The Price of Prospective Lending: Evidence from Short Sale Constraints*

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ABSTRACT

Institutional investors can generate revenue by lending shares to short sellers. In this paper, I show that security prices incorporate expected future security lending profit. To determine whether institutional investors anticipate lending profits, I look at price behavior following a failure-to-deliver in the equity lending market. Failure-to-deliver represents situations in which it is difficult to locate securities available for borrowing, leading to high bargaining power for the lender and prospective increases in lending profits. I use closed-end funds to measure how failures influence deviations from intrinsic value. The results show that the prospect of future lending profits pushes the price of closed-end funds above its NAV. Closed-end funds with reported failures trade at a 2.63% premium with respect to their NAV. The results of this study imply that overpricing caused by the presence of short sale constraints is not solely due to the restriction of negative information but also partly a result of rational capitalized lending revenue.

Keywords: Security Lending, Failure-to-deliver, Short Sale Constraints, Closed-end Funds

JEL: G12, G14

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The securities lending market has grown dramatically in the past decade. In July 2008, short interest on the New York Stock Exchange reached a peak of 18.6 million shares, equal to 4.7% of the total shares outstanding.[1] The US equity lending market increased in size from $270 billion in 2008 to $320 billion in 2009.[2] Greater short sale volume led to increased lending revenue for institutional investors. According to Data Explorers Ltd, investment companies earned almost $1.4 billion in 2008 from lending their securities. Mutual funds reported $1 billion in lending revenue and pension funds added $500 million to their overall portfolio returns. Through lending shares to short sellers, institutional investors benefit by generating lending revenue. Kaplan et al. (2010) estimate, based on a lending experiment for an anonymous money manager, the returns per year of lending high-fee stocks to be around 2.78 to 4.64% for the trial period September 5th to 18th, 2008.

In this paper, I show that this lending profit is capitalized into prices. I build on the theoretical research by Duffie et al. (2002), who present a dynamic model of asset valuation in which short selling requires searching for security lenders and bargaining over the lending fee. They argue that investors are willing to pay more than their valuation, if they expect to profit from lending it in the future when the opportunity arises.

To understand how lending expectation can play a role in pricing, consider the example of Duffie et al. (2002). Suppose there are two groups of optimistic and pessimistic investors and two rounds of trades. The optimists assign a value of 100 to a security; the pessimistic investors assign a value of 90. In the final round of lending, the pessimistic investors would be willing to pay up to 10 in lending fee to short the asset. The optimists anticipate this lending fee and are willing to buy the security for 100+10=110. The prospect of lending fees increases prices above even the most optimistic buyer's valuation of the security's future dividends. In other words, the stock price is the expected future revenue associated with the potential to lend the asset, plus the expected valuation of the marginal investor.

In this paper, I address the following question: are investors willing to pay a premium associated with lending fees? The purpose is to examine whether security prices incorporate lending profits. To determine whether institutional investors anticipate lending profits, I examine how prices behave following a failure-to-deliver in the equity lending market. The search for a counter party is the mechanism that affects asset values as described by Duffie, Gârleanu and Pedersen (2002, 2007). Failure-to-deliver rep-

[1] http://www.nyse.com/press/1219746761185.html

[2] Source: Securities Lending Yearbook 2009, Data Explorers

resents situations in which it is difficult to locate securities available for borrowing, resulting increased bargaining power for the lender and prospective increases in lending profits which, in turn, should lead to higher prices. I relate the price to Net Asset Value (NAV) of closed-end funds to identify deviations from intrinsic value. I then determine whether there is a positive correlation between the occurrence of a failure-to-deliver and the premium to NAV, after accounting for both rational and sentiment driven influences on deviations from NAV.[3]

The results show that closed-end funds with reported delivery failures trade at a 2.63% premium. More specifically, a 1% of shares outstanding uncovered short sale position leads to a 3.05% increase in premium to NAV. The results are robust to variations in failure measurement, to alternative estimation techniques and to endogeneity concerns. The failure premium is related to future lending fee and loan quantity. The failure premium decreases with the availability of inventory and the number of active lending agents, consistent with lower bargaining power among lenders when demanding higher future lending fees. As additional support for the fee capitalization hypothesis, I also find that the premium associated with a failure is less pronounced during the low fee period and triggers institutional investor interest.

