios of stocks sorted on loan supply ratio. If the loan supply channel is primarily the reason $\hat{R}$ improves loan fee predictability, then I would expect to see $\hat{R}$ having strong predictive power among the low loan supply stocks and weak predictive power among the high loan supply stocks.

[Table 8]

This, however, doesn't appear to be the case. Although $\hat{R}$ is a relatively strong out-of-sample predictor in both panels, $\hat{R}$ is a much stronger out-of-sample predictor in Panel B, which is based on stocks with high loan supply ratios. This indicates that among stocks with high loan supply, where loan supply is unlikely to be a binding constraint, the expected return is a very strong predictor of future loan fees. This fact casts doubt on the supply channel story, since expected return forecasts do not strongly predict loan fees for stocks with constrained loan supply.

6.3 Demand Channel Test

In Table 9, I decompose the R^2_{OS} for 2 portfolios of stocks sorted on short interest ratio. If the loan demand channel is the primary reason $\hat{R}$ improves loan fee predictability, then I would expect to see $\hat{R}$ having strong predictive power among the high short interest ratio stocks.

[Table 9]

In both Panels A and B, $\hat{R}$ is a relatively strong predictor of future loan fees, although it is a slightly stronger predictor among the high short interest ratio stocks. This fact, in conjunction with the finding in Subsection 6.2, suggests that demand is the primary channel through which forecasted expected returns impact loan fee predictability. Short sellers are drawn to short low $\hat{R}$ stocks to profit on their poor future performance, which drives up the loan fee.

7 Conclusion

Loan fees are an important cost that short sellers bear. The past two decades of research in the short selling space have firmly established the link between loan fees and subsequent realized returns. However, none have studied the relationship between ex-ante, forecasted expected returns and subsequent loan fees, which speaks to how future loan fees are endogenously affected by the demand for lendable shares. I find that forecasted expected returns strongly, negatively predict loan fees, both in the time series and cross section.

Using the above fact, I conduct a loan fee forecasting exercise, as the predictability of loan fees would be a topic of consequence for short sellers and equity lenders. I find that loan fee levels are highly predictable out-of-sample, with an average 1-month ahead R^2_{OS} of 73%. The strong predictability remains (although fades to some extent) at horizons up to 1 year.

Moreover, I forecast future loan fee changes, and I find that loan fee changes are also predictable out-of-sample, with an average 1-month ahead R^2_{OS} of 8%. As a comparison, the return forecasting literature finds that the average 1-month ahead R^2_{OS} for portfolios of stock returns is only around 1%.

Upon decomposing the out-of-sample R^2, I find that loan fees are primarily predictable through two channels: the past loan fee and the expected return. I document that loan fees are highly persistent through time. Moreover, the expected return channel sheds new light on loan fee determination; short sellers increase their demand for stock loans when expected return forecasts worsen, which drives up the future loan fee.

Furthermore, I explore the implications of loan fee predictability. I find evidence that loan fee predictability positively predicts future short interest, loan fees, and price efficiency. This result suggests that short sellers trade based on loan fee predictability, as loan fee predictability mitigates the risk of stock loans becoming unexpectedly expensive.

Finally, I explore the channel through which forecasted expected returns impact loan fee predictability. After running the out-of-sample forecasting exercise for portfolios of stocks sorted on loan demand and loan supply separately, I find evidence that suggests the loan demand channel is stronger than the loan supply channel. It appears that short sellers are drawn to borrow stocks with low expected returns in order to profit on the stocks' poor future performance, and this behavior makes future loan fees more predictable.

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Figure 1. BLNK Loan Fee Costs. In red, with units displayed on the right vertical axis, is the time series of loan fees in percent per annum. In blue, with units displayed on the left vertical axis, is the time series of cumulative aggregate loan fee costs paid to borrow BLNK during 2021, in millions of dollars.

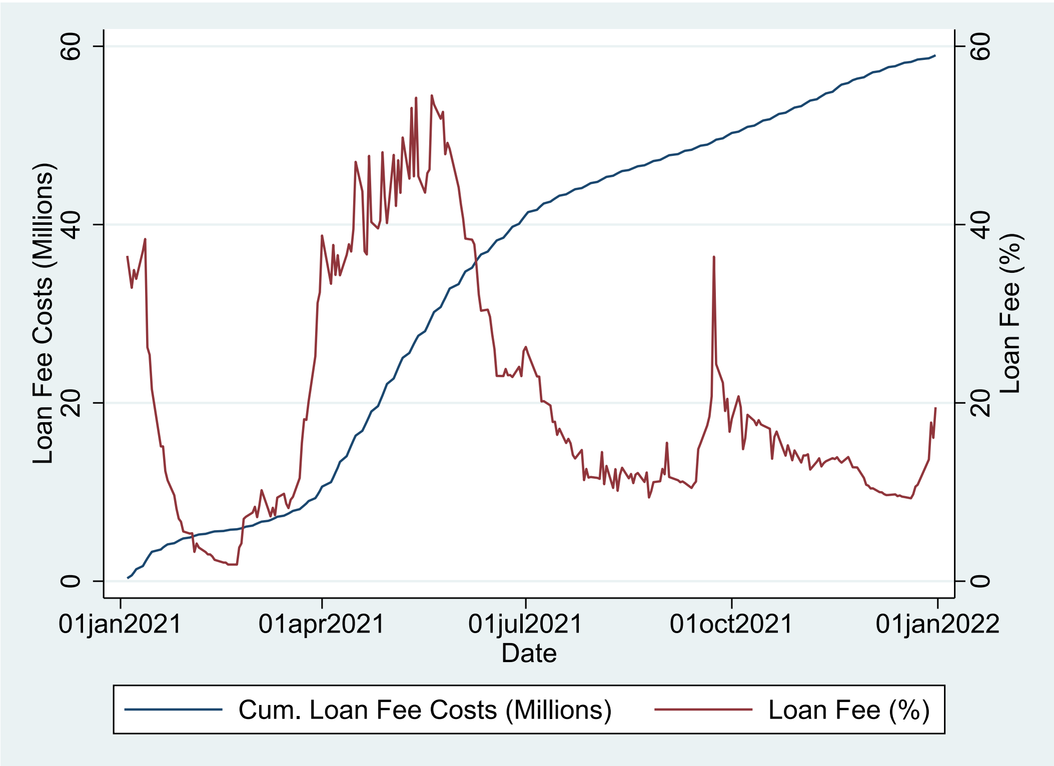

Table 1. Summary Statistics, calculated from stock-month panel. In Panel A, loan fees are in basis points and are annualized. The P&L and loan fee cost variables are only populated in 2021, which explains the low sample size. In Panel B, realized returns ($R_{i,t}$) are monthly. $\hat{R}_{i,t+1|t}$ denotes 1-month ahead expected return forecasts, where the superscript indicates from which Lewellen (2014) model the expected return forecast is calculated. $\hat{R}_{i,t+1:t+12|t}$ denotes 1-year ahead expected return forecasts. The variables in Panel C are the Lewellen (2014) return signals. The autocorrelations in Panel D are calculated on a stock-by-stock basis using an AR1 model with monthly data. I require that stocks must have at least 1 year of populated data to be included in Panel D.

Panel A: Short Selling Variables

Variable	Mean	p10	p25	p50	p75	p90	SD	N
Loan Fee (bp)	272.3	30.0	30.0	33.9	82.3	505.0	842.4	254544
Short Interest Ratio	0.05	0.00	0.01	0.03	0.06	0.12	0.06	254108
Loan Supply Ratio	0.30	0.09	0.18	0.25	0.29	0.41	0.32	254318
Utilization	0.11	0.00	0.01	0.04	0.12	0.31	0.17	251856
Total Monthly Net MTM P&L (millions)	-6.08	-26.89	-5.08	-0.10	1.06	12.42	114.34	46922
Total Monthly Gross MTM P&L (millions)	-6.01	-26.76	-5.05	-0.09	1.08	12.53	114.25	46922
Total Monthly Loan Fee Costs (thousands)	67.86	0.47	2.58	13.51	47.49	125.25	370.45	46922

Panel B: Realized and Expected Returns

Variable	Mean	p10	p25	p50	p75	p90	SD	N
$R_{i,t}$	0.85%	-13.19%	-5.59%	0.55%	6.53%	14.55%	12.90%	524971
$\hat{R}_{i,t+1\|t}^{LewellenModel1}$	0.52%	-0.17%	0.17%	0.49%	0.82%	1.23%	0.63%	524971
$\hat{R}_{i,t+1\|t}^{LewellenModel2}$	0.55%	-0.24%	0.27%	0.59%	0.93%	1.28%	0.74%	364320
$\hat{R}_{i,t+1\|t}^{LewellenModel3}$	0.38%	-0.60%	0.08%	0.52%	0.89%	1.22%	0.94%	350301
$\hat{R}_{i,t+1:t+12\|t}^{LewellenModel3}$	5.66%	-2.90%	3.40%	7.33%	10.20%	12.63%	8.29%	325385

Panel C: Return Signals

Variable	Mean	p10	p25	p50	p75	p90	SD	N
$LogSize_{-1}$	6.64	3.83	5.15	6.68	8.11	9.41	2.11	524971
$LogB/M_{-1}$	-0.59	-1.92	-1.23	-0.57	-0.02	0.54	1.14	524971
$Return_{-2,-12}$	0.12	-0.40	-0.16	0.07	0.30	0.63	0.52	524971
$LogIssues_{-1,-36}$	0.17	-0.10	-0.01	0.03	0.19	0.56	0.46	470412
$Accruals_{Yr-1}$	-0.03	-0.13	-0.07	-0.04	0.00	0.07	0.12	408074
ROA_{Yr-1}	-0.04	-0.24	-0.02	0.02	0.06	0.11	0.24	521328
$LogAG_{Yr-1}$	0.10	-0.13	-0.03	0.05	0.16	0.38	0.30	519232
$DY_{-1,-12}$	0.02	0.00	0.00	0.00	0.02	0.05	0.03	524971
$LogReturn_{-13,-36}$	0.05	-0.74	-0.23	0.14	0.42	0.73	0.65	451593
$LogIssues_{-1,-12}$	0.06	-0.03	0.00	0.01	0.03	0.19	0.22	524615
$Beta_{-1,-36}$	1.07	0.25	0.61	1.01	1.47	1.98	0.70	524971
$StdDev_{-1,-12}$	0.13	0.06	0.08	0.11	0.16	0.23	0.08	524971
$Turnover_{-1,-12}$	0.21	0.03	0.07	0.13	0.23	0.39	0.37	524971
$Debt/Price_{Yr-1}$	1.29	0.00	0.04	0.26	0.76	2.02	4.43	524971
$Sales/Price_{Yr-1}$	2.17	0.08	0.24	0.56	1.38	3.61	6.72	523260

Panel D: Autocorrelations (1-month)

Variable	Mean	p10	p25	p50	p75	p90	SD
Loan Fee	0.62	0.13	0.44	0.67	0.82	0.92	0.63
Short Interest Ratio	0.64	0.05	0.43	0.72	0.89	0.96	0.47
Loan Supply Ratio	0.90	0.70	0.87	0.95	0.99	1.02	0.19
Utilization	0.72	0.33	0.54	0.74	0.89	0.96	1.05
$\hat{R}_{i,t+1\|t}$	0.89	0.78	0.88	0.93	0.96	0.98	0.13
$\hat{R}_{i,t+1:t+12\|t}$	0.92	0.82	0.90	0.95	0.97	0.99	0.12

Table 2. Panel regressions of loan fees on expected returns, controlling for stock fixed effects. The dependent variables (with subscript $t+1$) are 1-month ahead of the regressors. Expected return forecasts are made in month t for the 1-year horizon (months $t+1$ through $t+12$). Sensitivities to the Fama & French (2014) 5 factors are estimated using 3-year rolling averages. Robust standard errors are employed.

