Short Selling Risk

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ABSTRACT

Short sellers face unique risks, such as the risk that stock loans become expensive and the risk that stock loans are recalled. We show that short selling risk affects prices among the cross-section of stocks. Stocks with more short selling risk have lower returns, less price efficiency, and less short selling.

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"Some stocks are hard to borrow. Herbalife is not, especially, but it is risky to borrow…If Carl Icahn were to launch a tender offer, say, it might get a lot more expensive to short Herbalife, and the convertible trade would become considerably less fun."

Matt Levine, Former Investment Banker, BloombergView (2014)

Short selling is a risky business. Short sellers must identify mispriced securities, borrow shares in the equity lending market, post collateral, and pay a loan fee each day until the position closes. In addition to the standard risks that many traders face, such as a margin calls and regulatory changes, short sellers also face the risk of loan recalls and the risk of changing loan fees. To date, the existing literature has viewed these risks as a static cost to short sellers, and empirical papers have shown that static impediments to short selling significantly affect asset prices and efficiency.[1] The idea in the literature is simple: if short selling is costly, short sellers may be less likely to trade, and, as a result, prices may be biased or less efficient (e.g., Miller (1977), Diamond and Verrecchia (1987), and Lamont and Thaler (2003)).

In this paper, we examine the costs of short selling from a different perspective. Specifically, we show that the *dynamic* risks associated with short selling result in significant

[1] To test the impact of impediments to short selling, existing studies have examined a wide variety of potential measures of short sale constraints including regulatory action (Diether, Lee, and Werner (2009); Jones (2008); Boehmer, Jones, and Zhang (2013); Battalio and Schultz (2011)); institutional ownership (Nagel (2005); Asquith, Pathak, and Ritter (2005)); the availability of traded options (Figlewski and Webb (1993), Danielsen and Sorescu (2001)); and current loan fees (Jones and Lamont (2002); Cohen, Diether, and Malloy (2009)). However, all of these are static measures of short sale constraints (i.e., they examine how conditions *today* constrain short sellers), while we focus on the dynamics of short selling constraints (i.e., we examine how the risk of changing *future* constraints impacts short sellers).

limits to arbitrage. In particular, stocks with more short selling risk have lower future returns, less price efficiency, and less short selling.

Consider two stocks – A and B – that are identical in every way except for their short selling risk. Specifically, stock A and stock B have identical fundamentals and they have identical loan fees and number of shares available *today*. However, *future* loan fees and share availability are more uncertain for stock B than for stock A. In other words, there is considerable risk that future loan fees for stock B will be higher and future shares of stock B will be unavailable for borrowing. Since higher loan fees reduce the profits from short selling and limited share availability can force short sellers to close their position before the arbitrage is complete, a short seller would prefer to short stock A because it has lower short selling risk. In this paper, we present the first evidence that uncertainty regarding future short sale constraints is a significant risk, and we show that this risk affects trading and asset prices.

The short selling risk we describe has theoretical underpinnings in several existing models. For example, in D'Avolio (2002b) and Duffie, Garleanu, and Pedersen (2002), short selling fees and share availability are a function of the difference of opinions between optimists and pessimists, and short selling risk emerges as these differences evolve. As noted by D'Avolio (2002), "…a short seller is concerned not only with the level of fees, but also with fee variance." Accordingly, we focus on the variance of lending fees as our natural proxy for short selling risk. To get the best possible measure of this proxy, we project the variance of lending fees on several equity lending market characteristics and firm characteristics. We use fitted values from this forecasting model (*ShortRisk*) as our measure of short selling risk.[2]

[2] Our results are robust to using alternate measures of short selling risk, including the unconditional historical variance of loan fees for each stock. These results are shown in the internet appendix.

Using this measure, we examine whether short selling risk affects arbitrage activity. If short selling risk limits the ability of arbitrageurs to trade and correct mispricing, then it should be related to returns, market efficiency, and short selling activity. We find that it is. First, we show that our short selling risk proxy is related to future returns. A long-short portfolio formed based on *ShortRisk* earns a 9.6% annual five-factor alpha. Moreover, in a Fama-MacBeth (1973) regression framework we confirm the return predictability of short selling risk after controlling for a variety of firm characteristics. In addition, we consider the Stambaugh, Yu, and Yuan (2015) mispricing measure (*MISP*) and find that *MISP*'s ability to predict returns is greatest among stocks with high short selling risk. Thus, higher short selling risk appears to limit the ability of arbitrageurs to correct mispricing, and as a result, these stocks earn lower future returns.[3]

Next, we test whether increases in short selling risk are associated with decreases in price efficiency. We examine the Hou and Moskowitz (2005) measure of price delay and find that short selling risk is associated with significantly larger price delay, even after controlling for current loan market conditions (Saffi and Sigurdsson (2011)). A one standard deviation increase in *ShortRisk* is associated with a 9.1% increase in price delay. In other words, the risk of future short selling constraints is associated with decreased price efficiency today, independent of short constraints that may exist at the time a short position is initiated.

[3] This result is consistent with models of limits to arbitrage. For example, the model in Schleifer and Vishny (1997) predicts that stocks that are riskier to arbitrage will exhibit greater mispricing and have higher average returns to arbitrage.

Of course, if short selling risk is truly a limit to arbitrage, then we would expect this risk to affect trading activity, especially for trades with a long expected time to completion.[4] Ofek, Richardson, and Whitelaw (2004) note that the, "…difficulty of shorting may increase with the horizon length, as investors must pay the rebate rate spread over longer periods and short positions are more likely to be recalled." To test this prediction, we turn to one of the only cases where mispricing *and* the expected holding horizon of a trade can be objectively measured ex-ante. Specifically, we examine deviations between stock prices and the synthetic stock price implied from put-call parity. Ofek, Richardson, and Whitelaw (2004) and Evans et al. (2009) show that deviations between the actual and synthetic stock price often imply that a short seller would short sell the underlying stock and purchase the synthetic stock, with the expectation that the two prices will converge upon the option expiration date.

Accordingly, we measure mispricing using the natural log of the ratio of the actual stock price to the implied stock price (henceforth *put-call disparity*) as in Ofek, Richardson, and Whitelaw (2004), and we examine whether short sellers trade less on mispricings when short selling risk is high and when the option has a long time to maturity. We find that they do. In other words, arbitrageurs short significantly less when short selling risk is high, and, as a result, there is more mispricing today. Moreover, both of these effects are significantly larger for long horizon trades.

When *ShortRisk* and days to expiration are at the 25th percentile in our sample, short volume is approximately 5.1% below its unconditional mean and *put-call disparity* today is approximately 13.9% above its unconditional mean. However, when *ShortRisk* and days to expiration are at the 75th percentile in our sample, short volume is 21.7% below its unconditional

[4] We thank an anonymous referee and the editor for suggesting this point.

mean and *put-call disparity* today is approximately 149% above its unconditional mean.[5] In other words, higher short selling risk leads to significantly less short selling by arbitrageurs and greater mispricing today, and longer holding horizons magnify both of these effects.

Of course, it is natural to expect that the risks we describe here could be correlated with other well-known predictors of returns. For example, Ang et al. (2006) show that high idiosyncratic volatility is associated with low future returns. We find that all of our results still hold after controlling for other known predictors of returns, including liquidity and idiosyncratic volatility (e.g., Ang et al. (2006), Pontiff (2006)).

Overall, our results make several contributions. First, and most importantly, we are the first paper to show that uncertainty regarding future short selling constraints acts as a significant limit to arbitrage; we show that higher short selling risk is associated with lower future returns, decreased price efficiency, and less short selling activity by arbitrageurs. We also show that these effects are magnified for trades with a long expected holding horizon. In addition, we show that short selling risk is particularly high when there are extreme returns, indicating that short selling risk may have an adverse correlation with returns. Finally, we note that our findings may help explain existing anomalies, including the low short-interest puzzle (Lamont and Stein (2004)). We also posit that short selling risk may explain the puzzling fact that short interest data predict future returns even though short interest is publicly observable. In other words, the fact that short interest data predict returns and is publicly released by the exchanges begs the question: *why don't other investors arbitrage away the predictive ability of short interest?* Our results provide a partial explanation: *short selling is risky*.

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[5] The 25th and 75th percentiles of *ShortRisk* are 1.54 and 5.38, respectively. The 25th and 75th percentiles of months to expiration are 2 and 5 months, respectively.

The remainder of this paper proceeds as follows: Section I briefly describes the existing literature, Section II describes the data used in this study, Section III characterizes our findings, and Section IV concludes.

I. Background

Although we consider short sale constraints from a dynamic perspective, a large literature has considered these constraints from a static perspective. In this section, we briefly discuss existing work concerning short sale constraints and limits to arbitrage. We then formalize the hypotheses introduced in the beginning of the paper.

A. Existing Literature

On the theoretical side, multiple papers have argued that short sale constraints can have an economically significant effect on asset prices (e.g., Miller (1977), Harrison and Kreps (1978), Diamond and Verrecchia (1987)). In addition, empiricists have investigated multiple forms of short selling constraints, including regulatory restrictions and equity loan fees.

Several papers have analyzed the effect of short sale constraints by examining changes in the regulatory environment. For example, Diether, Lee, and Werner (2009) examine the effects of the Reg SHO pilot and find that short selling activity increased when the uptick rule was lifted. Boehmer, Jones, and Zhang (2013) find that the U.S. short selling ban reduced market quality and liquidity. More broadly, Beber and Pagano (2013) find that worldwide short selling restrictions slowed price discovery.

The equity loan market also provides an opportunity for researchers to study the impact of short sale constraints. Using loan fees from the equity loan market, Geczy, Musto, and Reed

(2002) suggest that short selling constraints have a limited impact on well-accepted arbitrage portfolios such as size, book-to-market, and momentum portfolios. Using institutional ownership as a proxy for supply in the equity loan market, Hirshleifer, Teoh, and Yu (2011) examine the relation between short sales and both the accrual and net operating asset anomalies. They find that short sellers do try to arbitrage mispricings, but short sale constraints appear to limit their ability to arbitrage them away.

Several papers abstract away from specific short sale constraints and instead use the general fact that short selling is more constrained than buying to examine possible asymmetries in long-short portfolio returns. Stambaugh, Yu, and Yuan (2012) examine a variety of anomalies and find that they tend to be more pronounced on the short side, consistent with the idea that short selling is riskier, thereby leading to less short selling by arbitrageurs. In a related paper, Stambaugh, Yu, and Yuan (2015) note that idiosyncratic volatility is negatively related to returns among underpriced stocks but is positively related to returns among overpriced stocks. More recently, Drechsler and Drechsler (2014) document a shorting premium and show that asset pricing anomalies are largest for stocks with high equity lending fees.

Finally, in a recent working paper, Prado, Saffi, and Sturgess (2014) examine the cross-sectional relation between institutional ownership, short sale constraints, and abnormal stock returns. They find that firms with lower levels of institutional ownership and/or more concentrated institutional ownership tend to have higher equity lending fees, and these firms also tend to earn abnormal returns that are significantly more negative.

B. Hypothesis Development

In this paper, we empirically examine the risk that future lending conditions might move against a short seller. In what follows, we use existing theory to motivate our empirical measures and develop testable predictions.

Several extant papers lend support for the idea that short selling risk will impact arbitrage activity. Mitchell, Pulvino, and Stafford (2002) empirically examine arbitrage activity for situations in which the market value of a company is less than its subsidiary and find that short selling risk can limit arbitrage activity. They specifically discuss short selling risk, noting that, "The possibility of being bought-in at an unattractive price provides a disincentive for arbitrageurs to take a large position." Consistent with this, D'Avolio (2002b) develops a theoretical model of equilibrium in the lending market and finds that, "In a multiperiod setting, a short seller is concerned not only with the level of fees, but also with fee variance. This is because current regulations stipulate that lenders maintain the right to cancel a loan at any time and hence preclude most large institutions from providing guaranteed term loans."