Second, I contrast the pricing of funds with reported failures to the pricing of funds with other forms of short sale constraints in place. I look at the dynamic relation between prices, lending fees and short sales and relate the cross-sectional variation in the pricing of various measures of short sale constraints to the cross-sectional variation in lending expectation arising from these constraints. The premium associated with failures is statistically and economically higher than the premium associated with other forms of short sale constraints. The empirical pattern in the pricing of the various measures of constraints is consistent with the reduced lending profit expectations that arise from the other short sale constraint measures. The results strongly suggest that future lending expectation plays a role in equity pricing.

This paper contributes to the literature on short sale constraints and valuation and to the literature on the informativeness of short sales. Seneca (1967), Miller (1977), Harrison and Kreps (1978), Figlewski (1981), and Morris (1996), among others, argue that security prices are upward biased when short sale

[3]Several papers assess the overvaluation hypothesis by examining the relation between short sales and returns, a negative ex post calendar time abnormal return being consistent with overvaluation. Conventional portfolio analysis cannot capture the full bias in pricing, nor does it allow me to disentangle whether the price inflation can be attributed to a reduction in the information content of prices or whether the prospect of lending profits elevates prices above the most optimistic buyers valuation.

constraints exist because negative information is not fully released in prices. However, the results of this study suggest that overpricing is not solely due to restriction on negative information but also partly a result of capitalized lending profits.

The paper provides new insights into the dynamic relation between search frictions, prices, lending fees and short sales. Evans et al. (2009) show that the incidence of failing is related to high equity loan costs. I find that failure-to-deliver predicts a higher probability of higher future fees and increased short sale frequency, as measured by the amount of shares on loan. This suggest that failures-to-deliver proxy for increased lending revenue and that the capitalization of lending profit drives prices up. The results explain Autore, Boulton and Braga-Alves's (2010) finding that stocks reaching threshold levels of failures with low short interest become more overvalued than threshold stocks with high short interest. According to Duffie et al. (2002) the price and the lending fee reflect that a given share can potentially be lent several times in the future. Their model predicts that as short interest accumulates over time, the quantity of unfilled positions declines, so that the expected lending frequency for each share is reduced. Hence depressing the lending fee as well as the price. The capitalization of lending profit also explains why Autore et al. (2010) find lower reversals of the overvaluation when the number of failures decreases.

Additionally, evidence on the evolution of short sale price and frequency, following the occurrence of other constraints, provides an interesting outlook on how constraints differ in terms of future short sale activity. The analysis further stresses the large cross-sectional pricing differences among various measures of constraints. Most prior research looks at the pricing implications of one constraint at a time. This paper shows that various constraints can have different pricing implications. Importantly, this study shows that pricing differences originate from heterogeneous lending expectations following constraints. Failure-to-deliver gives rise to lender expropriation and utilization and short sales lead to an increase in lending frequency. The differences in the pricing of the constraints line up with future lending outlook. The fact that lending expectations mirror pricing is consistent with the premise that lending revenue plays a role in pricing.

This study also extends prior research by analyzing price behavior utilizing closed-end funds. Several papers assess the overvaluation hypothesis by examining the relation between short sale constraints and returns. The consensus conclusion is that short sale constraints predict abnormally low future returns.[4] Interestingly, compared to the highest premium associated with failures, I report significantly higher abnormal returns for stocks with reported failures than for stocks subject to other short sale constraints measures. Miller (1977) posits that short selling constraints lead to overvaluation in the presence of differences of opinion, which in turn leads to lower subsequent returns. One would expect stocks with reported failures to give rise to the lowest performance (greatest correction). The findings of this paper offer an interpretation, namely that the future lending profits attenuate the correction.

The results from this study imply that short selling constraints can cause prices to deviate from the intrinsic value due to the loss of information *and* the capitalization of future lending gains. To the best of my knowledge, this paper is the first to empirically show that future lending expectation plays a role in equity pricing.[5]

The remainder of the paper is organized as follows. Section I discusses the general issues of short sale constraints and reviews related literature. In Section II, I describe the loan data and the closed-end fund sample in detail. Section III presents the empirical relation between failure-to-deliver and valuation and explores the dynamic relation between failure and future short sale quantity and prices. Section IV takes advantage of the cross-sectional variation in various forms of short sale constraints and jointly explains the response of future short sale fee, and loan quantity to the presence of the various constraints. In section V, I show the pricing implications for future common equity stock returns. Finally, section VI concludes.