	$LoanFee_{i,t+1}$		$Utilization_{i,t+1}$		$ShortInterestRatio_{i,t+1}$		$LoanSupplyRatio_{i,t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\hat{R}_{i,t+1:t+12\|t}$	-0.188***	-0.017***	-0.362***	-0.052***	-0.061***	-0.003**	0.195***	0.055***
	(-28.178)	(-4.737)	(-38.232)	(-8.109)	(-23.710)	(-2.311)	(14.966)	(8.447)
$R_{i,t}$		0.004***		-0.009***		-0.002***		0.004***
		(3.640)		(-5.551)		(-6.574)		(3.834)
$\beta_{i,t}^{MKT}$		0.029*		0.275***		0.026***		-0.051*
		(1.775)		(7.617)		(3.846)		(-1.810)
$\beta_{i,t}^{SMB}$		0.020**		-0.120***		-0.022***		0.094***
		(2.076)		(-5.652)		(-5.298)		(5.223)
$\beta_{i,t}^{HML}$		-0.013		-0.010		-0.003		0.043**
		(-1.432)		(-0.424)		(-0.556)		(2.476)
$\beta_{i,t}^{RMW}$		0.005		-0.073***		-0.029***		-0.060***
		(0.855)		(-6.121)		(-13.331)		(-6.717)
$\beta_{i,t}^{CMA}$		-0.001		0.078***		-0.009***		0.036***
		(-0.226)		(6.954)		(-4.167)		(4.236)
$LoanFee_{i,t}$		0.829***						
		(119.930)						
$Utilization_{i,t}$				0.839***				
				(230.149)				
$ShortInterestRatio_{i,t}$						0.933***		
						(474.900)		
$LoanSupplyRatio_{i,t}$								0.922***
								(155.226)
Stock FE	X	X	X	X	X	X	X	X
N	143620	141407	141716	139479	143312	141090	143468	141247
R^2	0.765	0.925	0.651	0.901	0.738	0.969	0.905	0.984

Table 3. Fama-MacBeth regressions of loan fees on expected returns. Expected return forecasts are made in month t for the 1-year horizon (months $t+1$ through $t+12$). All regressors are contemporaneous with the dependent variables. Sensitivities to the Fama & French (2014) 5 factors are estimated using 3-year rolling averages. Newey-West standard errors with 4 lags are employed.

	$LoanFee_{i,t}$		$Utilization_{i,t}$		$ShortInterestRatio_{i,t}$		$LoanSupplyRatio_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\hat{R}_{i,t+1:t+12\|t}$	-0.435***	-0.447***	-1.107***	-1.021***	-0.305***	-0.262***	0.457***	0.390**
	(-7.810)	(-7.511)	(-12.625)	(-13.765)	(-5.988)	(-5.878)	(2.792)	(2.171)
$R_{i,t}$		-0.012**		-0.020**		-0.007*		0.006
		(-2.306)		(-2.034)		(-1.852)		(0.374)
$\beta_{i,t}^{MKT}$		-0.354*		1.711***		0.920***		0.772
		(-1.873)		(3.427)		(3.546)		(0.591)
$\beta_{i,t}^{SMB}$		-0.375***		0.949***		1.258***		-7.266***
		(-3.207)		(5.603)		(10.232)		(-7.255)
$\beta_{i,t}^{HML}$		0.132		-0.508*		-0.322**		-0.889
		(1.027)		(-1.778)		(-1.996)		(-0.766)
$\beta_{i,t}^{RMW}$		-0.011		-0.195		0.194**		-0.469
		(-0.182)		(-1.218)		(1.999)		(-1.425)
$\beta_{i,t}^{CMA}$		0.140*		0.210		-0.051		0.589
		(1.676)		(0.908)		(-0.602)		(1.185)
Constant	4.989***	5.988***	16.421***	12.956***	6.908***	4.542***	27.889***	33.335***
	(7.220)	(6.200)	(20.776)	(27.517)	(21.408)	(13.543)	(35.152)	(16.800)
N	141903	141903	139995	139995	141595	141595	141752	141752
R^2	0.275	0.299	0.204	0.229	0.101	0.175	0.014	0.050

Table 4. R^2_{OS} **from forecasting loan fee levels**. Expected return forecasts are made in month t for the 1-year horizon (months $t+1$ through $t+12$). The "Portfolio" column indicates the subsample over which the forecasting regressions are run and over which R^2_{OS} is calculated. Along with estimating the forecasting regressions over the full cross section of stocks, I also estimate the regressions over different terciles of expected return forecast ($\hat{R}$), loan fee, and utilization.

	Forecasting Horizon				
Portfolio	h=1	h=3	h=6	h=9	h=12
All Stocks	73%	36%	22%	22%	26%
$\hat{R}$ Low	71%	29%	5%	-10%	-17%
$\hat{R}$ Mid	73%	41%	0%	3%	-29%
$\hat{R}$ High	93%	72%	69%	55%	43%
Loan Fee Low	98%	94%	85%	75%	59%
Loan Fee Mid	93%	65%	45%	50%	56%
Loan Fee High	71%	34%	21%	22%	25%
Utilization Low	79%	53%	35%	28%	17%
Utilization Mid	80%	44%	29%	32%	31%
Utilization High	70%	32%	18%	18%	24%

Table 5. R^2_{OS} **from forecasting loan fee changes**. In this table, the forecasted variable is $\Delta LoanFee_{i,t+h} = LoanFee_{i,t+h} - LoanFee_{i,t}$. Expected return forecasts are made in month t for the 1-year horizon (months $t+1$ through $t+12$). The "Portfolio" column indicates the subsample over which the forecasting regressions are run and over which R^2 is calculated. Along with estimating the forecasting regressions over the full cross section of stocks, I also estimate the regressions over different terciles of expected return forecast ($\hat{R}$), loan fee, and utilization.

	Forecasting Horizon				
Portfolio	h=1	h=3	h=6	h=9	h=12
All Stocks	8%	20%	38%	55%	64%
$\hat{R}$ Low	8%	21%	35%	53%	65%
$\hat{R}$ Mid	4%	13%	35%	41%	48%
$\hat{R}$ High	13%	24%	53%	64%	70%
Loan Fee Low	11%	27%	49%	62%	66%
Loan Fee Mid	10%	25%	47%	59%	67%
Loan Fee High	9%	22%	40%	57%	66%
Utilization Low	9%	27%	41%	56%	63%
Utilization Mid	9%	18%	35%	47%	59%
Utilization High	8%	21%	38%	57%	66%

Table 6. R^2_{OS} **decomposition**. This table displays the relative R^2_{OS} contribution from each variable after forecasting loan fee levels. The percentages indicate the percentage of variation in future loan fees explained by each variable. The portfolio considered in this table (for the forecasting regressions and R^2 calculation) is the low (bottom tercile) $\hat{R}$ stocks. Expected return forecasts are made in month t for the 1-year horizon (months $t+1$ through $t+12$).

	Forecasting Horizon				
Variable	h=1	h=3	h=6	h=9	h=12
$LoanFee$	89.8%	59.8%	33.0%	24.4%	17.7%
$\hat{R}$	1.1%	2.2%	3.4%	4.9%	4.4%
$Vol(LoanFees)$	-10.2%	-9.1%	-5.5%	-4.4%	-4.9%
$Utilization$	0.5%	0.9%	1.4%	1.6%	1.7%
$ShortIntRatio$	0.1%	0.4%	1.0%	1.4%	2.0%
$Turnover$	0.3%	-1.1%	-1.1%	0.0%	-0.9%
$MeanReturn$	-0.4%	-0.5%	-0.1%	0.2%	0.9%
$ReturnVolatility$	0.3%	0.8%	0.9%	0.4%	1.0%
$Mkt-Rf$	0.0%	0.0%	0.0%	0.0%	0.0%
SMB	0.0%	0.0%	0.0%	0.0%	0.0%
HML	0.0%	0.0%	0.1%	0.0%	0.0%
RMW	0.0%	0.0%	0.0%	0.0%	0.0%
CMA	0.0%	0.0%	0.0%	0.0%	0.0%
MOM	0.0%	0.0%	0.0%	0.0%	0.0%
Rf	-0.1%	-0.2%	-0.2%	0.0%	0.0%
BAB	0.0%	0.0%	0.0%	0.0%	0.0%
DVL	0.0%	0.0%	-0.1%	0.0%	0.0%
VIX	0.0%	-0.3%	-0.6%	0.3%	0.0%

Table 7. Implications of loan fee predictability on future loan demand and price efficiency. $LoanFeeR^2_{i,t}$ is calculated using 3-year rolling regressions of 1-quarter ahead loan fees on all the variables in the forecasting model. In Panel A, the dependent variable is the 1-quarter ahead short interest ratio. In Panel B, the dependent variable is the 1-quarter ahead price inefficiency measure (calculated from Hou & Moskowitz (2005)). The sample considered in columns 1-4 is all stocks, whereas columns 5-8 consider only low (bottom tercile) $\hat{R}$ (1-month ahead expected return forecast) stocks.