In D'Avolio (2002b), a short seller can respond to changes in lending market conditions by, "buying back the shares and returning them to the lender, or re-establishing the short at the higher loan fee." Thus, the model shows that share recalls and loan fee increases are two manifestations of the same underlying event: changes in lending conditions that leave the loan market temporarily out of equilibrium. As a result, recalls and fee changes are not independent risks: a share recall can be seen as an extremely high loan fee. Consistent with theoretical models, we develop two empirical measures of short selling risk in Section II, below. We view our measures as proxies for the risk of short sale constraints that arise from changing lending market conditions.

The model in D'Avolio (2002b) also suggests that lending market conditions will impact arbitrage activity.[6] Specifically, the model shows that short selling is less attractive to arbitrageurs when short selling risk is high.[7] While D'Avolio (2002b) does not explicitly model the short seller's demand function in the multiperiod case with short selling risk, a related model in D'Avolio and Perold (2003) shows that short sellers will be less likely to trade if the probability of binding future short sale constraints is high. Furthermore, this model also suggests that the expected trading horizon will matter; D'Avolio and Perold (2003) show that short sellers' willingness to trade will be low when, "the expected price correction is unlikely to occur in the near future."

Accordingly, we use these results to generate several testable predictions regarding the impact of short selling risk. First, we hypothesize that high short selling risk will be associated with less trading by short sellers, consistent with the predictions in D'Avolio (2002 and 2002b) and D'Avolio and Perold (2003). Second, consistent with models of limits to arbitrage (e.g., Schleifer and Vishny (1997)), we hypothesize that stocks with higher arbitrage risk, in this case short selling risk, will exhibit greater mispricing. Third, as suggested by Ofek, Richardson, and Whitelaw (2004) and D'Avolio and Perold (2003), we hypothesize that the impact of short selling risk will be greater for trades with a longer expected holding horizon. Finally, we note

[6] The model in Stambaugh, Yu, and Yuan (2015) can generate similar predictions. Specifically, if we introduce a stochastic loan fee to the model, the solution to the utility maximization problem shows that portfolio weights are decreasing in the variance of loan fees, and, as a consequence, mispricing is an increasing function of the variance of loan fees. A theoretical derivation of this result is available from the authors upon request.

[7] The model focuses primarily on a one-period case, in which equity lending conditions are known with certainty. However, the paper includes a multiperiod extension that discusses short selling risk.

that the existing literature finds that short selling leads to improved price efficiency (Saffi and Sigurdsson (2011)). This generates a fourth prediction: we hypothesize that stocks with more short selling risk will have less price efficiency.

In sum, we hypothesize that arbitrageurs may be less willing to short when future lending conditions are more uncertain and when the expected holding horizon is longer. As a result, short selling risk may impact returns, price efficiency, and trading volume.

II. Data

To test the hypotheses discussed above, we combine daily equity lending data with data from the Center for Research in Security Prices (*CRSP*), *Compustat*, the NYSE Trade and Quote (*TAQ*) database, and *OptionMetrics*, as discussed in detail below.

A. Equity Lending Data

The equity lending data used in our analyses come from *Markit*. The data are sourced from a variety of contributing customers including beneficial owners, hedge funds, investment banks, lending agents, and prime brokers; the market participants that contribute to this database are believed to account for the majority of all equity loans in the U.S. The initial database includes information on a variety of overseas markets and share classes. However, we exclude data on non-U.S. firms, ADRs, and ETFs, and we drop firms that have a stock price below $5 or a market capitalization below $10 million; we also require each firm to have at least 50 non-missing days each year to be included in the sample. The resulting database includes approximately 220,000 observations at the firm-month level for 4,500 U.S. equities over the 5.5-year period from July 1, 2006 through December 31, 2011.

The equity lending database includes several variables from the equity loan market. Of primary interest are shares borrowed *(Short Interest)*, the active quantity of shares available to be borrowed (*Loan Supply*), the active utilization rate (*Utilization*), the weighted average loan fee across all shares currently on loan (*Loan Fee*), the weighted average loan fee for all new loans over the past day (*New Loan Fee*), and the weighted average number of days that transactions have been open (*Loan Length*). A stock's *Loan Supply* represents the total number of shares that institutions are actively willing to lend, expressed as a percentage of shares outstanding. The *Utilization* is the quantity of shares loaned out as a percentage of *Loan Supply*. Finally, *Loan Fee*, often referred to as *specialness*, is the cost of borrowing a share in basis points per annum.

INSERT TABLE I ABOUT HERE

Panel A of Table I contains summary statistics for the equity lending database. For the typical firm, approximately 18% of outstanding shares are available to be borrowed and around 4% of shares outstanding are actually on loan at any given point. The median loan fee is only 11 basis points per annum; however, it is well known that loan fees exhibit considerable skewness, as indicated by the mean of 85 basis points and the 99th percentile of 1,479 basis points. The median loan is open for approximately 65 days, highlighting the fact that short sellers often hold their position open for several months and thus are exposed to loan fee changes. Of course, the magnitude of loan fees may seem small when compared to other risks faced by arbitrageurs, especially when looking at the median loan fee of 11 bps. However, the 99th percentile of loan fees in our sample is 14.79% per year; as discussed in Kolasinski, Reed, and Ringgenberg (2013), loan fees can increase to levels that significantly decrease the profitability of nearly any trade. Moreover, in Panel C we examine the within-firm (i.e., time-series) properties of lending market conditions. We calculate the mean, median, 1st, and 99th percentiles of loan fees and utilization by firm, and then display the cross-sectional mean of these summary statistics. The mean of the 99th percentile of loans fees is 301 bps points while the 1st percentile is 7 basis points; in other words, the average stock experiences dramatic variation in its loan fees over time.

In addition to the equity lending data discussed above, we use publicly available data from the SEC website to add information on failures to deliver. Failures to deliver occur when shares are not delivered by the standard three-day settlement date (often referred to as t+3); the SEC provides the aggregate net balance of shares that failed to be delivered on each date. The data provide information on the cumulative number of shares that have not been delivered, which does not necessarily indicate the number of new failures on any given date, as some failed positions may persist for several days. If the net balance of failed shares is below 10,000 for a given firm, the SEC does not release any information and we record a balance of zero failures for that day. As shown in Table I, failures to deliver (*Qty. Failures*) are relatively rare with a mean of 0.36% of shares outstanding and a median of 0.00% of shares outstanding.

B. Data Compilation

We match the equity lending database at the firm-month level with information from *CRSP*, *Computstat*, *TAQ*, and *OptionMetrics*. From *CRSP*, we add closing stock prices, closing ask and bid prices, shares outstanding, volume, and monthly returns, including dividend distributions. From *TAQ*, we add short sales volume for each stock using the regulation SHO database.[8] From *OptionMetrics*, we add option best bid and offer prices, expiration dates, and strike prices. As in Ofek, Richardson, and Whitelaw (2004), we drop contracts with bid-ask

[8] We exclude all canceled and invalid trades in *TAQ*.

spreads greater than 50%, absolute value of log moneyness greater than 0.5, or non-positive implied volatility. To minimize the impact of illiquidity, we focus on contracts with greater than 6 days but less than 181 days to maturity. From *Compustat* we add the natural log of the market-to-book ratio. We define book equity as total shareholder equity minus the book value of preferred stock plus the book value of deferred taxes and investment tax credit. If total shareholder equity is missing, we calculate it as the sum of the book value of common and preferred equity. If all of these are missing, we calculate shareholder equity as total assets minus total liabilities. Finally, we add NYSE breakpoints and Fama and French (2015) factors from Kenneth French's website and we add the Stambaugh, Yu, and Yuan (2015) mispricing score from Robert Stambaugh's website. Panel B of Table I contains summary statistics for the *CRSP* data. The mean market capitalization for the firms in our sample is $3.77 billion and the median market capitalization is $0.46 billion.

C. Measures of Short Selling Risk

Motivated by the theoretical results discussed in Section I.B, we define a measure of short selling risk (*ShortRisk*). The measure is motivated by D'Avolio (2002b), who notes that, "…a short seller is concerned not only with the level of fees, but also with fee variance." Consequently, we calculate the natural log of the variance of the daily *Loan Fee* for each stock over the past 12 months and we project this variable on a variety of lagged firm and lending market characteristics. The predicted values of the model, which we label *ShortRisk*, represents a trader's estimate of short selling risk given available information.

In our forecasting regression, we appeal to the prior literature in our choice of predictive variables. Because Aggarwal, Saffi, and Sturgess (2015) demonstrate the importance of utilization in the equity loan market, we consider prior loan utilization as a key forecasting variable. Moreover, because Geczy, Musto, and Reed (2002) demonstrate the usefulness of prices from new loans, we also consider the loan fees from new loans. Specifically, we use four equity lending market characteristics: (i) *VarNewFee*, (ii) *VarUtilization*, (iii) *TailNewFee*, and (iv) *TailUtilization*. *VarNewFee* is defined as the variance of loan fees for new equity loans and *VarUtilization* is defined as the natural log of the variance of the ratio of equity loan supply to loan demand (i.e., utilization). We also define two tail risk versions of these variables, *TailFee* and *TailUtilization*, which proxy for the likelihood of extreme loan fees and extreme utilization, respectively. Specifically, we define *TailNewFee* and *TailUtilization* as the 99th percentile of a normal distribution using the trailing annual mean and variance of loan fee and utilization, respectively.[9]

We also consider a number of potentially relevant firm characteristics, including a number of characteristics that are worth noting in this context. Perhaps most important are lagged values of fee risk, the number of fails to deliver, an indicator variable for stocks which had an IPO within the last 90 days, and an indicator variable for stocks with listed options.

INSERT TABLE II ABOUT HERE

The results from the following model are presented in Table II:

$$Var(LoanFees_{i,t+1}) = \alpha + \beta_1 VarNewFee_{i,t} + +\beta_2 VarUtilization_{i,t} + \beta_3 TailNewFee_{i,t} + \beta_4 TailUtilization_{i,t} + FE_i + FirmCharacteristics + \varepsilon_{i,t+1}, \tag{1}$$

[9] Our measures are based on the well-known value-at-risk measure and are calculated on each date for each stock as the mean of loan fee (utilization) + 2.33 × variance of loan fees (utilization), where the mean and variance are measured over the prior 250 trading days.

where FE_i indicates a firm fixed effect and *FirmCharacteristics* is a vector of time-varying firm characteristics. We display *t*-statistics calculated using standard errors clustered by firm and date. Although our main interest in this section is to find an accurate forecast of short selling risk, the results here shed some light on the underlying determinants of short selling risk. For example, the negative and statistically significant coefficient on the option indicator variable suggests that short selling risk is lower for stocks with traded options. Similarly, the positive and statistically significant coefficients on the dividend indicator and the number of fails to deliver suggest that short selling risk is higher immediately following an IPO and for stocks with a large number of failures in the securities lending market. Overall, the model can explain 97% of the variation in one-month-ahead short selling risk.

Accordingly, we use the predicted value from this model as a forecast of short selling risk, which we call *ShortRisk*.[10] Summary statistics for *ShortRisk* are shown in Panel D of Table I. The mean value of *ShortRisk* exceeds the median and the 99th percentile indicates that there is substantial variation in short selling risk in our sample of firms.

III. Results

In this section, we examine whether short selling risk affects prices and trading by arbitrageurs. Overall, our findings suggest that higher short selling risk is a significant limit to arbitrage.

[10] We thank an anonymous Associate Editor for suggesting this analysis.