I Literature Review

Short selling frictions are important in asset pricing. Seneca (1967), Miller (1977), Harrison and Kreps (1978), Figlewski (1981), Morris (1996), Chen et al. (2002), and Duffie et al. (2002), among others, argue that security prices are biased upward when short sales constraints exist. In static models, the price is as high as the valuation of the most optimistic investor (e.g., Miller (1977), Chen et al. (2002), D'Avolio (2002)). In a dynamic setting short sale constraints can cause prices to be higher than the

[4] E.g. Brent et al. (1990), Senchank and Starks (1993), Aitken et al. (1998), Aitken et al. (1998), Dechow et al. (2001), Danielsen and Sorescu (2001), Asquith et al. (2005), Desai et al. (2002),Geczy et al. (2002), Jones and Lamont (2002), D'Avolio (2002), Angel et al. (1998), Lamont (2004), Diether, Werner and Lee (2009), Boehmer et al. (2008*b*) and Boehmer et al. (2010).

[5] In the context of the Treasury repo market, Duffie (1996) documents that special repo rates increase the equilibrium price of the underlying instrument. In Duffie et al. (2002) the theoretical relation is extended to equity and fixed income security lending. In Duffie et al. (2007) they provide a theory of dynamic asset pricing that treats search and bargaining in over-the-counter markets.

valuation of all investors. In Harrison and Kreps' model (1978), differences of opinion, together with short sale constraints, create a speculative premium in which stock prices are higher than even the most optimistic investor's assessment of their value. When short sale constraints exist, an asset owner has the option to sell to more optimistic investors, which leads to high turnover, overpricing and even to bubbles as reported in Scheinkman and Xiong (2003) and Harrison et al. (2006). Duffie et al. (2002) attribute price inflation to capitalization of future lending fees. They present a dynamic model of asset valuation in which short selling requires searching for security lenders and bargaining over the lending fee. Search frictions allow for lender expropriation, and the expectation of lending fees, in turn, increases the equilibrium price.

Kolasinski et al. (2010) corroborate that the difficulty of finding shares leads to increased borrowing costs. Duffie, Gârleanu and Pedersen's model would further suggest an increase in prices following higher expected lending profits. The prospect of lending fees should increase prices above the most optimistic buyer's valuation of the security's future dividends. This suggests that short selling constraints can cause prices to deviate from the intrinsic value due to loss of information and capitalization of future lending gains.

Empirical evidence confirms that binding short sale constraints are associated with low future returns. The first strand of empirical literature on these constraints focuses on short interest as a proxy for short sale demand. Figlewski (1981) finds evidence that heavily shorted firms underperform less heavily shorted firms.[6] More recently, Boehmer et al. (2008*b*) and Boehmer et al. (2010) show that stocks with minimal short interest have higher abnormal returns than their heavily shorted counterparts. The positive abnormal returns on intensively traded stocks with low short interest are much larger and persistent. Heavily shorted stocks underperform lightly shorted stocks by a risk-adjusted average of 1.16% over 20 trading days. Aitken et al. (1998), Angel et al. (1998), Diether, Werner and Lee (2009) study daily short sales and subsequent returns and find that high daily short sales are followed quickly by negative abnormal returns. Boehme et al. (2006) find that underperformance of stocks with high short interest ratios is concentrated among small stocks with high dispersion of investor opinions.[7]

The negative relation between short sale constraints and future returns is also documented for

[6] Many studies, Brent et al. (1990), Senchank and Starks (1993), Aitken et al. (1998), Dechow et al. (2001), Asquith et al. (2005), Desai et al. (2002) confirm that stocks with high short interest experience low subsequent returns.

[7] The relation between short selling activity and future stock returns is found to be even stronger when there are no exchange-traded stock options Figlewski and Webb (1993), Senchank and Starks (1993), Christophe et al. (2004), if institutional ownership is larger D'Avolio (2002), Nagel (2005), Boehmer et al. (2008*b*), if analyst coverage is low Pownall and Simko (2005), and following earnings announcements Reed (2003), Berkman et al. (2009).

alternative proxies, such as option listings Danielsen and Sorescu (2001), breadth of ownership Chen et al. (2002), stock option lockups Ofek and Richardson (2003), firm anti-shorting actions Lamont (2004), rebate rates,[8] and a combination of short interest and institutional ownership Asquith et al. (2005). Cohen et al. (2007) find shorting demand to be an important predictor of future stock returns. An increase in shorting demand leads to a negative abnormal return of 2.98% in the following month. Chang et al. (2007) use the unique institutional setting of the Hong Kong stock market which only permits short sales of securities included on an official list. Using an event study methodology, the authors analyze the price effects following the addition of individual stocks to the list, and find that stock prices decrease when short sales restrictions are repealed.