	Panel A: Dependent Variable: $ShortIntRatio_{i,t+3}$							
	All Stocks				Low $\hat{R}$ Stocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$LoanFeeR^2_{i,t}$	1.614***	0.492***	0.516***	0.356***	1.910***	0.740***	0.804***	0.634***
	(25.502)	(12.959)	(13.102)	(8.478)	(10.119)	(6.133)	(6.575)	(5.164)
$ShortIntRatio_{i,t}$		0.763***	0.764***	0.766***		0.704***	0.707***	0.704***
		(204.335)	(202.354)	(199.428)		(96.176)	(96.290)	(94.209)
$\hat{R}_{i,t+1\|t}$			0.034**				0.120***	
			(2.439)				(4.136)	
$LogSize_{i,t}$				-0.065**				0.143**
				(-2.274)				(2.404)
$LogB/M_{i,t}$				-0.070***				0.028
				(-2.843)				(0.741)
$Return_{i,t}$				0.133***				0.272***
				(7.244)				(6.451)
$LogIssues_{i,t}$				0.189***				0.085
				(3.465)				(1.038)
$Accruals_{i,t}$				0.316***				0.441***
				(3.885)				(3.542)
$ROA_{i,t}$				0.033				0.025
				(0.341)				(0.173)
$LogAG_{i,t}$				0.141***				0.077
				(3.677)				(1.041)
$DY_{i,t}$				1.598***				1.955***
				(4.165)				(2.874)
$LogReturn_{i,t}$				0.221***				0.324***
				(11.823)				(8.107)
$LogIssues_{i,t}$				0.224**				0.384***
				(2.556)				(3.350)
$Beta_{i,t}$				0.050***				0.049*
				(4.342)				(1.899)
$StdDev_{i,t}$				-1.194***				-0.793***
				(-7.704)				(-2.902)
$Turnover_{i,t}$				-0.263***				-0.392***
				(-4.953)				(-6.265)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$Debt/Price_{i,t}$				-0.009*				-0.029***
				(-1.737)				(-2.593)
$Sales/Price_{i,t}$				0.006				0.017
				(1.216)				(1.465)
Constant	3.635***	0.709***	0.670***	1.310***	5.742***	1.431***	1.415***	0.846**
	(77.494)	(22.104)	(18.414)	(5.992)	(38.709)	(13.641)	(13.469)	(2.013)
Stock FE	X	X	X	X	X	X	X	X
N	105924	105924	105924	105730	26880	26880	26880	26818
R^2	0.761	0.904	0.904	0.905	0.787	0.895	0.896	0.897

	Panel B: Dependent Variable: $PriceDelay_{i,t+3}$							
	All Stocks				Low $\hat{R}$ Stocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$LoanFeeR^2_{i,t}$	-0.129***	-0.132***	-0.150***	-0.161***	-0.270***	-0.278***	-0.270***	-0.332***
	(-7.257)	(-7.394)	(-8.351)	(-8.683)	(-6.665)	(-6.846)	(-6.637)	(-8.108)
$LoanFee_{i,t}$		0.003***	0.002***	0.001***		0.003***	0.003***	0.002***
		(4.947)	(3.465)	(2.643)		(4.277)	(4.871)	(2.580)
$\hat{R}_{i,t+1\|t}$			-0.026***				0.017**	
			(-6.234)				(2.471)	
$LogSize_{i,t}$				-0.100***				-0.141***
				(-10.942)				(-9.950)
$LogB/M_{i,t}$				0.015*				0.000
				(1.938)				(0.012)
$Return_{i,t}$				-0.042***				-0.003
				(-7.162)				(-0.286)
$LogIssues_{i,t}$				-0.002				0.015
				(-0.112)				(0.767)
$Accruals_{i,t}$				0.012				-0.008
				(0.479)				(-0.234)
$ROA_{i,t}$				-0.096***				-0.058*
				(-3.732)				(-1.727)
$LogAG_{i,t}$				-0.006				-0.017
				(-0.437)				(-0.822)
$DY_{i,t}$				-0.066				-0.704***
				(-0.450)				(-3.307)
$LogReturn_{i,t}$				0.001				0.046***
				(0.226)				(4.343)
$LogIssues_{i,t}$				-0.038				0.004
				(-1.603)				(0.164)
$Beta_{i,t}$				0.004				0.014*
				(0.839)				(1.874)
$StdDev_{i,t}$				0.112**				-0.091
				(2.347)				(-1.345)

$Turnover_{i,t}$				-0.050***				-0.051***
				(-4.865)				(-4.142)
$Debt/Price_{i,t}$				0.005**				0.006**
				(2.550)				(1.968)
$Sales/Price_{i,t}$				-0.003**				-0.001
				(-2.257)				(-0.586)
Constant	0.306***	0.302***	0.330***	1.078***	0.575***	0.567***	0.566***	1.556***
	(22.867)	(22.571)	(23.594)	(15.644)	(18.002)	(17.714)	(17.691)	(15.797)
Stock FE	X	X	X	X	X	X	X	X
N	105905	105905	105905	105711	26870	26870	26870	26808
R^2	0.191	0.191	0.191	0.197	0.214	0.215	0.215	0.226

Table 8. Supply channel test. This table displays the R^2_{OS} decomposition when running the forecasting regressions on below-median loan supply stocks (in Panel A) and above-median loan supply stocks (in Panel B) separately. Expected return forecasts are 1-year ahead, and the sample considered here is low (bottom tercile) $\hat{R}$ stocks.

Panel A: Stocks with below-median loan supply ratio					
	Forecasting Horizon				
	h=1	h=3	h=6	h=9	h=12
$\hat{R}$	0.9%	1.7%	2.6%	3.5%	2.7%
Vol(Loan Fee)	-9.7%	-8.3%	-4.3%	-3.5%	-3.0%
Utilization	0.6%	0.9%	1.4%	1.3%	1.2%
Short Int Ratio	0.1%	0.5%	1.4%	1.9%	2.7%
Turnover	0.2%	-0.2%	0.0%	0.0%	-1.1%
Mean Return	-0.4%	-0.7%	0.0%	0.3%	1.2%
Return Volatility	0.3%	0.7%	0.8%	0.1%	0.6%
Mkt-Rf	0.0%	0.0%	0.0%	0.0%	0.0%
SMB	0.0%	0.0%	0.0%	0.0%	0.0%
HML	0.0%	0.0%	0.1%	0.0%	0.0%
RMW	0.0%	0.0%	0.0%	0.0%	0.0%
CMA	0.0%	0.0%	0.0%	0.0%	0.0%
MOM	0.0%	0.0%	0.0%	0.0%	0.0%
Rf	-0.1%	-0.3%	-0.2%	0.0%	0.0%
BAB	0.0%	0.0%	0.0%	0.0%	0.0%
DVL	0.0%	0.0%	-0.1%	0.0%	0.0%
VIX	0.0%	-0.4%	-0.7%	0.4%	0.0%

Panel B: Stocks with above-median loan supply ratio					
	Forecasting Horizon				
	h=1	h=3	h=6	h=9	h=12
$\hat{R}$	1.7%	3.3%	5.5%	8.9%	10.9%
Vol(Loan Fee)	-11.4%	-11.0%	-8.5%	-7.1%	-12.2%
Utilization	0.5%	1.0%	1.5%	2.4%	3.3%
Short Int Ratio	0.0%	-0.1%	0.1%	0.2%	0.0%
Turnover	0.4%	-2.9%	-3.7%	-0.1%	0.0%
Mean Return	-0.3%	-0.1%	-0.2%	-0.2%	-0.2%
Return Volatility	0.3%	1.0%	1.1%	1.2%	2.3%
Mkt-Rf	0.0%	0.0%	0.0%	0.0%	0.0%
SMB	0.0%	0.0%	0.0%	0.0%	0.0%
HML	0.0%	0.0%	0.0%	0.0%	0.0%
RMW	0.0%	0.0%	0.0%	0.0%	0.0%
CMA	0.0%	0.0%	0.0%	0.0%	0.0%
MOM	0.0%	0.0%	0.0%	0.0%	0.0%
Rf	-0.1%	-0.1%	0.0%	0.0%	0.1%
BAB	0.0%	0.0%	0.0%	0.0%	0.0%
DVL	0.0%	0.0%	0.0%	0.1%	0.0%
VIX	0.0%	-0.2%	-0.2%	0.2%	0.0%

Table 9. Demand channel test. This table displays the R^2_{OS} decomposition when running the forecasting regressions on below-median short interest ratio stocks (in Panel A) and above-median short interest ratio stocks (in Panel B) separately. Expected return forecasts are 1-year ahead, and the sample considered here is low (bottom tercile) $\hat{R}$ stocks.

Panel A: Stocks with below-median short interest ratio

	Forecasting Horizon				
	h=1	h=3	h=6	h=9	h=12
$\hat{R}$	0.6%	1.3%	2.3%	3.9%	1.6%
Vol(Loan Fee)	-10.9%	-15.3%	-6.2%	-4.8%	1.1%
Utilization	0.2%	0.5%	0.2%	1.9%	3.4%
Short Int Ratio	0.0%	-0.1%	-0.2%	-0.5%	-0.5%
Turnover	0.1%	-1.0%	0.1%	0.0%	0.0%
Mean Return	-0.3%	-2.9%	-0.8%	0.0%	-1.1%
Return Volatility	0.2%	2.8%	2.0%	2.7%	3.1%
Mkt-Rf	0.0%	0.0%	0.0%	0.1%	0.0%
SMB	0.0%	0.0%	0.0%	-0.1%	-0.1%
HML	0.0%	0.0%	0.1%	0.0%	0.1%
RMW	0.0%	0.0%	0.0%	0.0%	-0.1%
CMA	0.0%	0.0%	0.0%	0.0%	0.1%
MOM	0.0%	0.0%	0.0%	0.0%	0.3%
Rf	-0.1%	-0.3%	-0.3%	0.0%	0.2%
BAB	0.0%	0.0%	0.0%	0.0%	-0.1%
DVL	0.0%	0.0%	0.0%	-0.1%	-0.3%
VIX	-0.1%	-0.8%	-0.5%	-0.8%	0.5%