A. Does Short Selling Risk Impact Arbitrageurs?

Short sellers face a number of risks. In equilibrium, arbitrageurs should be compensated for the risks they take (e.g., Shleifer and Vishny (1997)). In this section, we begin by showing that high short selling risk is associated with lower future returns. We then show that high short selling risk is associated with decreased price efficiency and less short selling by arbitrageurs.

A.1. Short Selling Risk and Future Returns

To start, we form simple portfolios formed by conditioning on our risk measures. Specifically, each month we form portfolios by sorting firms into quintiles using the previous month's short selling risk. These equal-weighted portfolios are then held for one calendar month and the exercise is repeated.

Figure 1 shows a strong relation between short selling risk and future returns. In Panel A we plot the mean returns to portfolios formed by conditioning on short selling risk. Stocks in the low short selling risk quintile earn monthly returns of 0.58% per month while stocks in the high short selling risk quintile earn monthly returns of -0.49% per month. Thus, a long-short portfolio formed by buying stocks with low short risk and shorting stocks with high short risk earns 1.08% per month. In Panel B, we plot the cumulative returns to a long-short strategy over our 2006 to 2011 sample period. The long-short portfolios consistently earn large returns. Overall, Figure 1 shows a close connection between short selling risk and future returns.

INSERT FIGURE 1 ABOUT HERE

Of course, a key concern is whether our results are a form of the well-established relation between short selling and future returns. Several papers have shown that high short interest predicts low future returns at the stock level (Figlewski (1981), Senchack and Starks (1993), Boehmer, Jones, and Zhang (2008)) and Rapach, Ringgenberg, and Zhou (2016) show that short interest is a strong predictor of returns at the market level.

To address this issue, we first sort on short interest and then sort on our short selling risk measures. The mean returns to these portfolios are shown in Panels A and B of Table III and five-factor alphas from these portfolios are shown in Panels A and B in Table IV. In Panel A of Table III, we show the equal-weighted portfolio returns by quintiles formed on the previous month's *ShortRisk*. Conditioning on the level of short interest in each row, the last column shows mean portfolio returns to a strategy that goes long firms with *ShortRisk* in the lowest quintile and short firms with *ShortRisk* in the highest quintile. As shown in row 1 (*All Firms*), the long-short portfolio (shown in the gray box) earns a mean monthly return of 1.08%, which is statistically significant at the 1% level. In the remaining rows of Table III, Panel A, we show the returns for each quintile of short interest. Interestingly, a strategy that buys stocks with low *ShortRisk* and shorts stocks with high *ShortRisk* earns positive and statistically significant long-short portfolio returns in each of the five short interest quintiles. The monthly long-short portfolio returns (shown in the gray box) range from 0.63% to 1.19% (7.5% to 14.2% annualized). We stress that while the first row does not condition on short interest, the remaining rows do. The results are broadly similar to each other, indicating that the effect is not subsumed by the previously studied relation between short interest and returns.

INSERT TABLE III ABOUT HERE

INSERT TABLE IV ABOUT HERE

Of course, it is possible that our portfolio sorts inadvertently sort on other common risk factors. Accordingly, Table IV repeats the portfolio exercise with five-factor alphas (Fama and French (2015)). In all three panels the results confirm the findings in Table III. A long-short portfolio formed by conditioning on our short selling risk measure earns a five-factor alpha of 0.80% per month (shown in the gray box). We also find that the results generally remain significant and economically large after conditioning on the level of short interest. In other words, Table IV, as with Table III, is consistent with models of limits to arbitrage: we find that the returns to short selling are largest when arbitrage is riskiest.

To better understand how the results hold up throughout the cross section, we also examine sorts on firm size (market capitalization) to see if the relation between short selling risk and returns is concentrated in *Micro*, *Small*, or *Big* firms. As in Fama and French (2008), we define *Micro* firms as firms with market capitalization below the 20th percentile of the NYSE breakpoints from Kenneth French's website, *Small* firms as firms with market capitalization greater than or equal to the 20th percentile but less than the 50th percentile of NYSE breakpoints, and *Large* firms as firms with market capitalization greater than or equal to the 50th percentile. Within each size category, we sort into five buckets based on short selling risk. We then create *value*-weighted portfolios and look at the next month's return.[11]

Raw returns from this exercise are shown in Panel B of Table III, while Panel B in Table IV shows Fama and French (2015) five-factor alphas. The results are generally strongest in *Micro* and *Small* stocks; however, in Table III *Large* stocks do earn a positive long-short portfolio return (but for these stocks the results exhibit weaker statistical significance). In Table III we find positive and statistically significant long-short returns for both *Micro* and *Small* stocks, ranging from 0.65% to 1.04%. Similarly, in Table IV we find positive and statistically

[11] Because we require firms to have equity lending data, our sample contains fewer *Micro* stocks than the sample in Fama and French (2008). Specifically, 60% of all stocks in the Fama and French (2008) sample are *Micro* stocks but only 44% of the stocks in our sample are classified as *Micro*.

significant five-factor alphas for *Micro* and *Small* stocks, ranging from 0.38% to 0.88%. In a sense, the fact that our results are strongest among *Micro* and *Small* stocks is not surprising as there is relatively little short selling risk in the sample of *Large* stocks. The 99th percentile of loan fees in the *Micro* sample is 1,119 bps; however, the 99th percentile of loan fees in the *Large* stock sample is only 236 bps. Similarly, the 90th percentile is 189 bps for *Micro* stocks and only 20 bps for the *Large* stocks. In addition, we note that while *Micro* and *Small* stocks represent a relatively small portion of total market capitalization, they are a large portion of the market, by number. In our analyses, these stocks represent approximately 75% of the sample. Thus, while our results are weaker among *Large* stocks, they do occur throughout a large portion of U.S. equities.

Interestingly, we also note that our sort results suggest that low short selling risk stocks are also priced differently. While the *high* short selling risk portfolios consistently earn negative returns, many of the *low* short selling risk portfolios earn high returns, a result consistent with Boehmer, Huszar, and Jordan (2010). Nonetheless, taken together, our sort results indicate that arbitrageurs are being compensated for the risk they take on their short positions.[12]

[12] In untabulated results, we repeat the sorts from Panels A and B of Tables III and IV, only we first sort on current *loan fees* instead of *short interest*. We find that short risk generally matters the most when loan fees are high. However, the results confirm that short selling risk matters even after controlling for the relation between the level of loan fees and future returns.

Finally, we adopt the regression approach of Boehmer, Jones, and Zhang (2008) to control for more firm characteristics.[13] In particular, we run monthly Fama-MacBeth (1973) regressions of the form:

$$Ret_{i,t+1} = \alpha + \beta_1 Short\ Risk_{i,t} + \beta_2 Short\ Interest_{i,t} + Controls + \varepsilon_{i,t+1}, \qquad (2)$$

where the dependent variable is the buy and hold return percent over the subsequent month, excess of the one-month risk-free rate; *Short Interest*$_{i,t}$ is the quantity of shares borrowed as of the last day of the month for each firm, normalized by each firm's shares outstanding; and *Controls* represents several different control variables. *Market / Book* is the log of the market-to-book ratio from *Compustat*, *Market Cap* is the log of market capitalization, *Idio. Volatility* is the log of the monthly standard deviation of the daily residual from a Fama-French three-factor regression,[14] *Bid-Ask* is the log of the closing bid-ask spread calculated as a fraction of the closing mid-point, and *Return*$_{t-1}$ is the return on each stock lagged by one month.

INSERT TABLE V ABOUT HERE

Our contribution is to introduce a measure of an arbitrageur's short selling risk. The results are shown in Table V. In all models, the coefficient on *Short Interest* is consistent with Boehmer, Jones, and Zhang (2008); we find that short sales activity, as measured by *Short*

[13] While we follow a similar approach to that in Boehmer, Jones, and Zhang (2008), our specification includes several differences. First, we use a different sample period then Boehmer, Jones, and Zhang (2008) and we examine a different set of firms (we examine the entire *CRSP* universe of equities while they focus on NYSE firms). Moreover, we use a measure of *Short Interest* as an independent variable, while they use *Short Volume*.

[14] We calculate idiosyncratic volatility as the standard deviation, each month, of the daily residual from a Fama and French (1993) three-factor model estimated using daily return data over our entire sample period.

Interest, is negative. In other words, high levels of short selling are associated with future price decreases.

In all models the negative and statistically significant coefficient on *ShortRisk* is consistent with the hypothesis that short selling risk is a significant limit to arbitrage.[15] In particular, we find in model (1) that a one standard deviation increase in *ShortRisk* is associated with a 53 basis point decrease in future monthly returns (a decrease of approximately 6.3% per year). In other words, on average, the returns to short selling are larger in the presence of greater short selling risk.

In model (3), we consider how short selling risk, as a limit to arbitrage, interacts with mispricing as measured by Stambaugh, Yu, and Yuan (2015). We refer to the mispricing variable as *MISP*, and it is based on 11 anomalies from the existing literature.[16] High (low) values of the *MISP* variable are the most overpriced (underpriced) according to Stambaugh, Yu, and Yuan (2015). When we interact *ShortRisk* and *MISP*, we find a negative and statistically significant coefficient, which suggests that stocks that are both overpriced and risky to short have especially low returns going forward.[17] In other words, consistent with models of limits to arbitrage, we find that higher short selling risk appears to limit the ability of arbitrageurs to

[15] Because *ShortRisk* is a generated regressor (Pagan (1984)), we calculate the standard errors of the coefficients using a block bootstrap with 200 replications. The bootstrap does not significantly alter the standard errors. The results are qualitatively unchanged if we instead use Newey-West (1987) standard errors with 3 lags, where we set the lag length = $T^{1/4} = 66^{1/4} \approx 3$ as discussed in Greene (2002).

[16] Stambaugh, Yu, and Yuan (2015) do not use any short selling-based anomalies in their mispricing measure.

[17] In untabulated results, the coefficient estimate on *MISP*, when there is no interaction term, is negative and significant as in Stambaugh, Yu, and Yuan (2015).

correct mispricing, and, as a result, these stocks earn lower future returns. As *ShortRisk* and *MISP* increase, we find that future returns get lower. When both *ShortRisk* and *MISP* are at their 90th percentiles, the next month's return is 22 basis points lower than when both *ShortRisk* and *MISP* are at their 50th percentiles.

Overall, the findings in Tables III through V suggest that higher short selling risk limits the ability of arbitrageurs to correct mispricing; as a result, stocks with high short selling risk earn predictably lower future returns. Moreover, we note that we control for the current loan fee in models (2) and (3) of Table V, since it is well known that high equity loan fees predict low future stock returns (e.g., Jones and Lamont (2002), Beneish, Lee, and Nichols (2015), Drechsler and Drechsler (2014)). Thus, our results show that the risk of future short selling constraints affects returns even after controlling for current short sale constraints and other known predictors of returns.

This evidence also sheds light on an unresolved puzzle. Several papers have shown that high short interest predicts low future returns (Figlewski (1981), Senchack and Starks (1993), Asquith, Pathak, and Ritter (2005), Boehmer, Jones, and Zhang (2008), Rapach, Ringgenberg, and Zhou, (2016)), and thus it is puzzling that publicly available short interest data continue to have return predictability. Our results show that this puzzle is particularly strong among stocks with high short selling risk. Although the existing literature has been unable to fully explain the puzzle with static short selling constraints (e.g., Cohen, Diether, and Malloy (2009)), our paper suggests that *dynamic* constraints (i.e., short selling risk) may help explain more of the puzzle. In other words, short sellers continue to earn abnormal returns, in part because short selling is risky.