Market structure changes such as the removal of the price tests and bans on short sales have stirred the most recent empirical literature on short sale constraints. Although the results are not conclusive, Diether, Lee and Werner (2009), Alexander and Peterson (2008), and the SEC conclude that Regulation SHO's pilot program to suspend short sale price tests only had a limited influence on market quality. Boehmer et al. (2008*a*) examine the complete removal of the uptick rule and conclude that the relaxation of short sale constraints has no impact on prices. Boehmer et al. (2009) study the changes in stock prices, short sales and liquidity measures before and after the 2008 shorting ban. The announcement of the ban resulted in a sharp increase in prices, but this was not limited to the banned stocks. Berber and Marco (2011) examine the regulatory short sale interventions around the crises and finds that the bans on short sales around the world with the exception of the U.S. failed to support market prices, suggesting the announcement of TARP contaminates the U.S. results. On the other hand, Jones (2008) documents significant price effects when shorting was restricted during the Great Depression.

The consensus conclusion reached by the literature is that short sale constraints predict abnormally low future returns. The common interpretation is that short selling constraints lead to overvaluation which in turn leads to low returns. In this paper, I look at the dynamic relation between prices, lending fees and short sales to examine whether short selling constraints cause prices to be biased due the capitalization of future lending gains next to the loss of information. This paper builds on the prior theoretical research of Duffie et al. (2002) by investigating empirically whether security prices incorporate prospective lending profits.

[8]E.g. D'Avolio (2002), Geczy et al. (2002), Jones and Lamont (2002), Mitchell et al. (2002), Ofek et al. (2004), and Reed (2003)

II Data and Variable Definitions

A Data

In Duffie et al. (2002) the search for a counter-party is the mechanism through which lending fees increase and affect asset value. Failure-to-deliver relates to search frictions and is the frequency and quantity, as a fraction of shares outstanding, in which short-sellers fail to locate shares.[9]

Failure-to-deliver data are available from the SEC, and include total number of fails-to-deliver (i.e., the balance level outstanding) recorded in the National Securities Clearing Corporation's (NSCC) Continuous Net Settlement (CNS) system aggregated over all NSCC members.[10] Data prior to September 16, 2008 include only securities with a balance of total fails-to-deliver of at least 10,000 shares as of a particular settlement date whereas data on or after this date include all securities with a balance of total fails-to-deliver as of a particular settlement date.

I construct two variables based on the failure-to-deliver data. The first is an indicator variable that equals one if a failure has been reported for fund i at time t, and zero otherwise, and the second is the quantity of reported fails as a fraction of shares outstanding.

$$Failure_{i,t} = \left(\frac{\#failures-to-deliver_{i,t}}{shrout_{i,t}}\right) \tag{1}$$

$$FailID_{i,t} = \begin{cases} 1 & \text{if } failures-to-deliver > 0 \\ 0 & \text{otherwise} \end{cases}$$

I match the failure-to-deliver data from the SEC with lending data from Data Explorers Ltd., which collects data from custodians and prime brokers that lend and borrow securities. The data comprise daily stock level information on the dollar value and quantity of shares available for lending, and the value and quantity of shares of borrowed securities for the sample period July 2006 to December 2008. Saffi and Sigurdsson (2010) use the same data source to study how price efficiency and the return

[9] U.S. equity shares are normally delivered three days after a short transaction. Short sellers that have not located shares from owners by that time are said to have failed-to-deliver. See Evans et al. (2009) for the details regarding deliveries.

[10] Available at http://www.sec.gov/foia/docs/failsdata.htm

distribution are affected by short sale constraints. For more information regarding the equity lending data from Data Explorers I refer to their paper.

B Closed-end Funds

I use closed-end funds to capture the full bias in pricing following the occurrence of a short sale constraint. These funds offer several advantages, one of which is that the intrinsic value of these funds is known. This is the total value of all the securities in the fund divided by the number of shares in the fund, the so called net asset value (NAV) per share. This paper is not the first to study arbitrage bounds in the context of closed-end funds. Both Pontiff (1996) and Gemmill and Thomas (2002) underpin the validity of using closed-end funds to study the influence of arbitrage on fundamental valuation. In a similar spirit, I identify deviations from the intrinsic value, the Net Asset Value (NAV), and determine whether there is a positive association between the failure-to-deliver and the premium to NAV, accounting for both rational and sentiment driven influences on the deviations from NAV.