Panel B: Stocks with above-median short interest ratio

	Forecasting Horizon				
	h=1	h=3	h=6	h=9	h=12
$\hat{R}$	1.1%	2.2%	3.4%	4.9%	4.4%
Vol(Loan Fee)	-10.2%	-8.9%	-5.5%	-4.4%	-5.0%
Utilization	0.5%	0.9%	1.5%	1.6%	1.6%
Short Int Ratio	0.1%	0.4%	1.0%	1.5%	2.1%
Turnover	0.3%	-1.1%	-1.1%	0.0%	-0.9%
Mean Return	-0.4%	-0.4%	0.0%	0.2%	1.0%
Return Volatility	0.3%	0.7%	0.8%	0.3%	1.0%
Mkt-Rf	0.0%	0.0%	0.0%	0.0%	0.0%
SMB	0.0%	0.0%	0.0%	0.0%	0.0%
HML	0.0%	0.0%	0.1%	0.0%	0.0%
RMW	0.0%	0.0%	0.0%	0.0%	0.0%
CMA	0.0%	0.0%	0.0%	0.0%	0.0%
MOM	0.0%	0.0%	0.0%	0.0%	0.0%
Rf	-0.1%	-0.2%	-0.2%	0.0%	0.0%
BAB	0.0%	0.0%	0.0%	0.0%	0.0%
DVL	0.0%	0.0%	-0.1%	0.0%	0.0%
VIX	0.0%	-0.3%	-0.6%	0.4%	0.0%

Appendix

This section is the appendix for Andrews (2022). In Appendix A, I provide supplemental commentary that further describes the loan fee forecasting exercise in Section 4 of the main text. In Appendix B, I prove the formula for out-of-sample R^2 decomposition. In Appendix C, I display a number of robustness checks.

A Supplemental Forecasting Details

In Section 4 of the main text, I showed out-of-sample results from the loan fee forecasting exercise. This subsection contains further details to supplement the information presented in the main text. Specifically, I report the regression coefficients from Equation 3 (the forecasting regression) in A.1, the in-sample R^2 decomposition in A.2, the out-of-sample median absolute forecasting errors in A.3, and the out-of-sample R^2_{OS} when forecasting stock returns in A.4.

A.1 Betas

In this subsection, I discuss the coefficients from the forecasting regression (Equation 3). I repress t-statistics in order to emphasize the signs and magnitudes of the betas. In order to conserve space, I also repress the coefficients on the asset pricing and macro factors, as most of them are relatively inconsequential compared to the stock characteristics.

In Table A.7, I show the betas for the portfolio of low forecasted expected return (low $\hat{R}_{i,t+1:t+12|t}$) stocks, defined as stocks in the bottom tercile of $\hat{R}$ within a given month. These are the stocks for which I would expect forecasted returns to have the strongest implications for future loan fees, as a low expected return should engender short demand. Subsequent tables show betas for other portfolios of stocks as well.

Table A.7 shows large coefficients on $LoanFee_{i,t}$, indicating a high degree of persistence of loan fees. At the 1-month horizon ($h = 1$), loan fees tend to be highly autocorrelated, with a ρ of 1.019. However, this persistence fades for longer term horizons; at the 1-year horizon ($h = 12$), ρ is only 0.609. This indicates that while loan fees tend to be highly persistent over short horizons, there is a significant amount of variation over longer term horizons.

Next, I observe negative coefficients on forecasted 1-year ahead expected returns ($\hat{R}_{i,t+1:t+12|t}$). This confirms the result from Table 2, which shows that forecasted expected returns negatively predict future loan fees.

Third, I note that volatility of loan fees (calculated using the standard deviation of daily loan fees over the previous month) negatively predicts future loan fees. The sign on this coefficient is likely due to the mean-reverting nature of loan fees; on average, after a highly volatile period, loan fees tend to revert to a lower, more stable level.

Fourth, I observe that loan utilization positively predicts future loan fees. This is to be expected. In equilibrium, loan fees should be driven by supply and demand of loan fees, so as the ratio of loan demand to supply increases, it seems intuitive that the price of stock loans would increase.

Fifth, I note a negative coefficient on short interest ratio. This is at first surprising, but it is likely only because short interest ratio is highly correlated with utilization (since short interest is the numerator of utilization).

The past average return (calculated as the mean of stocks' daily returns over the previous month) negatively predicts future loan fees. This is because stocks which have performed relatively well do not attract significant shorting demand, thus loan fees become lower.

Past return volatility (calculated as the standard deviation of stocks' daily returns over the previous month) positively predicts future loan fees. Stocks which have highly volatile return series tend to attract shorting demand due to the potential for capitalizing on a large price decrease.

A final point worth noting from these regressions is the in-sample R^2. The R^2 from predicting 1-month ahead loan fees in-sample is over 90%, which is quite high. The in-sample predictability remains high for longer horizons, although it fades to 47% at the 1-year horizon.

In subsequent tables, I report betas estimated over different portfolios of stocks and using different expected return forecasts. I report betas using 1-year ahead expected return forecasts for the full sample of stocks (see Table A.8), using 1-month ahead expected return forecasts for stocks with low $\hat{R}$ (see Table A.9), using 1-year ahead expected return forecasts for stocks with high loan fees (see Table A.10), and using 1-year ahead expected return forecasts for stocks with high utilization (see Table A.11). Most of the signs on the coefficients remain the same as in the baseline specification.

A.2 In-Sample R^2 Decomposition

In this subsection, I decompose the in-sample R^2 to determine the relative strength of each variable as an in-sample predictor of future loan fees. In order to do this, I implement a Shapley R^2 decomposition. In Table A.12, I report the R^2 decomposition for stocks with low $\hat{R}$.

In Table A.12, the total in-sample R^2 is displayed in the bottom row, which represents the explainable variation of future loan fees in-sample. The percentages that are displayed in other rows of this table indicate the percentage of explainable variation that is accounted for by each predictor. The sum of these percentages is 100%, not the total R^2 in the bottom row.

First, I observe that the past loan fee is the strongest in-sample predictor of future loan fees, explaining 63% of the explainable 1-month ahead loan fee variation and 54% of the explainable 1-year ahead variation. After the past loan fee, the second strongest in-sample predictor is past loan fee volatility, which explains 22% of the explainable 1-month ahead variation and 17% of the 1-year ahead variation. The fact that loan fee volatility is a strong in-sample predictor of loan fee levels stands in contrast to the out-of-sample R^2 decomposition in Subsection 4.4.

The third strongest in-sample predictor is the forecasted expected return, which explains 7% of the 1-month ahead loan fee variation and 13% of the 1-year ahead variation. It is notable that the 1-year ahead expected return forecast contributes most to loan fee predictability at longer-term horizons.

The fourth strongest predictor in-sample is utilization, which explains 4% of the 1-month ahead explainable variation and 9% of the 1-year ahead explainable variation. Though one might expect utilization to be one of the strongest predictors of loan fees, it is not as strong a predictor in-sample as past loan fee volatility and the expected return forecast.

In subsequent tables, I also report in-sample Shapley R^2 decompositions using 1-year ahead expected return forecasts and the full sample of stocks (see Table A.13) and 1-month ahead expected return forecasts and low $\hat{R}$ stocks (see Table A.14).

A.3 Median Absolute Forecasting Error

In Table 4, I displayed R^2_{OS} for loan fee levels, which indicated that loan fees are highly predictable out-of-sample. In this subsection, I will discuss the median absolute forecasting errors for different portfolios and across forecasting horizons to provide more information about the fit of the loan fee forecasts.

Table A.16 shows the median loan fee forecasting error in percent per annum. For example, from the first row, I note that when I run forecasting regressions and calculate R^2_{OS} using the full sample, the median absolute forecasting error for 1-month ahead loan fee prediction is 0.37%, or 37 basis points. This indicates that, for the typical stock, the forecasting model is able to predict the loan fee within 37 basis points of its true value. As I extend the forecasting horizon, the fit worsens, as expected. At the 1-year horizon, for the typical stock, the forecasting model predicts 1-year ahead loan fees within 1.85%, or 185 basis points, of the true loan fee.

Among low $\hat{R}$ stocks, the median forecasting error at the 1-month horizon is 83bp, while for middle $\hat{R}$ and high $\hat{R}$ stocks, the median forecasting errors are only 12bp and 9bp, respectively. At longer horizons, the forecasting model does a significantly better job matching loan fee levels for mid $\hat{R}$ and high $\hat{R}$ stocks than for low $\hat{R}$ stocks, as evidenced by 1-year ahead median forecasting errors of 42bp and 33bp, respectively, compared to a median error of 258bp for low $\hat{R}$ stocks.

When I examine the forecasting errors associated with forecasting loan fee levels for different portfolios sorted on loan fee levels, I find that the forecasting model does a very good job matching loan fee levels for the low and middle loan fee portfolios and appears to have difficulty matching the levels for high loan fee stocks. For low loan fee stocks, the forecasting model gets within 3bp of the true 1-month ahead loan fee and gets within 12bp of the true 1-year ahead loan fee for the median stock. For high loan fee stocks, however, the forecasting model produces a median absolute error of 301bp in predicting 1-month ahead loan fees and 926bp in predicting 1-year ahead loan fees.

The forecasting errors in the high loan fee portfolio seem large at first glance; however, two facts can help assuage this concern. First, stocks in the high loan fee portfolio have very high loan fee levels. The median loan fee in this portfolio is 680bp, while the mean is 1446bp. The largest monthly average loan fee I observe is 82638bp. The magnitude of some of the loan fees in the dataset helps put the median forecasting error of this portfolio in perspective. Second, I recall that the R^2_{OS} calculated in the previous subsection was quite high. For the high loan fee portfolio, the 1-month ahead R^2_{OS} was 71% and the 1-year ahead R^2_{OS} was 25%. Thus, even though the median forecasting error seems high for this portfolio in absolute terms, the forecasting model is explaining a large percentage of the total out-of-sample variation.

Examining the forecasting errors associated with the utilization portfolios shows that the forecasting model is matching future loan fees very closely for low and mid utilization stocks (with a 1-month ahead median absolute error of 12bp for low- utilization stocks and 20bp for mid-utilization stocks). The fit is slightly worse for high-utilization stocks, where I observe a 1-month ahead median forecasting error of 100bp.

Overall, the results in this table shed more light on the high degree of predictability of loan fee levels. Not only can the forecasting model explain a high percentage of their variation, but it can match many of their levels quite closely.