A.2. Short Selling Risk and Price Efficiency

Of course, if short selling risk is a limit to arbitrage it may also decrease price efficiency. In this section, we use our proxies for short selling risk to test whether more short selling risk is associated with less price efficiency. We first estimate the Hou and Moskowitz (2005) measures of price efficiency by regressing the weekly returns of stock *i* on the current value-weighted market return and four lags of the value-weighted market return. Intuitively, the coefficients on lagged market returns are a measure of price delay; if the return on stock *i* instantaneously reflects all available information, then the lagged returns should have little explanatory power. Specifically, for each stock *i* and year *y*, we estimate the following regression:

$$ret_{i,t} = \alpha + \beta_1^{i,y} r_{m,t} + (\textstyle\sum_{j=1}^{4} \delta_j^{i,y} r_{m,t-j}) + \varepsilon_{i,t}, \tag{3}$$

where $ret_{i,t}$ is the return on stock *i* in week *t* and $ret_{m,t}$ is the value-weighted market return from *CRSP* in week *t*. We then calculate two measures of price delay, labeled D1 and D2, as follows:

$$D1_{i,y} = 1 - \frac{R^2_{[\delta_1=\delta_2=\delta_3=\delta_4=0]}}{R^2} \tag{4}$$

where the denominator is the unconstrained R^2 and the numerator is the R^2 from a regression where the coefficients on all lagged market returns are constrained to equal zero, and

$$D2_{i,y} = \frac{\sum_{j=1}^{4} |\delta_j^{i,y}|}{|\beta_1^{i,y}| + \sum_{j=1}^{4} |\delta_j^{i,y}|} \tag{5}$$

where β and δ are the regression coefficients shown in equation (3). We then test to see if our proxies for short selling risk are associated with increased price delay (i.e., worse price efficiency). To do this, we estimate the following panel regression, similar to Saffi and Sigurdsson (2011):

$$PriceDelay_{i,y} = \alpha + \beta_1 ShortRisk + \beta_2 LoanFee + \beta_3 LoanSupply + Conrols + \varepsilon_{i,y}. \quad (6)$$

The results are shown in Table VI with *t*-statistics, calculated using a block bootstrap with 200 replications, shown below the coefficient estimates. We include year fixed effects in all models to control for possible unobserved heterogeneity. Saffi and Sigurdsson (2011) examine the relation between price efficiency and contemporaneous short sale constraints and they find that firms with high loan supply tend to have significantly better price efficiency. The statistically significant negative coefficient on *Loan Supply* confirms the findings of Saffi and Sigurdsson (2011). However, we also find that uncertainty regarding *future* short sale constraints is associated with decreased price efficiency. In all models, the positive and statistically significant coefficient on *ShortRisk* indicates that higher uncertainty about future loan fees is associated with a significantly larger price delay for the measure calculated in equation (4). In model (2), a one standard deviation increase in *ShortRisk* is associated with a 9.1% increase in price delay relative to its unconditional mean.[18] In other words, the risk of *future* short selling constraints is associated with decreased price efficiency *today*, independent of short constraints that may exist at the time a short position is initiated.

INSERT TABLE VI ABOUT HERE

Taking the results in Table VI together, a general pattern emerges: higher short selling risk is associated with decreased price efficiency.

A.3. Short Selling Risk and Expected Holding Horizon

[18] *ShortRisk* has a standard deviation of 4.04 and the Hou and Moskowitz price delay measure has an unconditional mean of 0.32; therefore, 9.1% = (0.0072 * 4.04) / 0.32.

If short selling risk is truly a limit to arbitrage, then we would expect this risk to affect trading activity (D'Avolio (2002)), especially for trades with a long expected time to completion. As Ofek, Richardson, and Whitelaw (2004) note, the risk of short selling will increase with the holding period. For example, an arbitrageur shorting a stock with a volatile rebate rate is much more concerned about the volatility if his expected holding horizon is long. As a result, the arbitrageur is less likely to put on the trade in the first place.

To test this prediction, we examine a unique environment in which both the magnitude of the mispricing and the expected holding horizon of a trade can be measured ex-ante. Specifically, we examine a measure of mispricing from Ofek, Richardson, and Whitelaw (2004), *put-call disparity*, which is defined as the log difference between the stock price from the spot market and the synthetic stock price implied from put-call parity in the options market. Ofek, Richardson, and Whitelaw (2004) and Evans et al. (2009) show that when *put-call disparity* is positive, a short seller would want to short sell the underlying stock and purchase the synthetic stock, and they would expect the two to converge by the option expiration date.

INSERT TABLE VII ABOUT HERE

Accordingly, Table VII examines the relation between *put-call disparity*, short selling risk, and holding horizon using OLS panel regressions of the form:

$$PutCallDisparity_{i,t} = \beta_1 Months\ to\ Exp_{i,t} + \beta_2 Short\ Risk_{i,t-1} + \beta_3 (Short\ Risk_{i,t-1} \times Months\ to\ Exp_{i,t}) + Controls + FE_i + FE_t + \varepsilon_{i,t}, \tag{7}$$

where *Months to Exp* is our measure of the expected holding horizon of the arbitrageur and defined as the number of months between an option's expiration date and the current date. *ShortRisk* is calculated as before but is now matched to the option expiration date. Specifically, we run predictive regressions as in equation (1), where the dependent variable is loan fee variance measured over 1 - 30 days, 31- 60 days, 61 - 90 days, and so on. Then we take this forecast, *ShortRisk*, and use it as a predictor of *PutCallDisparity* measured using the same option expiration window. This lets us match the holding horizon of the arbitrageur with the expected short selling risk she will face over that horizon.

We include firm and date fixed effects in all models to control for possible unobserved heterogeneity. The coefficient estimates are shown in Table VII with *t*-statistics (shown in parentheses below the coefficient estimates) calculated using a block bootstrap with 200 replications. To examine the general relation between short selling risk and mispricing, in model (1) we omit the interaction between *ShortRisk* and *Months to Exp*. In this specification, the positive and statistically significant coefficient on short risk suggests that the no-arbitrage put-call parity equation is more likely to be violated when short selling risk is high. In other words, the results provide additional support for our main hypothesis: short selling risk leads to more mispricing.

In models (2) and (3) we add an interaction term between *ShortRisk* and *Months to Exp* to test whether short selling risk matters more for trades with a longer expected holding period. We find evidence that it does. In model (3), the statistically significant coefficient of 0.0303 on the interaction term suggests that *put-call disparity* is 13.9% above its unconditional mean when both *ShortRisk* and *Months to Expiration* are at the 25th percentile in our sample, but the effect increases to 149% when both *ShortRisk* and *Months to Expiration* are at the 75th percentile of our sample.[19] In other words, there is significantly more mispricing today when short selling risk is

[19] The unconditional mean of *put-call disparity* is 0.46. When *ShortRisk* is at the 25th percentile of its distribution (1.54) and *Months to Expiration* are at the 25th percentile of its distribution (2 months), we find that *put-call disparity* is 13.9% higher = (0.0122 × 2 + -0.0348 × 1.54 + 0.0303 × 2 × 1.54) / 0.46. However, when *ShortRisk* is

high *and* the trade has a long expected holding horizon. Similarly, in model (2) we find that the impact of *ShortRisk* increases for options with a longer time to expiration.

Importantly, in models (1) and (2) we control for the current level of short sale constraints by including *Loan Fee* as a control variable. Ofek, Richardson, and Whitelaw (2004) and Evans et al. (2009) both find that the magnitude of *put-call disparity* is related to the level of short sale constraints today. We note that our results go beyond this finding: we show that even after controlling for the level of current short selling constraints, the *risk* of short selling constraints is associated with more mispricing today.

In models (1) through (3) of Table VII, we found that short selling risk is associated with more mispricing today. Existing theoretical work (e.g., D'Avolio and Perold (2003)) posits that higher mispricing today is the result of less trading by arbitrageurs. Accordingly, we next examine the relation between daily short sale volume, short selling risk, and expected holding horizon using OLS panel regressions of the form:

$$\begin{aligned} Short\ Volume_{i,t} = {} & \beta_1 PutCallDisparity_{i,t} + \beta_2 Months\ To\ Exp_{i,t} + \beta_3 Short\ Risk_{i,t-1} \\ & + \beta_4 (Short\ Risk_{i,t-1} \times Months\ to\ Exp_{i,t}) + Controls + FE_i + FE_t + \varepsilon_{i,t}, \end{aligned} \tag{8}$$

where short volume is the number of shares shorted each day from *TAQ*, expressed as a fraction of shares outstanding. The results are shown in models (4) through (6) of Table VII; we include firm and date fixed effects in all models with standard errors calculated using a block bootstrap with 200 replications. As with models (1) through (3), $ShortRisk$ is again calculated as a prediction of loan fee variance measured over 1 - 30 days, 31 - 60 days, 61 - 90 days, and so on, matching the holding horizon of *PutCallDisparity* and *Months to Expiration*. This lets us match

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at the 75th percentile of its distribution (5.38) and *Months to Expiration* are at the 75th percentile of its distribution (5 months), we find that *put-call disparity* is 149% higher = (0.0122 × 5 + -0.0348 × 5.38 + 0.0303 × 5 × 5.38)) / 0.46.

the holding horizon of the arbitrageur with the expected short selling risk she will face over that horizon.

Consistent with theory (e.g., D'Avolio and Perold (2003)), we find that short volume is decreasing in both the holding horizon and short selling risk. In model (4), the negative and statistically significant coefficient of -0.0763 on *ShortRisk* implies that a one standard deviation increase in short selling risk is associated with 9.2% decrease in short volume, relative to its unconditional mean. In other words, short sellers trade less *today* when short risk is high over the expected holding horizon of their trade.

Following the logic that motivated the analysis in equation (7), we expect short risk to matter more for trades with a longer expected holding horizon. Thus, in models (5) and (6) we again examine the interaction between *Short Risk* and *Months to Expiration*. In all models, the negative coefficient on the interaction term shows that the effect of short risk is strongest when *Months to Expiration* is larger; in other words, we find short sellers trade less when the expected holding period is long. In model (6), the results suggest that short volume is 5.1% lower when both *Short Risk* and *Months to Expiration* are at the 25th percentile in our sample, but the effect increases to 21.7% when both *Short Risk* and *Months to Expiration* are at the 75th percentile of our sample.[20] In other words, short sellers trade significantly less when short selling risk is high and this effect is compounded by long holding horizons.

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[20] The unconditional mean of short volume/shares outstanding is 2.26. When *ShortRisk* is at the 25th percentile of its distribution (1.54) and *Months to Exp* are at the 25th percentile of its distribution (2 months), we find that short volume is 5.1% lower = (-0.0004 × 2 + -0.0731 × 1.54 + -0.0001 × 2 × 1.54) / 2.26. However, when *ShortRisk* is at the 75th percentile of its distribution (5.38) and *Months to Exp* are at the 75th percentile of its distribution (5 months), we find that short volume is 21.7% lower = (-0.0004 × 5 + -0.0731 × 5.38 + -0.0001× 5 × 5.38) / 2.26.

The result in Table VII also relates to a long-standing question in the existing short selling literature. Several papers find it puzzling that investors do not short sell stocks in larger amounts (e.g., Lamont and Stein (2004) and Duarte, Lou, and Sadka (2006)). Our results here suggest that short sellers trade less when short selling risk is high, especially for trades with a long expected holding horizon. In other words, short selling risk may help explain why there is so little short selling.

B. Noise Trader Risk and Short Selling Risk

In the preceding subsections, we documented and examined several unique risks faced by short sellers and found that higher short selling risk is associated with lower future returns, less price efficiency, and less trading by arbitrageurs. In this section, we explore the relation between short selling risk and other limits to arbitrage. For example, Lamont (2012) notes that lending market conditions appear to deteriorate precisely when short sellers most want to trade, and he notes that some firms actively try to impact lending market conditions to prevent short sellers from trading. As a result, short selling risk may be related to other market conditions, and these covariances may exacerbate existing limits to arbitrage.