The number of closed-end funds (sharecode=14) within the CRSP database with the Net Asset Value Data from the Compustat PDE file from June 2006 through to December 2008 totals 388. I am able to match 297 of these to the loan data from Data Explorers. The sample used in this paper appears to be slightly larger funds that are also and more actively traded, the two samples do not significantly differ in terms of premium to NAV or returns. I merge the loan data from Data Explorers and the SEC with information from a variety of sources. These include data on stock returns, shares outstanding, and volume from CRSP and institutional holdings from CDA/Spectrum. I match the monthly NAV to the daily loan data on the last trading day of the month.

Table I shows the cross-sectional variation in closed-end fund pricing during the sample period. On average, closed-end funds trade at a discount to NAV. The average discount over the sample period is 5%. In 2006 it stands at 2.20% which steadily increases to a 7.38% average discount in 2008. However, there is considerable cross-sectional variation in the discounts. The number of premium and discount funds is displayed in panel B of Table I. Although premium funds are a minority, 53 funds traded at a premium to NAV in a given month in 2006, 76 in 2007 and 81 in 2008. In contrast, 99 funds traded at a discount in 2006, 201 in 2007 and 265 in 2008. Premium and discount funds differ considerably in terms of fund and loan characteristics. As can be seen from panel C, premium funds are slightly larger and institutional investors appear less inclined to hold premium funds. Inventory quantities are significantly lower for premium funds. The lower inventory records might be the reason underlying the higher utilization levels and possibly the larger frequency and size of the number of reported failures for premium funds. Closed-end funds trading at a premium also have higher short sale fees.

[Table I about here]

Table II presents summary statistics of the failure-to-deliver data for both the common equity universe as for the closed-end fund sample. Closed-end funds offer the additional advantage that shorting constraints and costs are most relevant. The frequency of reported failures is greater for the closed end funds sample than that of the common equity. The failure quantity relative to shares outstanding is lower for the closed end funds. On average almost 22% of the closed end fund observations have a reported failure and the average failure quantity is 0.05% of shares outstanding. In 2007 the average reported failures for closed end funds is the highest at 0.7%. In panel C I compare funds with reported failures at a given point in time to funds without reported failures. Funds with reported failures are larger, but more interestingly trade at a premium to NAV in comparison to funds without reported failures. Funds with a failure have a larger fraction of their shares outstanding on loan, lower inventory and therefore higher utilization levels. Funds with reported failures also have higher loan fees.

[Table II about here]

III Failure and the Premium to NAV

A Hypothesis

Miller (1977), argues that in the presence of differences of opinions security prices are biased upward when short sales constraints exist. Negative information is kept out of the market and the prices will be set by the most optimistic majority. Duffie, Gârleanu and Pedersen's model would further suggest an increase in prices following higher expected lending profits. The prospect of lending fees should increase prices above the most optimistic buyer's valuation of the security's future dividends. This suggests that short selling constraints can cause prices to deviate from the intrinsic value due to loss of information and capitalization of future lending gains.

The first testable hypothesis is therefore: *H1: Failure-to-deliver should lead to overvaluation as measured by an increased premium to NAV of closed-end funds.*[11]

For future lending expectation to play a role in prices, the premium associated with a failure should be related to future lending profits. *H2: Failure-to-deliver positively predicts an increase in lending frequency and/or lending fee.*

Failure-to-deliver represents situations in which it is difficult to locate securities available for borrowing, resulting increased bargaining power for the lender and prospective increases in lending profits which, in turn, should lead to higher prices. However, the failure premium should decrease with the availability of inventory and the number of active lending agents, consistent with lower bargaining power among lenders when demanding higher future lending fees.

H3: The premium should be decreasing in the level of inventory and the number of active lending agents.

If lending profits are capitalized into prices than the premium associated with the occurrence of a failure, should be lower in a low fee period. According to Data Explorers, the average total return from security lending increased from 20 bp in 2006-2007 to 1.1% in 2008. If lending fees do play a role in pricing, their effects should be less pronounced in the 2006-2007 period.

H4: The premium should also be less pronounced during the 2006-2007 low fee period.