A.4 Out-of-Sample R^2 for Returns

In this subsection, I forecast stock returns using the forecasting model as a benchmark for comparison. As a reference, Haddad, Kozak, & Santosh (2020) find an R^2 of around 1% when predicting 1-month ahead stock returns at the portfolio level. Note that as I am forecasting returns, I do not modify the list of regressors in Equation 3 to obtain the best possible fit when forecasting returns. My goal is not to obtain the highest possible R^2 in predicting returns, but rather to verify that I calculate R^2 below 1% for 1-month ahead returns and to provide an accurate comparison between loan fee predictability and stock return predictability. The out-of-sample R^2 values from predicting returns are displayed in Table A.18.

As expected, in Table A.18, the R^2_{OS} when calculating 1-month ahead returns is always below 1% using the forecasting model; in fact, it is almost always negative. This fits my intuition, as I did not select the regressors for my forecasting model to predict returns.

Table A.18 provides validation that the forecasting model which I created to forecast loan fees does not do a very good job predicting 1-month ahead returns out-of-sample. More importantly, I am able to compare the R^2_{OS} from forecasting loan fee changes to the R^2_{OS} in this table and conclude that loan fee levels and changes are both much more highly predictable out-of-sample than stock returns.

B Proof of R^2_{OS} decomposition formula

Proof of R^2_{OS} decomposition formula.

$$\begin{aligned}
R^2 &= 1 - \frac{var(\varepsilon)}{var(y)} \\
&= \frac{var(y) - var(\varepsilon)}{var(y)} \\
&= \frac{var(\hat{y}) + 2cov(\hat{y}, \varepsilon)}{var(y)} \\
&= \frac{cov(\hat{y}, y - \varepsilon) + 2cov(\hat{y}, \varepsilon)}{var(y)} \\
&= \frac{cov(\hat{y}, y + \varepsilon)}{var(y)} \\
&= \beta \frac{cov(x, y + \varepsilon)}{var(y)},
\end{aligned}$$

which implies $R^2_j = \beta_j \frac{cov(x_j, y+\varepsilon)}{var(y)}$.

C Appendix Tables

Table A.1. Cross-sectional correlations among firm variables. All variables are time-series averages, so the dataset is fully cross-sectional with no time series dimension. This table displays correlations among the cross-sectional stock or firm characteristics.

Variables	Loan Fee	Utilization	Short Int Ratio	Loan Supply	Log Size	Log B/M	Momentum 1-Year	Beta	Volatility	Turnover
Loan Fee	1.000									
Utilization	0.485	1.000								
Short Int Ratio	-0.065	0.424	1.000							
Loan Supply	-0.090	-0.158	-0.115	1.000						
Log Size	-0.421	-0.173	0.169	0.049	1.000					
Log B/M	-0.015	-0.162	-0.322	0.464	-0.283	1.000				
Momentum 1-Year	-0.122	0.012	0.145	-0.024	0.333	-0.052	1.000			
Beta	0.051	0.360	0.418	-0.002	0.229	-0.208	-0.062	1.000		
Volatility	0.438	0.519	0.287	-0.090	-0.490	-0.083	-0.414	0.382	1.000	
Turnover	0.432	0.433	0.212	0.055	0.020	-0.029	0.059	0.382	0.257	1.000

Table A.2. Expected return signals from Lewellen (2014).

Variable	Description	Related Literature
$LogSize_{-1}$	Log market value of equity at the end of the prior month	Banz (1981), Fama and French (1992)
$LogB/M_{-1}$	Log book value of equity minus log market value of equity at the end of the prior month	Stattman (1980), Rosenberg et al. (1985), Fama and French (1992), Fama and French (1993), Fama and French (2008)
$Return_{-2,-12}$	Stock return from month -12 to month -2	Jegadeesh and Titman (1993), Fama and French (1996), Fama and French (2008), Jegadeesh and Titman (2001), Novy-Marx (2012)
$LogIssues_{-1,-36}$	Log growth in split-adjusted shares outstanding from month -36 to month -1	Fama (1998), Daniel and Titman (2006), Pontiff and Woodgate (2008), Fama and French (2008)
$Accruals_{Yr-1}$	Change in non-cash net working capital minus depreciation in the prior fiscal year	Sloan (1996), Fairfield et al. (2003), Richardson et al. (2005), Fama and French (2008)
ROA_{Yr-1}	Income before extraordinary items divided by average total assets in the prior fiscal year	Basu (1983), Bernard and Thomas (1990), Fama and French (1992), Fama and French (2006a), Fama and French (2008), Lakonishok et al. (1994), Chan et al. (1996), Chen et al. (2010)
$LogAG_{Yr-1}$	Log growth in total assets in the prior fiscal year	Titman et al. (2004), Cooper et al. (2008)
$DY_{-1,-12}$	Dividends per share over the prior 12 months divided by price at the end of the prior month	Litzenberger and Ramaswamy (1982), Miller and Scholes (1982)
$LogReturn_{-13,-36}$	Log stock return from month -36 to month -13	De Bondt and Thaler (1985), De Bondt and Thaler (1987)
$LogIssues_{-1,-12}$	Log growth in split-adjusted shares outstanding from month -12 to month -1	Fama (1998), Daniel and Titman (2006), Pontiff and Woodgate (2008), Fama and French (2008)
$Beta_{-1,-36}$	Market beta estimated from weekly returns from month -36 to month -1	Black et al. (1972), Fama and MacBeth (1973), Fama and French (1992), Fama and French (2006b)
$StdDev_{-1,-12}$	Monthly standard deviation, estimated from daily returns from month -12 to month -1	Ang et al. (2006)
$Turnover_{-1,-12}$	Average monthly turnover (shares traded/shares outstanding) from month -12 to month -1	Lee and Swaminathan (2000)
$Debt/Price_{Yr-1}$	Short-term plus long-term debt divided by market value at the end of the prior month	Bhandari (1988), Fama and French (1992)
$Sales/Price_{Yr-1}$	Sales in the prior fiscal year divided by market value at the end of the prior month	Fama and French (1992), Lakonishok et al. (1994)

Table A.3. Fama-MacBeth regressions of realized returns on signals. This table displays the results from Fama-MacBeth regressions of 1-month ahead realized returns on lagged firm and stock characteristics proposed by Lewellen (2014). Model 3, with 15 predictors, is used in my expected return forecasts throughout the paper.

	Model 1: 3 Predictors (1)	Model 2: 7 Predictors (2)	Model 3: 15 Predictors (3)
$LogSize_{-1}$	-0.119**	-0.104**	0.030
	(-2.108)	(-2.215)	(0.819)
$LogB/M_{-1}$	0.459***	0.406***	0.578***
	(7.610)	(6.050)	(9.105)
$Return_{-2,-12}$	0.042	-0.047	0.128
	(0.108)	(-0.132)	(0.425)
$LogIssues_{-1,-36}$		-0.510***	-0.474***
		(-3.493)	(-2.916)
$Accruals_{Yr-1}$		-0.357	-0.408
		(-1.132)	(-1.415)
ROA_{Yr-1}		-0.133	-0.046
		(-0.319)	(-0.145)
$LogAG_{Yr-1}$		-0.107	0.118
		(-0.602)	(0.846)
$DY_{-1,-12}$			-5.444***
			(-3.271)
$LogReturn_{-13,-36}$			-0.045
			(-0.319)
$LogIssues_{-1,-12}$			-0.229
			(-0.847)
$Beta_{-1,-36}$			-0.070
			(-0.382)
$StdDev_{-1,-12}$			4.353***
			(3.523)
$Turnover_{-1,-12}$			-1.288***
			(-5.567)
$Debt/Price_{Yr-1}$			-0.040***
			(-3.213)
$Sales/Price_{Yr-1}$			-0.004
			(-0.416)
Constant	1.777***	1.941***	0.905**
	(2.836)	(3.020)	(2.196)
N	1084139	644552	615450
R^2	0.023	0.031	0.065

Table A.4. Fama-MacBeth regressions of realized returns on expected return forecasts. This table displays the average cross-sectional slopes when regressing realized 1-month returns on 1-month expected return forecasts. The Fama-MacBeth slopes, t-statistics, and R^2 values displayed here are comparable to those in Lewellen (2014), providing validation for my expected return measures.

Dependent Variable: Realized Return				
E[R] Model	**Slope**	**SE**	**t-stat**	R^2
Model 1: 3 Predictors	0.623***	0.182	3.42	0.67%
Model 2: 7 Predictors	0.676***	0.182	3.72	1.15%
Model 3: 15 Predictors	0.775***	0.155	5.00	1.70%

Table A.5. Panel regressions of loan fees on expected returns, controlling for stock fixed effects. The dependent variables (with subscript $t+1$) are 1-month ahead of the regressors. Expected return forecasts are made in month t for the 1-year horizon (months $t+1$ through $t+12$). Sensitivities to the Fama & French (2014) 5 factors are estimated using 3-year rolling averages. Robust standard errors are employed.

	$LoanFee_{i,t+1}$		$Utilization_{i,t+1}$		$ShortInterestRatio_{i,t+1}$		$LoanSupplyRatio_{i,t+1}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\hat{R}_{i,t+1\|t}$	-1.528***	-0.130***	-1.199***	-0.169***	-0.842***	-0.035***	2.364***	0.616***
	(-34.131)	(-5.593)	(-17.041)	(-4.084)	(-46.830)	(-4.206)	(26.434)	(15.660)
$R_{i,t}$		0.002**		-0.003		-0.002***		0.004***
		(2.162)		(-1.645)		(-7.779)		(3.727)
$\beta_{i,t}^{MKT}$		-0.030**		0.201***		0.003		-0.008
		(-2.055)		(6.164)		(0.475)		(-0.311)
$\beta_{i,t}^{SMB}$		0.029***		-0.168***		-0.021***		0.140***
		(3.249)		(-8.246)		(-5.410)		(8.229)
$\beta_{i,t}^{HML}$		0.007		0.016		0.006		0.044**
		(0.805)		(0.696)		(1.393)		(2.533)
$\beta_{i,t}^{RMW}$		0.006		-0.062***		-0.030***		-0.029***
		(1.173)		(-5.386)		(-14.428)		(-3.603)
$\beta_{i,t}^{CMA}$		-0.006		0.143***		-0.015***		0.031***
		(-1.183)		(12.957)		(-7.099)		(3.633)
$LoanFee_{i,t}$		0.850***						
		(142.613)						
$Utilization_{i,t}$				0.862***				
				(299.254)				
$ShortInterestRatio_{i,t}$						0.937***		
						(546.171)		
$LoanSupplyRatio_{i,t}$								0.956***
								(266.702)
Stock FE	X	X	X	X	X	X	X	X
N	167498	165261	165594	163333	167190	164944	167346	165101
R^2	0.735	0.925	0.616	0.906	0.710	0.968	0.834	0.982

Table A.6. Fama-MacBeth regressions of loan fees on expected returns. Expected return forecasts are made in month t for the 1-month horizon (month $t+1$). All regressors are contemporaneous with the dependent variables. Sensitivities to the Fama & French (2014) 5 factors are estimated using 3-year rolling averages. Newey-West standard errors with 4 lags are employed.