INSERT FIGURE 2 ABOUT HERE

As a first pass, we conduct a simple analysis shown in Figures 2 and 3. We sort stocks by their past 20-day return ranking and compare their return ranking to changes in share availability and changes in loan fees. The results are striking: in Panel A of Figure 2 there is a strong U-shaped pattern in loan fees (shown by gray vertical bars), indicating that loan fees tend to be high for stocks with extreme returns. Specifically, in our sample of U.S. equities over the period July 1, 2006 through December 31, 2011, the unconditional mean loan fee is 85 basis points per annum. However, for the 2% of stocks that experienced the largest price increase over the previous 20 days, the mean loan fee is almost three times larger with a mean value of 236 basis points per annum, a movement that corresponds to nearly 40% of one standard deviation. In Panel B, we examine loan fee *changes* and again find that loans fees tend to increase for stocks with extreme stock returns.

INSERT FIGURE 3 ABOUT HERE

In fact, we find that loan fees increase significantly when past returns are in either the *highest* or the *lowest* quartile of returns. Moreover, in Figure 3 we find a strong hump-shaped pattern in loan supply, indicating that the supply of shares available to be borrowed exhibits a similar pattern. While the unconditional mean loan supply is 18% of shares outstanding, the mean loan supply is only 12% for the 2% of stocks that experienced the largest price increase over the previous 20 days, a movement that corresponds to over 40% of one standard deviation. In other words, when a short seller's position moves against her, it is also likely that it will be more difficult to borrow shares in the equity lending market.

INSERT TABLE VIII ABOUT HERE

In Table VIII, we formulate a regression specification designed to statistically test the patterns shown in Figures 2 and 3. We run an OLS panel regression of the form:

$$LendingMarketCondition_{i,t} = \alpha + \beta_1 LowPastReturns_{i,t-1,t-20} + \beta_2 HighPastReturns_{i,\,t-1,t-20} + \varepsilon_{i,t}, \quad (9)$$

where the dependent variable, *Lending Market Condition*$_{i,t}$, is either *Loan Fee*$_{i,t}$ or *Loan Supply*$_{i,t}$. The results confirm the findings: when returns are in either the lowest or the highest decile of past returns, we find that loan fees are higher and loan supply is lower. Specifically, in model (2) we find that firms in the bottom decile of past returns tend to have loan fees that are 13 basis point higher and firms that are in the top decile of past returns tend to have loan fees that are 10 basis points higher. Compared to the unconditional mean (median) loan fee of 85 bps (11 bps), these results are economically large and the latter result suggests that loan fees increase precisely when a short seller's position has moved against her. Similarly, in model (4) we find that firms in the top decile of past returns tend to have significantly lower loan supply. In fact, the statistically significant coefficient estimate of -0.7117 on *High Past Returns*$_i$ in model (4) suggests that loan supply levels fall when past returns are high, precisely when it is most costly for a short seller.

One potential concern with these results is that we have omitted a firm characteristic in the specification that jointly determines extreme returns and high loan fees. For example, small stocks or illiquid stocks might have high loan fees and also extreme returns. To address this issue, models (2) and (4) include firm fixed effects so that the coefficients are estimated within-firm. Although the magnitude of the coefficient shrinks, the conclusion remains the same: loan fees rise when a stock's return is extremely high or extremely low and loan supply contracts precisely when a stock's return is extremely high. In other words, short selling risk is not only a limit to arbitrage on its own, but it may actually magnify other previously studied limits to arbitrage.

IV. Conclusion

Most of the short selling literature takes a static view of short selling costs: if loan fees are high or shares unavailable today, prices may be too high today. In this paper we propose a dynamic, risk-based view. Among a cross-section of approximately 4,500 U.S. stocks traded from July 2006 through December 2011, we find that long-short portfolios based on short selling risk have five-factor alphas of 75 basis points per month. Furthermore, we find that short selling risk is associated with decreased price efficiency and less short selling today. Overall, we find that short selling risk is associated with more mispricing and less short selling, especially for trades with longer holding periods.

This evidence sheds light on two puzzles in the short selling literature. Specifically, several papers have shown that high short interest predicts low future returns, and thus it is puzzling that publicly available short interest data continue to have return predictability. Our results show that this puzzle is particularly strong among stocks with high short selling risk, which suggests that dynamic short sale constraints may explain some of the puzzle. Moreover, the literature finds it puzzling that investors do not short sell stocks in larger amounts. We find that short sellers trade less when short selling risk is high, which suggests that dynamic short sale constraints help explain the low level of short selling. Taking the two puzzles together, the overall idea emerges: when short selling is risky, short sellers are less likely to trade and prices are too high.

REFERENCES

Aggarwal, Reena, Pedro A. C. Saffi, and John Sturgess, 2015, The role of institutional investors in voting: evidence from the securities lending market, *Journal of Finance* 70, 2309-2346.

Ang, Andrew, Robert Hodrick, Yuhang Xing, and Xiaoyan Zhang, 2006, The cross-section of volatility and expected returns, *Journal of Finance* 61, 259-299.

Asquith, Paul, Parag A. Pathak, and Jay R. Ritter, 2005, Short interest, institutional ownership, and stock returns, *Journal of Financial Economics* 78, 243-276.

Battalio, Robert, and Paul Schultz, 2011, Regulatory uncertainty and market liquidity: the 2008 short sale ban's impact on equity option markets, *Journal of Finance* 66, 2013-2053.

Beber, Alessandro, and Marco Pagano, 2013, Short-selling bans around the world: evidence from the 2007–09 crisis, *Journal of Finance* 68, 343-381.

Beneish, Messod Daniel, Charles M. C. Lee, and Craig Nichols, 2015, In short supply: equity overvaluation and short selling, *Journal of Accounting and Economics* 60, 33-57.

Boehmer, Ekkehart, Zsuzsa Huszar, and Brad Jordan, 2010, The good news in short interest, *Journal of Financial Economics* 96, 80-97.

Boehmer, Ekkehart, Charles Jones, and Xiaoyan Zhang, 2008, Which shorts are informed? *Journal of Finance* 63, 491-527.

Boehmer, Ekkehart, Charles M. Jones, and Xiaoyan Zhang, 2013, Shackling the short sellers: the 2008 shorting ban, *Review of Financial Studies* 26, 1363-1400.

Cohen, Lauren, Karl B. Diether, and Christopher J. Malloy, 2009, Shorting demand and predictability of returns, *Journal of Investment Management* 7, 36-52.

D'Avolio, Gene, 2002, The market for borrowing stock, *Journal of Financial Economics* 66, 271-306.

D'Avolio, Gene, 2002b, Appendix to "The market for borrowing stock": Modeling equilibrium, unpublished manuscript.

D'Avolio, Gene M., and André F. Perold, 2003, Short selling in practice: Intermediating uncertain share availability, Working Paper.

Danielsen, Bartley, and Sorin Sorescu, 2001, Why do option introductions depress stock prices? An empirical study of diminishing short sale constraints, *Journal of Financial and Quantitative Analysis* 36, 451-484.

Diamond, Douglas W., and Robert E. Verrecchia, 1987, Constraints on short-selling and asset price adjustment to private information, *Journal of Financial Economics* 18, 277-311.

Diether, Karl B., Kuan-Hui Lee, and Ingrid M. Werner, 2009, It's SHO time! Short-sale price tests and market quality, *Journal of Finance* 64, 37-73.

Drechsler, Itmar, and Qingyi Drechsler, 2014, The shorting premium and asset pricing anomalies, Working Paper.

Duarte, Jefferson, Xiaoxia Lou, and Ronnie Sadka, 2006, Can liquidity events explain the low-short-interest puzzle? Implications from the options market, Working Paper.

Duffie, Darrell, Nicolae Gârleanu, and Lasse Heje Pedersen, 2002, Securities lending, shorting, and pricing, *Journal of Financial Economics* 66, 307-339.

Evans, Richard B., Christopher C. Geczy, David K. Musto, and Adam V. Reed, 2009, Failure is an option: Impediments to short selling and options prices, *Review of Financial Studies* 22, 1955-1980.

Fama, Eugene F. and James D. MacBeth, 1973, Risk, return, and equilibrium: Empirical tests, *Journal of Political Economy* 81, 607-636.

Fama, Eugene, and Kenneth French, 1993, Common risk factors in the returns on stocks and bonds, *Journal of Financial Economics* 33, 3-56.

Fama, Eugene, and Kenneth French, 2008, Dissecting anomalies, *Journal of Finance* 63, 1653-1678.

Fama, Eugene, and Kenneth French, 2015, A five-factor asset pricing model, *Journal of Financial Economics* 116, 1-22.

Figlewski, Stephen, 1981, The informational effects of restrictions on short sales: Some empirical evidence, *Journal of Financial and Quantitative Analysis* 16, 463-476.

Figlewski, Stephen, and Gwendolyn P. Webb, 1993, Options, short sales, and market completeness, *Journal of Finance* 48, 761-777.

Geczy, Christopher C., David K. Musto, and Adam V. Reed, 2002, Stocks are special too: An analysis of the equity lending market, *Journal of Financial Economics*, 66, 241-269.

Greene, William H., 2002, *Econometric Analysis* (Prentice-Hall, Upper Saddle River, NJ).

Harrison, Michael J., and David M. Kreps, 1978, Speculative investor behavior in a stock market with heterogeneous expectations, *Quarterly Journal of Economics* 92, 323-336.

Hirshleifer, David, Siew Hong Teoh, and Jeff Jiewei Yu, 2011, Do short-sellers arbitrage accrual-based return anomalies? *Review of Financial Studies* 24, 2429-2461.

Hou, K., and T. J. Moskowitz, 2005, Market frictions, price delay, and the cross-section of expected returns, *Review of Financial Studies* 18, 981-1020.

Jones, Charles M., and Owen A. Lamont, 2002, Short-sale constraints and stock returns, *Journal of Financial Economics* 66, 207-239.

Jones, Charles, 2008, Shorting restrictions – revisiting the 1930s, Working Paper.

Kolasinski, Adam C., Adam V. Reed, and Matthew C. Ringgenberg, 2013, A multiple lender approach to understanding supply and search in the equity lending market, *Journal of Finance* 68, 559-595.

Lamont, Owen A., 2012, Go down fighting: Short sellers vs. firms, *Review of Asset Pricing Studies* 2, 1-30.

Lamont, Owen A., and Jeremy C. Stein, 2004, Aggregate short interest and market valuations, *American Economic Review Papers and Proceedings* 94, 29-32.

Lamont, Owen A., and Richard H. Thaler, 2003, Can the market add and subtract? Mispricing in tech stock carve-outs, *Journal of Political Economy* 111, 227-268.

Levine, Matt, 2014, What happened to Herbalife yesterday? *BloombergView*, February 4.

Miller, Edward M., 1977, Risk, uncertainty, and divergence of opinion, *Journal of Finance* 32, 1151-1168.

Mitchell, Mark, Todd Pulvino, and Erik Stafford, 2002, Limited arbitrage in equity markets, *Journal of Finance* 57, 551-584.

Nagel, Stefan, 2005, Short sales, institutional investors and the cross-section of stock returns, *Journal of Financial Economics* 78, 277-309.

Newey, Whitney K. and Kenneth D. West, 1987, A simple, positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix, *Econometrica* 55, 703-708.

Ofek, Eli, Matthew Richardson, and Robert Whitelaw, 2004, Limited arbitrage and short sales restrictions: Evidence from the options markets, *Journal of Financial Economics* 74, 305-342.

Pagan, Adrian, 1984, Econometric issues in the analysis of regressions with generated regressors, *International Economic Review* 25, 221-247.

Prado, Melissa Porras, Pedro A. C. Saffi, and John Sturgess, 2014, Ownership structure, limits to arbitrage and stock returns: Evidence from equity lending markets, Working Paper.

Pontiff, Jeffrey, 2006, Costly arbitrage and the myth of idiosyncratic risk, *Journal of Accounting and Economics* 42, 35-52.

Rapach, David E., Matthew C. Ringgenberg, and Guofu Zhou, 2016, Aggregate short interest and return predictability, *Journal of Financial Economics* 121, 46-65.

Saffi, Pedro A. C., and Kari Sigurdsson, 2011, Price efficiency and short selling, *Review of Financial Studies* 24, 821-852.

Senchack Jr., A. J., and Laura T. Starks, 1993, Short-sale restrictions and market reaction to short-interest announcements, *Journal of Financial & Quantitative Analysis* 28, 177-194.

Shleifer, Andrei and Robert W. Vishny, 1997, The limits of arbitrage, *Journal of Finance* 52, 35-55.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2012, The short of it: Investor sentiment and anomalies, *Journal of Financial Economics* 104, 288-302.

Stambaugh, Robert F., Jianfeng Yu, and Yu Yuan, 2015, Arbitrage asymmetry and the idiosyncratic volatility puzzle, *Journal of Finance* 70, 1903-1948.

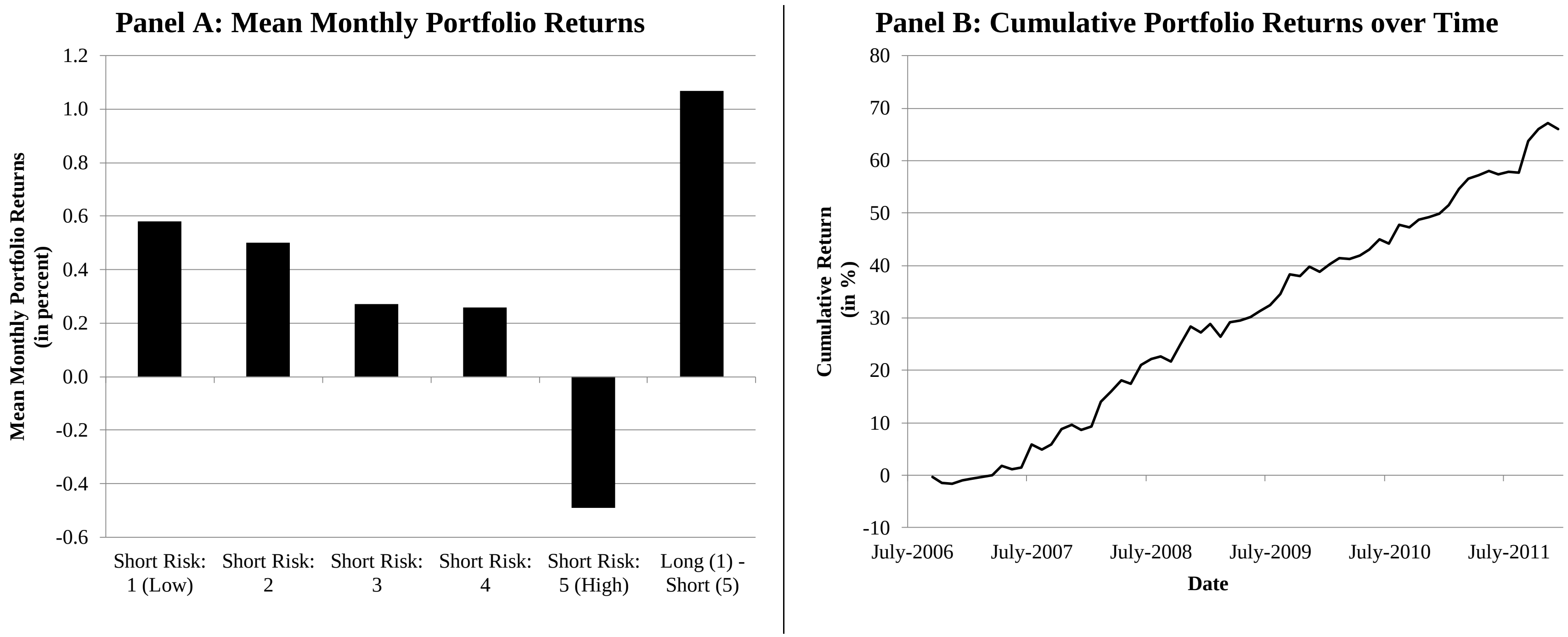

Figure 1. Portfolio Returns from Conditioning on Short Selling Risk. Panel A displays mean monthly percentage returns for portfolios and Panel B plots the cumulative return to long-short portfolios calculated over the period July 2006 through December 2011. Each month, portfolios are formed by sorting into quintiles using the previous month's short selling risk and these portfolios are held for one month. At the far right of the figure in Panel A, we display returns from a long-short portfolio that takes a long position in the low short selling risk portfolio (quintile 1) and a short position in the high short selling risk portfolio (quintile 5). In Panel B, we plot the cumulative returns to a long-short portfolio that buys stocks in the lowest quintile of short selling risk and shorts stocks in the highest quintile of short selling risk. These equal-weighted portfolios are then held for one calendar month.

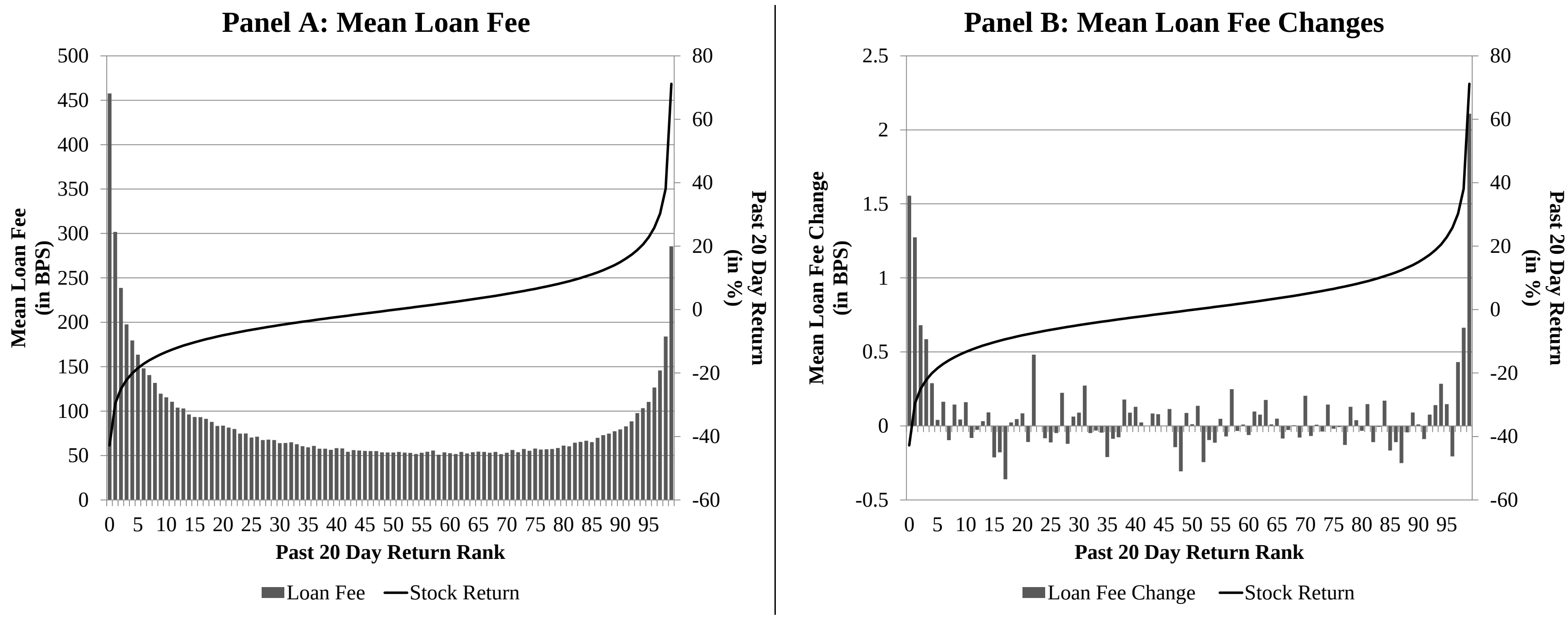

Figure 2. Mean Loan Fees Conditional on Stock Returns over the Previous 20 Days. The figures in Panel A and Panel B plot mean loan fees and mean loan fee changes, respectively, conditional on stock returns over the previous 20 days. Each day, the stock return over the previous 20 days (i.e., date *t*-1, *t*-20) is ranked into 50 equally sized bins and then the mean loan fee or loan fee change on date *t* is calculated for each bin. In each panel the left vertical axis denotes the *Loan Fee* in basis points per annum. The loan fee measures the cost of borrowing a stock and is calculated as the difference between the rebate rate for a specific loan and the prevailing market rebate rate. The rebate rate for an equity loan is the rate at which interest on collateral is rebated back to the borrower. The right vertical axis shows the mean value of past 20-day returns in each of the 50 return bins, and the horizontal axis shows the 50 return bins.

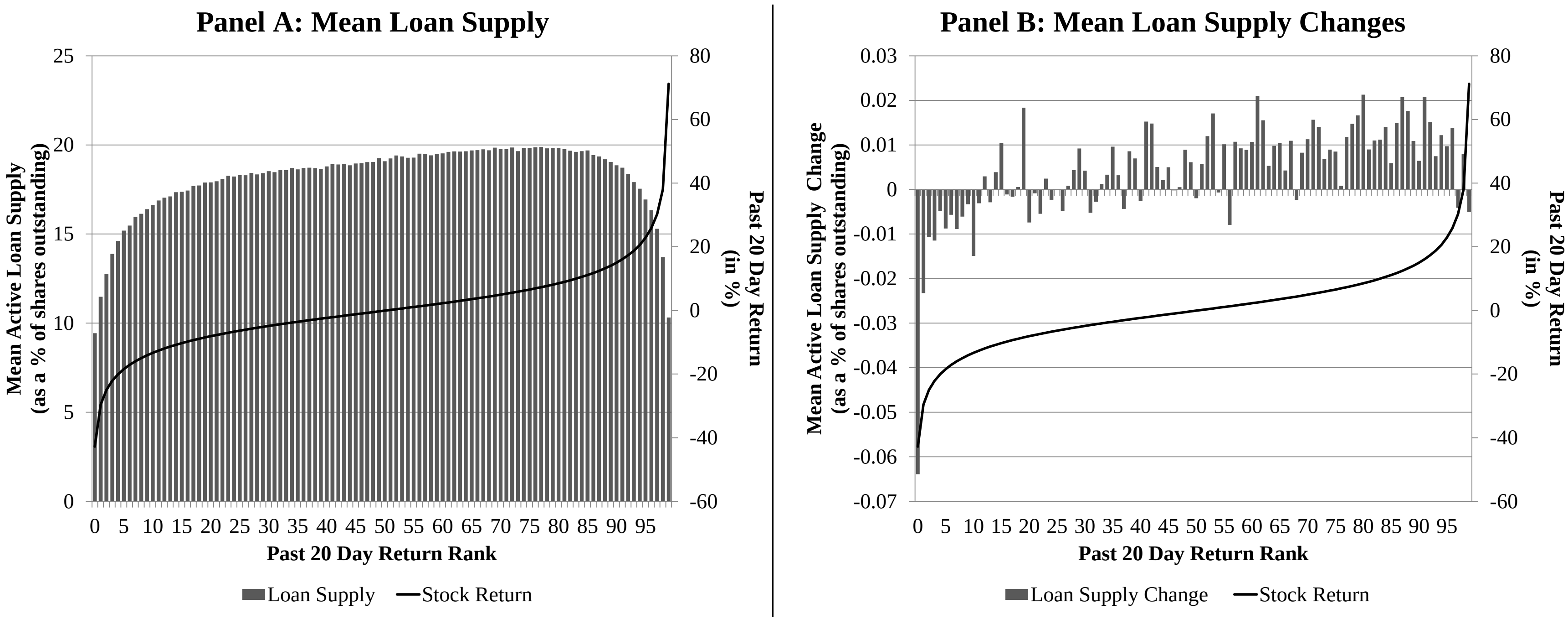

Figure 3. Mean Loan Supply Conditional on Stock Returns over the Previous 20 Days. The figures in Panel A and Panel B plot mean loan supply and mean loan supply changes, respectively, conditional on stock returns over the previous 20 days. Each day, the stock return over the previous 20 days (i.e., date *t*-1, *t*-20) is ranked into 50 equally sized bins and then the mean loan supply or loan supply change on date *t* is calculated for each bin. In each panel the left vertical axis denotes the *Active Loan Supply* as a percentage of shares outstanding. The right vertical axis shows the mean value of past 20-day returns in each of the 50 return bins, and the horizontal axis shows the 50 return bins.