	$LoanFee_{i,t}$		$Utilization_{i,t}$		$ShortInterestRatio_{i,t}$		$LoanSupplyRatio_{i,t}$	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\hat{R}_{i,t+1\|t}$	-3.773***	-3.819***	-9.394***	-8.207***	-2.588***	-2.118***	7.173***	6.860***
	(-7.613)	(-7.253)	(-14.493)	(-13.406)	(-6.678)	(-6.081)	(4.974)	(4.116)
$R_{i,t}$		-0.017***		-0.029***		-0.009**		0.011
		(-3.303)		(-3.148)		(-2.497)		(0.697)
$\beta_{i,t}^{MKT}$		-0.436*		0.715		0.569**		1.087
		(-1.875)		(1.605)		(2.297)		(0.917)
$\beta_{i,t}^{SMB}$		-0.359***		1.447***		1.342***		-5.843***
		(-3.131)		(6.562)		(12.740)		(-5.238)
$\beta_{i,t}^{HML}$		0.138		-0.894***		-0.522**		-1.637
		(0.856)		(-2.834)		(-2.534)		(-1.469)
$\beta_{i,t}^{RMW}$		-0.261***		-1.287**		0.066		0.221
		(-3.166)		(-2.443)		(0.634)		(0.285)
$\beta_{i,t}^{CMA}$		0.249***		0.625**		0.037		0.386
		(2.811)		(2.525)		(0.451)		(0.838)
Constant	3.662***	4.541***	14.254***	10.584***	5.856***	3.807***	27.292***	31.303***
	(7.636)	(6.375)	(14.461)	(25.605)	(35.737)	(21.107)	(38.298)	(20.885)
N	165762	165762	163854	163854	165454	165454	165611	165611
R^2	0.239	0.268	0.190	0.235	0.103	0.180	0.039	0.083

Table A.7. Forecasting betas from in-sample estimation. In this table, I display coefficients from estimating the forecasting regression in Equation 3. Expected return forecasts are made in month t for the 1-year horizon (months $t+1$ through $t+12$). The coefficients in this table were estimated over low expected return stocks (stocks within the bottom tercile of 1-year ahead expected returns). t-statistics are omitted to emphasize the signs on the coefficients. I also control for asset pricing and macro factors but choose not to display them due to the small magnitudes.

	Dependent Variable: $LoanFee_{i,t+h}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	h=1	h=3	h=6	h=9	h=12	h=24
$LoanFee_{i,t}$	1.019***	0.966***	0.817***	0.662***	0.609***	0.486***
$\hat{R}_{i,t+1:t+12}$	-0.045***	-0.100***	-0.196***	-0.272***	-0.270***	-0.132***
$Vol(LoanFee_{i,t})$	-0.444***	-0.619***	-0.690***	-0.554***	-0.576***	-0.292***
$Utilization_{i,t}$	0.022***	0.043***	0.081***	0.104***	0.115***	0.070***
$ShortIntRatio_{i,t}$	-0.035***	-0.078***	-0.146***	-0.180***	-0.209***	-0.100***
$Turnover_{i,t}$	1.307*	-2.111**	2.013	-0.443	-0.949	-15.100***
$MeanReturn_{i,t}$	-2.945***	-5.744***	-6.293***	-6.859***	-8.770***	-7.903***
$Volatility_{i,t}$	1.691***	5.035***	8.464***	12.093***	16.090***	20.377***
Factor Controls	X	X	X	X	X	X
N	29903	29808	29776	29773	29763	24714
R^2	0.914	0.814	0.679	0.544	0.466	0.299

Table A.8. Forecasting betas from in-sample estimation. In this table, I display coefficients from estimating the forecasting regression in Equation 3. Expected return forecasts are made in month t for the 1-year horizon (months $t+1$ through $t+12$). The coefficients in this table were estimated over the full cross section of stocks. t-statistics are omitted to emphasize the signs on the coefficients. I also control for asset pricing and macro factors but choose not to display them due to the small magnitudes.

	Dependent Variable: $LoanFee_{i,t+h}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	h=1	h=3	h=6	h=9	h=12	h=24
$LoanFee_{i,t}$	1.018***	0.966***	0.827***	0.682***	0.625***	0.493***
$\hat{R}_{i,t+1:t+12}$	-0.030***	-0.067***	-0.128***	-0.180***	-0.194***	-0.132***
$Vol(LoanFee_{i,t})$	-0.418***	-0.583***	-0.649***	-0.519***	-0.534***	-0.244***
$Utilization_{i,t}$	0.018***	0.035***	0.064***	0.082***	0.090***	0.060***
$ShortIntRatio_{i,t}$	-0.030***	-0.065***	-0.122***	-0.152***	-0.173***	-0.103***
$Turnover_{i,t}$	0.974**	-2.328***	1.864**	-0.131	-0.764	-16.437***
$MeanReturn_{i,t}$	-1.992***	-3.926***	-4.292***	-4.654***	-5.739***	-4.949***
$Volatility_{i,t}$	0.947***	3.536***	6.715***	9.560***	12.442***	17.771***
Factor Controls	X	X	X	X	X	X
N	96886	96664	96581	96565	96592	80919
R^2	0.915	0.811	0.677	0.549	0.474	0.302

Table A.9. Forecasting betas from in-sample estimation. In this table, I display coefficients from estimating the forecasting regression in Equation 3. Expected return forecasts are made in month t for the 1-month horizon (month $t+1$). The coefficients in this table were estimated over low expected return stocks (stocks within the bottom tercile of 1-month ahead expected returns). t-statistics are omitted to emphasize the signs on the coefficients. I also control for asset pricing and macro factors but choose not to display them due to the small magnitudes.

	Dependent Variable: $LoanFee_{i,t+h}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	h=1	h=3	h=6	h=9	h=12	h=24
$LoanFee_{i,t}$	1.023***	0.968***	0.812***	0.654***	0.599***	0.474***
$\hat{R}_{i,t+1}$	-0.378***	-1.076***	-2.376***	-3.440***	-3.513***	-2.389***
$Vol(LoanFee_{i,t})$	-0.459***	-0.641***	-0.704***	-0.566***	-0.576***	-0.292***
$Utilization_{i,t}$	0.023***	0.041***	0.076***	0.096***	0.108***	0.056***
$ShortIntRatio_{i,t}$	-0.036***	-0.075***	-0.144***	-0.183***	-0.212***	-0.086***
$Turnover_{i,t}$	1.506**	-2.066**	1.674	-0.952	-1.673	-15.602***
$MeanReturn_{i,t}$	-3.156***	-5.958***	-6.460***	-6.896***	-8.775***	-7.613***
$Volatility_{i,t}$	2.120***	5.465***	8.689***	12.075***	15.885***	19.062***
Factor Controls	X	X	X	X	X	X
N	30552	30458	30428	30424	30420	25371
R^2	0.912	0.812	0.680	0.552	0.476	0.309

Table A.10. Forecasting betas from in-sample estimation. In this table, I display coefficients from estimating the forecasting regression in Equation 3. Expected return forecasts are made in month t for the 1-year horizon (months $t+1$ through $t+12$). The coefficients in this table were estimated over high loan fee stocks (top loan fee tercile). t-statistics are omitted to emphasize the signs on the coefficients. I also control for asset pricing and macro factors but choose not to display them due to the small magnitudes.

	Dependent Variable: $LoanFee_{i,t+h}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	h=1	h=3	h=6	h=9	h=12	h=24
$LoanFee_{i,t}$	1.011***	0.949***	0.788***	0.623***	0.563***	0.414***
$\hat{R}_{i,t+1:t+12}$	-0.038***	-0.094***	-0.198***	-0.284***	-0.295***	-0.194***
$Vol(LoanFee_{i,t})$	-0.435***	-0.609***	-0.689***	-0.565***	-0.570***	-0.375***
$Utilization_{i,t}$	0.021***	0.034***	0.059***	0.068***	0.074***	0.010
$ShortIntRatio_{i,t}$	-0.026***	-0.070***	-0.134***	-0.155***	-0.181***	-0.015
$Turnover_{i,t}$	2.292**	-1.063	3.798*	1.853	1.043	-12.428***
$MeanReturn_{i,t}$	-4.856***	-9.411***	-10.060***	-11.286***	-13.591***	-11.475***
$Volatility_{i,t}$	3.277***	8.787***	12.812***	17.769***	22.201***	25.903***
Factor Controls	X	X	X	X	X	X
N	15884	15750	15695	15692	15713	13885
R^2	0.903	0.792	0.641	0.502	0.434	0.272

Table A.11. Forecasting betas from in-sample estimation. In this table, I display coefficients from estimating the forecasting regression in Equation 3. Expected return forecasts are made in month t for the 1-year horizon (months $t+1$ through $t+12$). The coefficients in this table were estimated over high utilization stocks (top utilization tercile). t-statistics are omitted to emphasize the signs on the coefficients. I also control for asset pricing and macro factors but choose not to display them due to the small magnitudes.

	Dependent Variable: $LoanFee_{i,t+h}$					
	(1)	(2)	(3)	(4)	(5)	(6)
	h=1	h=3	h=6	h=9	h=12	h=24
$LoanFee_{i,t}$	1.025***	0.978***	0.858***	0.695***	0.633***	0.489***
$\hat{R}_{i,t+1:t+12}$	-0.036***	-0.085***	-0.162***	-0.231***	-0.237***	-0.157***
$Vol(LoanFee_{i,t})$	-0.482***	-0.687***	-0.772***	-0.619***	-0.624***	-0.369***
$Utilization_{i,t}$	0.023***	0.037***	0.059***	0.081***	0.092***	0.066***
$ShortIntRatio_{i,t}$	-0.026***	-0.061***	-0.113***	-0.143***	-0.166***	-0.114***
$Turnover_{i,t}$	2.282***	-0.896	2.635**	0.447	0.195	-12.273***
$MeanReturn_{i,t}$	-3.308***	-6.268***	-6.816***	-7.588***	-9.261***	-6.348***
$Volatility_{i,t}$	1.394***	5.219***	8.389***	12.856***	16.603***	18.885***
Factor Controls	X	X	X	X	X	X
N	26629	26550	26522	26495	26483	23273
R^2	0.917	0.819	0.699	0.578	0.505	0.345

Table A.12. In-sample Shapley R^2 decomposition. Expected return forecasts are made in month t for the 1-year horizon (months $t+1$ through $t+12$). The sample used here is low $\hat{R}$ stocks (bottom tercile).

	Dependent Variable: $LoanFee_{i,t+h}$				
	(1)	(2)	(3)	(4)	(5)
	h=1	h=3	h=6	h=9	h=12
$LoanFee_{i,t}$	63.2%	63.3%	60.6%	56.1%	54.1%
$\hat{R}_{i,t+1:t+12\|t}$	6.9%	7.7%	9.8%	12.6%	13.2%
$Volatility(LoanFee_{i,t})$	22.3%	20.7%	18.9%	17.3%	16.6%
$Utilization_{i,t}$	4.0%	4.6%	6.0%	7.8%	8.7%
$ShortInterestRatio_{i,t}$	0.3%	0.4%	0.6%	0.9%	1.1%
$Turnover_{i,t}$	1.0%	0.9%	1.0%	1.1%	1.1%
$MeanReturn_{i,t}$	0.2%	0.4%	0.4%	0.6%	0.8%
$Volatility_{i,t}$	2.0%	2.1%	2.6%	3.6%	4.3%
Total R^2	91.3%	81.3%	67.7%	54.2%	46.3%

Table A.13. In-sample Shapley R^2 decomposition. Expected return forecasts are made in month t for the 1-year horizon (months $t+1$ through $t+12$). The sample used here contains all stocks.

	Dependent Variable: $LoanFee_{i,t+h}$				
	(1)	(2)	(3)	(4)	(5)
	h=1	h=3	h=6	h=9	h=12
$LoanFee_{i,t}$	64.1%	64.1%	61.7%	57.6%	55.3%
$\hat{R}_{i,t+1:t+12\|t}$	5.6%	6.3%	7.9%	10.2%	11.2%
$Volatility(LoanFee_{i,t})$	22.3%	20.8%	19.1%	17.7%	17.0%
$Utilization_{i,t}$	3.9%	4.5%	5.8%	7.4%	8.2%
$ShortInterestRatio_{i,t}$	0.5%	0.5%	0.8%	1.1%	1.2%
$Turnover_{i,t}$	1.1%	1.0%	1.1%	1.2%	1.2%
$MeanReturn_{i,t}$	0.1%	0.2%	0.3%	0.4%	0.5%
$Volatility_{i,t}$	2.4%	2.6%	3.3%	4.5%	5.3%
Total R^2	91.5%	81.0%	67.5%	54.6%	47.1%

Table A.14. In-sample Shapley R^2 decomposition. Expected return forecasts are made in month t for the 1-month horizon (month $t+1$). The sample used here is low $\hat{R}$ stocks.

	Dependent Variable: $LoanFee_{i,t+h}$				
	(1)	(2)	(3)	(4)	(5)
	h=1	h=3	h=6	h=9	h=12
$LoanFee_{i,t}$	63.1%	63.1%	60.1%	55.1%	52.9%
$\hat{R}_{i,t+1\|t}$	6.5%	7.4%	10.0%	13.4%	14.3%
$Volatility(LoanFee_{i,t})$	22.6%	20.9%	18.9%	17.1%	16.5%
$Utilization_{i,t}$	4.0%	4.5%	5.9%	7.5%	8.4%
$ShortInterestRatio_{i,t}$	0.4%	0.4%	0.7%	0.9%	1.2%
$Turnover_{i,t}$	1.1%	0.9%	1.1%	1.2%	1.1%
$MeanReturn_{i,t}$	0.2%	0.4%	0.5%	0.6%	0.9%
$Volatility_{i,t}$	2.2%	2.3%	2.9%	4.0%	4.7%
Total R^2	91.2%	81.1%	67.8%	54.9%	47.2%

Table A.15. Out-of-sample R^2 from forecasting loan fee levels. Expected return forecasts are made in month t for the 1-month horizon (month $t+1$). The "Portfolio" column indicates the subsample over which the forecasting regressions are run and the portfolio over which R^2 is calculated.

	Forecasting Horizon				
Portfolio	h=1	h=3	h=6	h=9	h=12
All Stocks	78%	48%	33%	29%	28%
$\hat{R}$ Low	77%	44%	25%	16%	12%
$\hat{R}$ Mid	75%	46%	26%	19%	13%
$\hat{R}$ High	90%	75%	56%	48%	40%
Loan Fee Low	99%	95%	91%	79%	62%
Loan Fee Mid	96%	84%	69%	65%	60%
Loan Fee High	76%	43%	29%	26%	26%
Utilization Low	84%	63%	46%	39%	21%
Utilization Mid	84%	57%	43%	39%	36%
Utilization High	75%	43%	28%	24%	25%

Table A.16. Median absolute forecasting errors (in percent per annum) when forecasting loan fee levels. The "Portfolio" column indicates the subsample over which the forecasting regressions are run and the portfolio over which R^2 is calculated.

	Forecasting Horizon				
Portfolio	h=1	h=3	h=6	h=9	h=12
All Stocks	0.37	0.74	1.14	1.57	1.85
$\hat{R}$ Low	0.83	1.53	2.07	2.42	2.58
$\hat{R}$ Mid	0.12	0.23	0.37	0.39	0.42
$\hat{R}$ High	0.09	0.17	0.24	0.29	0.33
Loan Fee Low	0.03	0.05	0.08	0.08	0.12
Loan Fee Mid	0.24	0.41	0.55	0.72	1.07
Loan Fee High	3.01	5.68	8.07	8.80	9.26
Utilization Low	0.12	0.28	0.39	0.51	0.61
Utilization Mid	0.20	0.34	0.71	0.93	1.14
Utilization High	1.00	1.84	2.45	2.87	3.31

Table A.17. Out-of-sample R^2 decomposition. This table reports the out-of-sample R^2 decomposition when forecasting loan fee levels. The sample considered here is low (bottom tercile) $\hat{R}$ stocks. Expected return forecasts are made in month t for the 1-month horizon (month $t+1$).

	Forecasting Horizon				
Variable	h=1	h=3	h=6	h=9	h=12
$LoanFee$	91.7%	64.3%	38.6%	24.9%	13.1%
$\hat{R}$	1.2%	3.2%	4.7%	3.9%	0.3%
$Vol(LoanFees)$	-10.7%	-11.2%	-8.7%	-6.0%	-4.2%
$Utilization$	0.5%	0.7%	0.8%	0.6%	-0.1%
$ShortIntRatio$	0.1%	0.3%	1.0%	1.6%	2.2%
$Turnover$	0.3%	-1.0%	-0.6%	-0.2%	-1.4%
$MeanReturn$	-0.5%	-0.7%	-0.3%	0.1%	0.7%
$ReturnVolatility$	0.5%	1.2%	1.2%	0.7%	-0.1%
$Mkt-Rf$	0.0%	0.0%	0.0%	0.2%	0.0%
SMB	0.0%	0.0%	0.0%	0.0%	0.0%
HML	0.0%	0.0%	0.0%	0.0%	0.0%
RMW	0.0%	0.0%	0.0%	0.0%	0.0%
CMA	0.0%	0.0%	0.1%	0.0%	-0.1%
MOM	0.0%	0.0%	0.0%	0.0%	0.0%
Rf	0.0%	0.1%	0.4%	1.0%	1.0%
BAB	0.0%	0.0%	0.0%	0.0%	0.0%
DVL	0.0%	-0.1%	-0.1%	0.0%	0.0%
VIX	-0.1%	-0.4%	-0.4%	0.9%	1.9%

Table A.18. Out-of-sample R^2 from forecasting returns. Stock returns are forecasted from month t to $t+1$. Note that all 1-month ahead R^2 are below 1%, verifying that the loan fee forecasting model of this paper does not outperform return forecasting models of other papers.

	Forecasting Horizon
Portfolio	h=1
All Stocks	-1.0%
$\hat{R}$ Low	-1.4%
$\hat{R}$ Mid	-0.4%
$\hat{R}$ High	-2.4%
LF Low	-2.0%
LF Mid	-0.4%
LF High	-1.3%
Util Low	-1.3%
Util Mid	0.4%
Util High	-3.4%

Table A.19. Forecasting Robustness: Estimation window first 50%, out-of-sample window last 50%. This table verifies the main results of the paper when using a different breakpoint: loan fees continue to be predictable out-of-sample, primarily due to the autoregressive nature of loan fees. The expected return channel appears less strong in Panel B, likely due to the fact that the out-of-sample window is quite long. The breakpoint between the estimation window and out-of-sample period is halfway through the sample, and the exact breakpoint differs slightly depending on the forecasting horizon. Specifically, the breakpoints are: 2/2018 for lag h=1, 4/2018 for lag h=3, 7/2018 for lag h=6, 10/2018 for lag h=9, and 1/2019 for lag h=12.