Table I
Summary Statistics

Table I displays summary statistics. The sample combines equity lending data from *Markit* with data from *CRSP*, *Compustat*, NYSE *TAQ*, and *OptionMetrics*. The sample contains approximately 4,500 U.S. equities over the period July 1, 2006 through December 31, 2011. Panel A displays the *Mean*, *Median*, *1st Percentile*, *99th Percentile*, and *Standard Deviation* values of selected equity lending variables. *Loan Supply* represents the total number of shares owned by institutions with lending programs, expressed as a percentage of shares outstanding. *Short Interest* is the total quantity of shares that were loaned out as a percentage of shares outstanding. *Short Volume* is the natural log of 1 + short volume as a fraction of shares outstanding from *TAQ* (multiplied by 100 for scaling). *Utilization* is the quantity of shares loaned out as a percentage of shares available to be borrowed. *Loan Fee*, often referred to as *specialness*, is the cost of borrowing a share in basis points per annum. *Loan Length* is the weighted average number of days that loans have been open. *Qty. Failures* is the total quantity of shares that were not delivered as scheduled, expressed as a percentage of shares outstanding. Panel B displays information regarding firm characteristics: *Market Capitalization* and *Monthly Return* are from *CRSP*. Panel C displays time-series properties of the lending market. For each firm, we first calculate the time-series summary statistics, and the table presents the cross-sectional mean of these values. Panel D displays information on our short selling risk measure as defined in Section II of the text.

Variable	Mean	Median	1st	99th	Standard Deviation
Panel A: Lending Market Characteristics					
Loan Supply	18.56%	19.28%	0.00%	46.42%	13.17%
Short Interest	4.43%	2.18%	0.00%	27.33%	5.99%
Short Volume	2.16	1.48	0.18	11.50	2.07
Utilization	13.68%	4.13%	0.00%	85.04%	20.15%
Loan Fee	85.13 bps	11.57 bps	-12.28 bps	1,479.29 bps	372.67 bps
Loan Length (in days)	81.46	65.00	2.00	373.00	82.61
Qty. Failures	0.36%	0.00%	0.00%	7.27%	3.39%
Panel B: Firm Characteristics					
Market Capitalization	$3.77B	$0.46B	$0.01B	$62.81B	$16.33B
Monthly Return	0.31%	0.26%	-33.84%	35.53%	12.45%
Panel C: Time-Series Properties of Lending Market Characteristics					
Loan Fee	70.65 bps	49.01 bps	6.75 bps	301.42 bps	68.48 bps
Utilization	21.58%	18.35%	4.00%	72.09%	17.07%
Panel D: Short Selling Risk					
Short Risk	4.04	3.63	-0.92	12.11	4.04

Table II
Forecasting Model of Future Short Selling Risk

This table shows estimates from an OLS panel regression predicting short selling risk using the model:

$$Var(LoanFees_{i,t+1}) = \alpha + \beta_1 VarNewFee_{i,t} + +\beta_2 VarUtilization_{i,t} + \beta_3 TailNewFee_{i,t} + \beta_4 TailUtilization_{i,t} + FE_i + FirmCharacteristics + \varepsilon_{i,t+1},$$

where *VarNewFee* is the variance of loan fees for new equity loans, *VarUtilization* is the natural log of the variance of the ratio of equity loan supply to loan demand (i.e., utilization), and *TailNewFee* and *TailUtilization* are the 99^{th} percentile of a normal distribution using the trailing annual mean and variance of loan fee and utilization, respectively. FE_i indicates a firm fixed effect and *FirmCharacteristics* is a vector of time-varying firm characteristics that include the lagged value of fee risk, the natural log of one plus the number of shares that failed to deliver (as a percentage of shares outstanding), the natural log of trading volume (as a percentage of shares outstanding), the natural log of the bid-ask spread (as a fraction of the closing mid-price), the natural log of market capitalization, the natural log of return volatility (calculated as the standard deviation of daily stock returns each month), an indicator variable for stocks paying a dividend this month, an indicator variable for stocks that had an IPO within the previous 90 days, and an indicator variable for stocks with listed options. *t*-statistics, calculated using standard errors clustered by firm and date, are shown below the estimates in italics. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Explanatory Variables	**Dependent Variable: Var($LoanFee_{t+1}$)** (1)	(2)	(3)
VarNewFee	0.7680***	0.7316***	0.0611***
	(24.49)	*(27.27)*	*(5.42)*
VarUtilization	0.1348***	0.1242***	0.0151***
	(9.50)	*(9.88)*	*(3.39)*
TailNewFee	0.1266***	0.1244***	0.0050*
	(7.24)	*(7.49)*	*(1.69)*
TailUtilization	-0.0929	-0.0568	-0.0160
	(-1.60)	*(-1.06)*	*(-1.28)*
Qty. Failures		0.0061**	0.0094***
		(2.25)	*(4.70)*
Volume		0.2858***	0.0813***
		(7.12)	*(6.43)*
Bid-Ask		0.1408***	0.0330***
		(7.06)	*(2.89)*
Market Cap		-0.6539***	0.0330
		(-6.59)	*(1.22)*
Var($LoanFee_t$)			0.9100***
			(65.42)
Volatility			0.0830***
			(2.78)
Dividend Indicator			0.0139
			(1.10)
IPO Indicator			0.1533**
			(2.06)
Option Indicator			-0.0434**
			(-2.47)
N	164,811	162,663	162,657
R^2	0.82	0.83	0.97

Table III

Monthly Portfolio Returns from Conditioning on Short Selling Risk

This table contains monthly returns (in percent) for portfolios calculated over the period July 2006 through December 2011. In Panel A we examine equal-weighted portfolios formed by first sorting into quintiles using the previous month's short interest and then sorting into quintiles using the previous month's short selling risk. Panel B we examine value-weighted portfolios formed by first sorting into quintiles using the previous month's market capitalization as in Fama and French (2008), and then sorting into quintiles using the previous month's short selling risk. All portfolios are held for one month. The last column in each panel (Long-Short) shows returns to a long-short portfolio where firms with short selling risk in the lowest (highest) quintile are assigned to the long (short) portfolio. *t*-statistics are below the estimates in italics. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Panel A: ShortRisk and Short Interest (EW Portfolios)

		Short Risk 1	**Short Risk 2**	**Short Risk 3**	**Short Risk 4**	**Short Risk 5**	**Long-Short**
	All Firms	0.58***	0.50***	0.27***	0.26***	-0.49***	1.08***
		(8.23)	*(7.05)*	*(3.84)*	*(3.61)*	*(-5.61)*	*(9.55)*
Short Interest	**1 (Low)**	0.21	0.55***	0.46***	-0.16	-0.42**	0.63**
		(1.25)	*(3.38)*	*(2.90)*	*(-0.94)*	*(-2.23)*	*(2.49)*
	2	0.75***	0.81***	0.35**	0.31**	-0.44**	1.19***
		(4.79)	*(5.25)*	*(2.40)*	*(2.11)*	*(-2.50)*	*(5.04)*
	3	0.82***	0.74***	0.20	0.38**	-0.30	1.12***
		(5.39)	*(4.96)*	*(1.30)*	*(2.51)*	*(-1.64)*	*(4.72)*
	4	0.55***	0.32**	0.29*	0.26	-0.32	0.87***
		(3.60)	*(2.16)*	*(1.89)*	*(1.52)*	*(-1.62)*	*(3.47)*
	5 (High)	0.30*	0.52***	0.19	0.09	-0.85***	1.15***
		(1.88)	*(3.25)*	*(1.13)*	*(0.45)*	*(-3.96)*	*(4.30)*

Panel B: ShortRisk and Firm Size (VW Portfolios)

		Short Risk 1	**Short Risk 2**	**Short Risk 3**	**Short Risk 4**	**Short Risk 5**	**Long-Short**
Size	**Micro**	-0.03	0.05	0.03	-0.51***	-1.07***	1.04***
	(44% of sample)	*(-0.24)*	*(0.41)*	*(0.25)*	*(-4.05)*	*(-7.38)*	*(5.66)*
	Small	0.52***	0.40***	0.37**	0.28**	-0.13	0.65***
	(31% of sample)	*(4.23)*	*(3.32)*	*(2.93)*	*(2.04)*	*(-0.79)*	*(3.19)*
	Big	0.18*	0.21**	0.14	0.33***	-0.06	0.24
	(25% of sample)	*(1.74)*	*(2.13)*	*(1.42)*	*(3.64)*	*(-0.71)*	*(1.42)*

Table IV

Monthly Five-Factor Alphas from Conditioning on Short Selling Risk

The table contains monthly Fama-French (2015) five-factor alphas (in percent) calculated over the period July 2006 through December 2011. In Panel A we examine equal-weighted portfolios formed by first sorting into quintiles using the previous month's short interest and then sorting into quintiles using the previous month's short selling risk. In Panel B we examine value-weighted portfolios formed by first sorting into quintiles using the previous month's market capitalization as in Fama and French (2008), and then sorting into quintiles using the previous month's short selling risk. All portfolios are held for one month. The last column in each panel (Long-Short) shows returns to a long-short portfolio where firms with short selling risk in the lowest (highest) quintile are assigned to the long (short) portfolio. The reported alphas are the intercept from regressing portfolio returns, excess of the one-month risk free rate, on the excess market return, SMB, HML, RMW, and CMA factors. *t*-statistics are below the estimates in italics. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

		Panel A: ShortRisk and Short Interest (EW Portfolios)					
		Short Risk 1	**Short Risk 2**	**Short Risk 3**	**Short Risk 4**	**Short Risk 5**	**Long-Short**
	All Firms	0.22***	0.18***	0.03	-0.05	-0.58***	0.80***
		(3.24)	*(2.66)*	*(0.48)*	*(-0.63)*	*(-6.60)*	*(7.71)*
Short Interest	**1 (Low)**	0.08	0.54***	0.36*	0.15	0.27	-0.19
		(0.42)	*(2.81)*	*(1.87)*	*(0.73)*	*(1.15)*	*(-0.65)*
	2	0.56***	0.33**	0.19	0.05	-0.59***	1.15***
		(3.71)	*(2.26)*	*(1.36)*	*(0.35)*	*(-3.28)*	*(5.37)*
	3	0.48***	0.27*	-0.04	0.07	-0.70***	1.17***
		(3.38)	*(1.94)*	*(-0.32)*	*(0.51)*	*(-4.06)*	*(5.66)*
	4	0.10	-0.22	0.03	-0.11	-0.54***	0.64***
		(0.71)	*(-1.58)*	*(0.20)*	*(-0.68)*	*(-2.79)*	*(2.89)*
	5 (High)	-0.15	0.16	-0.17	-0.27	-0.96***	0.80***
		(-1.05)	*(1.09)*	*(-1.10)*	*(-1.49)*	*(-4.68)*	*(3.37)*

		Panel B: ShortRisk and Firm Size (VW Portfolios)					
		Short Risk 1	**Short Risk 2**	**Short Risk 3**	**Short Risk 4**	**Short Risk 5**	**Long-Short**
Size	**Micro**	-0.03	0.01	-0.02	-0.36***	-0.91***	0.88***
	(44% of sample)	*(-0.28)*	*(0.07)*	*(-0.19)*	*(-2.88)*	*(-6.32)*	*(5.04)*
	Small	0.14	0.09	0.20*	0.09	-0.24	0.38**
	(31% of sample)	*(1.22)*	*(0.84)*	*(1.68)*	*(0.67)*	*(-1.53)*	*(2.10)*
	Big	0.02	-0.02	0.03	0.10	0.05	-0.02
	(25% of sample)	*(0.25)*	*(-0.23)*	*(0.37)*	*(1.19)*	*(0.61)*	*(-0.14)*

Table V

Cross-sectional Relation between Monthly Percentage Returns and Short Selling Risk

The table contains Fama and MacBeth (1973) regression results. For each model, we run 63 monthly cross-sectional regressions of the form:

$$Ret_{i,t+1} = \alpha + \beta_1 Short\ Risk_{i,t} + \beta_2 Short\ Interest_{i,t} + Controls + \varepsilon_{i,t+1},$$

where *Ret* is the buy and hold return percent over the subsequent month, excess of the one-month risk-free rate. *ShortRisk* is the fitted value from a regression model which forecasts future loan fee variance. *Short Interest*$_{t=0}$ is the quantity of shares borrowed, normalized by shares outstanding; *Mispricing* is the mispricing measure from Stambaugh et al. (2015); *Market / Book* is the log of the market-to-book ratio; *Market Cap* is the log of market capitalization lagged by one month; *Idio. Volatility* is the log of idiosyncratic volatility from a Fama-French three-factor regression; *Bid-Ask* is the log of the closing bid-ask spread; *Return*$_{t-1}$ is the return on each stock lagged by one month; *Loan Fee* is the cost of borrowing a share in basis points per annum, and *Loan Supply* is the total number of shares that are actively available to be lent (as a fraction of shares outstanding). We report the time-series mean of the parameter estimates with *t*-statistics, calculated using a block bootstrap with 500 replications, shown below the coefficient estimates. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Dependent Variable	**Dependent Variable: Monthly Excess Return$_{t+1}$**		
	(1)	**(2)**	**(3)**
Short Risk	-0.0013***	-0.0008***	0.0013*
	(-4.31)	*(-2.80)*	*(1.91)*
Short Interest	-0.0020	-0.0042**	-0.0049***
	(-0.99)	*(-2.23)*	*(-2.63)*
Mispricing			0.0369***
			(3.09)
Short Risk × Misp			-0.0039***
			(-2.74)
Market / Book	-0.0080***	-0.0110***	-0.0121***
	(-4.58)	*(-5.31)*	*(-5.95)*
Market Cap	-0.0030***	-0.0048***	-0.0045***
	(-4.88)	*(-6.41)*	*(-6.07)*
Idio. Volatility		0.0026	0.0017
		(0.84)	*(0.62)*
Bid-Ask		-0.0057***	-0.0054***
		(-7.54)	*(-7.51)*
Return$_t$		-0.0204*	-0.0316**
		(-1.71)	*(-2.42)*
Return$_{t-1}$		-0.0164*	-0.0175*
		(-1.92)	*(-1.93)*
Loan Fee		-0.0008**	-0.0007*
		(-2.15)	*(-1.88)*
Loan Supply		-0.0001	-0.0000
		(-1.09)	*(-0.52)*
Intercept	0.0227	0.0013	-0.0334
	(-0.39)	*(0.06)*	*(-1.60)*
N	154,537	149,301	140,815
Average R^2	0.10	0.06	0.07

Table VI
Price Efficiency and Short Selling Risk

This table examines the relation between the Hou and Moskowitz (2005) measure of price efficiency and short selling risk using OLS panel models of the form:

$$PriceDelay_{i,y} = \alpha + \beta_1 ShortRisk + \beta_2 LoanFee + \beta_3 LoanSupply + Conrols + \varepsilon_{i,y},$$

where the dependent variable, *PriceDelay*, is the *D1* price delay measure from Hou and Moskowitz (2005). *Short Risk* is the fitted value from a regression model that forecasts future loan fee variance. *Loan Fee* is the mean cost of borrowing a share in basis points per annum, divided by 100 for scale purposes; *Loan Supply* is the mean total number of shares owned by institutions that are actively available to be lent (as a fraction of shares outstanding); *Qty. Failures* is the total quantity of shares that were not delivered as scheduled; *Market Cap.* is the log of mean market capitalization for each firm-year; *Volume* is the log of mean total trading volume for each firm (as a fraction of shares outstanding); *Bid-Ask Spread* is the mean bid-ask spread; *Listed Option* is an indicator for whether a stock has listed options. All variables are annual and we include year fixed effects in all models. *t*-statistics, calculated using a block bootstrap with 200 replications, are shown below the coefficient estimates. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Explanatory Variable	**Dependent Variable: Price Delay (D1)**		
	(1)	**(2)**	**(3)**
Short Risk	0.0067***	0.0072***	0.0070***
	(6.20)	*(7.32)*	*(6.72)*
Loan Supply	-0.0068***	-0.0015***	-0.0015***
	(-22.75)	*(-5.47)*	*(-5.48)*
Qty. Failures		-0.0008	-0.0010
		(-0.50)	*(-0.59)*
Market Cap.		-0.0212***	-0.0212***
		(-10.36)	*(-10.37)*
Volume		-0.0099**	-0.0098**
		(-3.03)	*(-3.02)*
Bid-Ask Spread		0.0546***	0.0545***
		(14.35)	*(14.33)*
Listed Option		-0.0118	-0.0120
		(-0.29)	*(-0.32)*
Loan Fee			0.0005
			(0.52)
Intercept	0.3924***	1.0344***	1.0348***
	(38.47)	*(27.22)*	*(27.23)*
Year Fixed Effect	*Yes*	*Yes*	*Yes*
N	15,662	14,904	14,904
$\mathbf{R^2}$	0.20	0.30	0.30

Table VII
Relation between Arbitrage, Short Selling Risk, and Time Horizon

This table contains OLS panel regression results examining the relation between option mispricing, short selling risk, and the time to option expiration according to the model:

$$y_{i,t} = \beta_1 Months\ To\ Exp_{i,t} + \beta_2 Short\ Risk_{i,t-1} + \beta_3 (Short\ Risk_{i,t-1} \times Months\ to\ Exp_{i,t}) + Controls + FE_i + FE_t + \varepsilon_{i,t},$$

where $y_{i,t}$ is *Put-Call Disparity* in models (1) through (3) and *Short Volume* in models (4) through (6). *Put-Call Disparity* is a measure of option mispricing calculated as the natural log of the ratio of the actual stock price to the option implied stock price as in Ofek, Richardson, and Whitelaw (2004). *Short Volume* is the number of shares shorted each date, from *TAQ*, as a fraction of shares outstanding. *Months to Expiration* is the number of months until the option expires. *Short Risk* is the fitted value from a regression model that forecasts future loan fee variance at the horizon of the option contract. *Loan Fee* is the mean cost of borrowing a share in basis points per annum, divided by 100 for scale purposes; *Option Liquidity* is the mean bid-ask spread of the call and put prices for a given maturity and strike; *Stock Liquidity* is the stock bid-ask spread; *Short Interest$_{t=0}$* is the quantity of shares borrowed each month for each firm, normalized by shares outstanding. All models include firm and date fixed effects. *t*-statistics, calculated using a block bootstrap with 200 replications, are shown below the coefficient estimates. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Explanatory	**Dependent Variable: Put-Call Disparity**			**Dependent Variable: Short Volume (%)**		
Variable	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
Months to Expiration	0.1215***	0.0100**	0.0122**	-0.0136***	0.0055	-0.0006
	(38.22)	*(2.06)*	*(2.28)*	*(-2.77)*	*(0.74)*	*(-0.08)*
Short Risk	0.0146***	-0.0782***	-0.0348***	-0.0763*	-0.0624	-0.0636
	(4.81)	*(-13.36)*	*(-8.64)*	*(-1.74)*	*(-1.45)*	*(-1.48)*
Short Risk × Months		0.0302***	0.0303***		-0.0056***	-0.0055***
		(18.93)	*(18.13)*		*(-3.63)*	*(-3.57)*
Loan Fee	0.0019***	0.0019***			-0.0004	-0.0004
	(20.02)	*(19.90)*			*(-0.73)*	*(-0.71)*
Option Liquidity		0.2212***	0.3455***			-0.4007***
		(6.84)	*(6.12)*			*(-3.94)*
Stock Liquidity		0.1517	0.5146**			-5.1249
		(1.15)	*(2.29)*			*(-0.94)*
Put-Call Disparity				0.0542	0.0768**	0.0765**
				(1.52)	*(2.03)*	*(2.02)*
Short Interest			0.0028***			
			(13.01)			
Firm Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Date Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
N	5,052,282	5,052,050	5,049,260	1,403,537	1,403,537	1,403,434
R^2	0.50	0.52	0.41	0.41	0.41	0.41

Table VIII
Loan Market Conditions as a Function of Past 20-Day Returns

This table shows the results from an OLS panel model examining loan fees and loan supply according to the following model:

$$LendingMarketCondition_{i,t} = \alpha + \beta_1 LowPastReturns_{i,t-1,t-20} + \beta_2 HighPastReturns_{i,\,t-1,t-20} + \varepsilon_{i,t}$$

where *Lending Market Condition*$_{i,t}$ is *Loan Fees*$_{i,t}$ in models (1) and (2) and *Loan Supply*$_{i,t}$ in models (3) and (4), *Low Past Returns*$_{it}$ = 1 if firm *i* had returns in the bottom decile of all firms from date *t*-1 *to t*-20 and = 0 otherwise, and *High Past Returns*$_{it}$ = 1 if firm *i* had returns in the top decile of all firms from date *t*-1 *to t*-20 and = 0 otherwise. We include firm fixed effects in models (2) and (4) and month-year fixed effects in all models. *t*-statistics calculated using robust standard errors clustered by firm and date are shown below the estimates in italics. *, **, *** denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Explanatory Variable	**Dependent Variable: Loan Fee$_{i,t}$**		**Dependent Variable: Loan Supply$_{i,t}$**	
	(1)	**(2)**	**(3)**	**(4)**
Low Past Returns	0.7009***	0.1337***	-3.0116***	-0.0508
	(24.20)	*(11.75)*	*(-13.42)*	*(-1.29)*
High Past Returns	0.4189***	0.0953***	-2.8617***	-0.7117***
	(25.46)	*(12.85)*	*(-17.83)*	*(-19.04)*
Firm Fixed Effect	*No*	*Yes*	*No*	*Yes*
Time Fixed Effect	*Yes*	*Yes*	*Yes*	*Yes*
N	4,287,629	4,287,629	4,972,250	4,972,250
Adj. R^2	0.08	0.62	0.02	0.82