Panel A: R^2_{OS}

	$\hat{R}$: 1-year ahead					$\hat{R}$: 1-month ahead				
	Forecasting Horizon									
Portfolio	h=1	h=3	h=6	h=9	h=12	h=1	h=3	h=6	h=9	h=12
All Stocks	81%	54%	24%	-2%	-19%	83%	58%	31%	5%	-15%
$\hat{R}$ Low	80%	53%	21%	-20%	-53%	82%	58%	28%	-9%	-41%
$\hat{R}$ Mid	80%	58%	25%	12%	-17%	80%	56%	35%	25%	12%
$\hat{R}$ High	93%	75%	52%	47%	37%	92%	78%	57%	48%	37%
Loan Fee Low	99%	96%	88%	75%	54%	99%	97%	93%	79%	56%
Loan Fee Mid	94%	73%	47%	35%	23%	96%	82%	63%	49%	30%
Loan Fee High	80%	53%	23%	-4%	-22%	82%	56%	27%	0%	-19%
Utilization Low	84%	60%	32%	11%	-11%	86%	65%	38%	22%	-6%
Utilization Mid	86%	56%	23%	14%	4%	88%	63%	35%	22%	8%
Utilization High	79%	53%	18%	-16%	-36%	81%	56%	23%	-11%	-34%

Panel B: R^2_{OS} Decomposition

	$\hat{R}$: 1-year ahead					$\hat{R}$: 1-month ahead				
Variable	Forecasting Horizon									
	h=1	h=3	h=6	h=9	h=12	h=1	h=3	h=6	h=9	h=12
Loan Fee	90%	68%	46%	27%	10%	91%	69%	46%	25%	4%
$\hat{R}$	0%	1%	1%	1%	1%	0%	1%	1%	1%	1%
Vol(Loan Fees)	-6%	-4%	-2%	-1%	-1%	-6%	-5%	-3%	-1%	0%
Utilization	0%	1%	1%	1%	1%	0%	1%	1%	1%	1%
Short Int Ratio	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Turnover	1%	-6%	-16%	-12%	-1%	1%	-6%	-14%	-11%	-1%
Mean Return	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%
Return Volatility	0%	1%	0%	0%	1%	0%	1%	1%	0%	0%
Mkt-Rf	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
SMB	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
HML	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
RMW	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
CMA	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
MOM	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
Rf	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
BAB	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
DVL	0%	0%	0%	0%	0%	0%	0%	0%	0%	0%
VIX	0%	0%	0%	0%	0%	0%	0%	0%	0%	1%

Table A.20. Forecasting Robustness: Estimation window first 90%, out-of-sample window last 10%. Note that I am unable to calculate out-of-sample R^2 over the last 10% of the sample for horizons h=9 months and h=12 months due to a short sample issue. In particular, a 9- or 12-month lag between the loan fee and right-hand side variables is more than 10% of the whole sample, so forecasting regressions do not yield any observations in the out-of-sample window when using a 9- or 12-month lag. The breakpoint between the estimation window and out-of-sample period is 90% through the sample, and the exact breakpoint differs slightly depending on the forecasting horizon. Specifically, the breakpoints are: 6/2020 for lag h=1, 8/2020 for lag h=3, 11/2020 for lag h=6, 2/2021 for lag h=9, and 5/2021 for lag h=12.

Panel A: R^2_{OS}

	$\hat{R}$: 1-year ahead			$\hat{R}$: 1-month ahead		
	Forecasting Horizon					
Portfolio	h=1	h=3	h=6	h=1	h=3	h=6
All Stocks	70%	43%	40%	79%	59%	52%
$\hat{R}$ Low	67%	35%	25%	79%	59%	59%
$\hat{R}$ Mid	67%	27%	11%	70%	40%	43%
$\hat{R}$ High	88%	42%	83%	87%	64%	41%
Loan Fee Low	99%	92%	77%	99%	93%	88%
Loan Fee Mid	86%	55%	50%	96%	88%	78%
Loan Fee High	69%	42%	39%	77%	54%	46%
Utilization Low	67%	49%	34%	80%	63%	47%
Utilization Mid	77%	43%	32%	83%	62%	53%
Utilization High	67%	43%	43%	78%	57%	52%

Panel B: R^2_{OS} Decomposition

	$\hat{R}$: 1-year ahead			$\hat{R}$: 1-month ahead		
Variable	Forecasting Horizon					
	h=1	h=3	h=6	h=1	h=3	h=6
Loan Fee	89%	64%	55%	93%	72%	59%
$\hat{R}$	2%	4%	5%	2%	5%	5%
Vol(Loan Fees)	-18%	-17%	-10%	-17%	-19%	-18%
Utilization	1%	1%	1%	1%	1%	-1%
Short Int Ratio	0%	1%	2%	0%	1%	2%
Turnover	2%	0%	0%	2%	0%	0%
Mean Return	0%	-2%	-5%	-1%	-2%	-2%
Return Volatility	0%	1%	5%	0%	2%	2%
Mkt-Rf	0%	0%	0%	0%	0%	0%
SMB	0%	0%	0%	0%	0%	0%
HML	0%	0%	0%	0%	0%	0%
RMW	0%	0%	0%	0%	0%	0%
CMA	0%	0%	0%	0%	0%	0%
MOM	0%	0%	0%	0%	0%	0%
Rf	0%	0%	0%	0%	0%	0%
BAB	0%	0%	0%	0%	0%	0%
DVL	0%	0%	0%	0%	0%	0%
VIX	0%	0%	0%	0%	0%	0%

Table A.21. Implications of loan fee predictability on future loan demand. $LoanFeeR^2_{i,t}$ is calculated using 3-year rolling regressions of 1-quarter ahead loan fees on all the variables in the forecasting model. Expected return forecasts are 1-year ahead. The sample considered in columns 1-4 is all stocks, whereas columns 5-8 consider only low (bottom tercile) $\hat{R}$ (1-year ahead expected return forecast) stocks.

	Dependent Variable: $ShortIntRatio_{i,t+3}$							
	All Stocks				Low $\hat{R}$ Stocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$LoanFeeR^2_{i,t}$	0.928***	0.346***	0.369***	0.153***	1.054***	0.490***	0.509***	0.250
	(14.066)	(8.325)	(8.466)	(3.274)	(4.500)	(3.007)	(3.116)	(1.527)
$ShortIntRatio_{i,t}$		0.737***	0.738***	0.741***		0.666***	0.668***	0.666***
		(164.672)	(164.631)	(162.518)		(73.413)	(73.923)	(73.683)
$\hat{R}_{i,t+1:t+12\|t}$			0.004*				0.011***	
			(1.942)				(2.584)	
$LogSize_{i,t}$				-0.005				0.285***
				(-0.143)				(3.556)
$LogB/M_{i,t}$				-0.089***				-0.080
				(-2.809)				(-1.512)
$Return_{i,t}$				0.126***				0.059
				(4.290)				(1.016)
$LogIssues_{i,t}$				0.284***				0.211**
				(4.396)				(2.229)
$Accruals_{i,t}$				0.398***				0.521***
				(4.159)				(3.468)
$ROA_{i,t}$				0.210*				0.220
				(1.707)				(1.224)
$LogAG_{i,t}$				0.082*				0.008
				(1.896)				(0.100)
$DY_{i,t}$				2.175***				1.703**
				(4.915)				(2.080)
$LogReturn_{i,t}$				0.196***				0.205***
				(8.698)				(4.318)
$LogIssues_{i,t}$				0.155				0.043
				(1.439)				(0.315)
$Beta_{i,t}$				0.105***				0.160***
				(7.843)				(5.053)
$StdDev_{i,t}$				-1.596***				-1.048***
				(-9.112)				(-3.342)
$Turnover_{i,t}$				-0.282***				-0.391***
				(-3.492)				(-4.262)
$Debt/Price_{i,t}$				-0.009*				-0.021**
				(-1.744)				(-2.181)
$Sales/Price_{i,t}$				0.010*				0.019*
				(1.864)				(1.741)
Constant	4.263***	0.984***	0.931***	1.152***	6.491***	1.954***	1.948***	0.514
	(85.669)	(25.908)	(19.850)	(4.110)	(34.347)	(13.257)	(13.220)	(1.002)
Stock FE	X	X	X	X	X	X	X	X
N	89441	89441	89441	89265	20955	20955	20955	20902
R^2	0.796	0.909	0.909	0.909	0.821	0.901	0.901	0.903

Table A.22. Implications of loan fee predictability on future price efficiency. The dependent variable is a measure of price inefficiency based on Hou & Moskowitz (2005) D1 Price Delay. $LoanFeeR^2_{i,t}$ is calculated using 3-year rolling regressions of 1-quarter ahead loan fees on all the variables in the forecasting model. Expected return forecasts are 1-year ahead. The sample considered in columns 1-4 is all stocks, whereas columns 5-8 consider only low (bottom tercile) $\hat{R}$ (1-year ahead expected return forecast) stocks.

	Dependent Variable: $PriceDelay_{i,t+3}$							
	All Stocks				Low $\hat{R}$ Stocks			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$LoanFeeR^2_{i,t}$	-0.095***	-0.095***	-0.101***	-0.109***	-0.273***	-0.273***	-0.270***	-0.299***
	(-4.872)	(-4.880)	(-5.137)	(-5.292)	(-5.371)	(-5.364)	(-5.309)	(-5.805)
$LoanFee_{i,t}$		0.000	0.000	0.000		0.000	0.001	0.001
		(0.461)	(0.066)	(0.409)		(0.045)	(0.721)	(1.074)
$\hat{R}_{i,t+1:t+12\|t}$			-0.001*				0.002**	
			(-1.790)				(2.531)	
$LogSize_{i,t}$				-0.127***				-0.159***
				(-10.986)				(-8.980)
$LogB/M_{i,t}$				0.011				-0.021*
				(1.169)				(-1.760)
$Return_{i,t}$				-0.019**				-0.005
				(-1.967)				(-0.306)
$LogIssues_{i,t}$				0.014				-0.005
				(0.728)				(-0.209)
$Accruals_{i,t}$				0.043				0.074*
				(1.428)				(1.892)
$ROA_{i,t}$				-0.030				-0.018
				(-1.004)				(-0.480)
$LogAG_{i,t}$				-0.022				-0.066***
				(-1.516)				(-2.938)
$DY_{i,t}$				0.052				-0.442*
				(0.321)				(-1.925)
$LogReturn_{i,t}$				0.033***				0.042***
				(4.273)				(3.357)
$LogIssues_{i,t}$				-0.011				-0.003
				(-0.395)				(-0.085)
$Beta_{i,t}$				0.031***				0.069***
				(6.453)				(8.104)
$StdDev_{i,t}$				0.039				-0.373***
				(0.712)				(-4.821)
$Turnover_{i,t}$				-0.026*				-0.027
				(-1.704)				(-1.535)
$Debt/Price_{i,t}$				0.007***				0.012***
				(3.154)				(3.862)
$Sales/Price_{i,t}$				-0.004**				-0.006**
				(-2.274)				(-2.444)
Constant	0.276***	0.275***	0.289***	1.185***	0.628***	0.628***	0.628***	1.619***
	(18.571)	(18.515)	(17.567)	(13.789)	(15.286)	(15.265)	(15.257)	(13.982)
Stock FE	X	X	X	X	X	X	X	X
N	89422	89422	89422	89246	20944	20944	20944	20891
R^2	0.214	0.214	0.214	0.218	0.224	0.224	0.224	0.238