Finally, for expected future revenue associated with the potential to lend the asset to be capitalized in prices, institutional investors need to be willing to pay a premium associated with lending fees. I therefore expect that the occurrence of a failure would trigger the interest of institutional investors and lead to increased institutional ownership. *H5: The occurrence of a failure should lead to increased institutional ownership.*

B Specification

To study the relation between valuation and search frictions, I regress the premium to NAV on failure-to-deliver and on the fund specific control variables. I estimate a panel regression using monthly

[11]Important to note is that security lending revenue is aggregated at the fund level and reported under investment income in the annual report.

NAV data from June 2006 to December 2008 matched to the end of the month daily loan data.[12] I include firm and period fixed effects, and panel corrected standard errors clustered by fund. To recover consistent estimates of the parameters, I include lags of the dependent variable.[13] The model is estimated using Arellano-Bond GMM estimator to account for the dynamic dependent variable and the endogeneity between valuation and the short sale variables. Simultaneity problems arise as conceivably short sales could be determined simultaneously along with the premium to NAV. The main hypothesis is failures lead to an increase in lending profits, as failure-to-deliver represents situations in which it is difficult to locate securities available for borrowing, resulting increased bargaining power for the lender and prospective increases in lending profits which, in turn, should lead to higher prices. However, it is not possible to rule out that the premium and short-selling constraints are endogenous, i.e. it could be the case that premium funds stocks attract short-sellers, thus increasing short sale quantity and the likelihood of a failure-to-deliver to occur. I attempt to mitigate these concerns with Arellano-Bond dynamic panel instrumental-variables (IV) regressions, treating failure and the premium as endogenous variables. The Arellano-Bond dynamic panel estimator is designed for panels with short time dimension and larger firm dimension, independent variables that are not strictly exogenous, fixed effects and with heteroscedasticity and autocorrelation within funds. The estimation relies on the first-differences to eliminate unobserved fund-specific effects and then uses lagged level and difference values of the endogenous variables as instruments for subsequent first-differences.

The regression specification for the relation between short sales constraints and the premium to NAV is as follows:

$$Prem_{it} = \alpha_i + \beta_1 Failure_{it} + \gamma' x_{it} + \beta_2 Prem_{it-1} + \beta_3 Prem_{it-2} + \delta_t + \epsilon_{it} \tag{2}$$

where $Prem_{it}$ is the premium to NAV, for fund i at time t. The premium is calculated as the price over net asset value. δ_t are period-specific time dummies. The Arellano-Bond test for autocorrelation dictates two lags. The inclusion of the lags reduces the sample size of closed-end funds to 168 funds. x is the vector of control variables.

[12] I first ascertain whether all the variables are stationary. I conduct a panel Augmented Dickey Fuller test and reject that the series are non-stationary.

[13] The inclusion of the lagged dependent variable also mitigates the effects of possible stale NAV estimates.

C Control variables

To isolate the bias in prices created by short sale constraints, I first need to account for possible factors that might influence the deviation from NAV.

The central puzzle about closed-end funds is that the fund share prices differ from the per share NAV. NAV premiums or discounts are considered a puzzle because they appear to contradict the no-arbitrage implication of an efficient market. Because two assets, which appear to offer a claim to the same risk-return distribution, trade at different prices. The discounts on closed-end funds existing explanations are related to tax considerations Malkiel (1977), agency costs Barclay et al. (1991), noise Lee et al. (1991), and the trade-off between management fees and certain benefits that come from investing in a closed-end fund. In Berk and Stanton (2007)'s model, the benefit to investors is the manager's ability, whereas Cherkes et al. (2009) suggest that liquidity is the main benefit.

I control for fund specific variables such as size, performance in the last 12 months, systematic risk, volatility and liquidity. Fund size and past performance are used as a proxy for management skills. I also include fund fixed effects to control for any time-invariant unobservable influences on the premium such as expense ratios, fund reputation, and dividend.[14] In addition, I follow Pontiff (1996) and include a replication risk measure, which captures the difficulty in replicating the fund's holdings.

Lee et al. (1991) propose that discounts and premiums in closed-end funds may reflect investor sentiment. To account for the influence of market-wide sentiment on the premium to NAV, I include period fixed effects in the panel specification. In addition, I include a systematic noise factor as in Gemmill and Thomas (2002). I follow Baker and Wurgler (2006) in constructing a stock market sentiment index to capture sentiment. To correct for sentiment influences in deviations from NAV, I calculate the sensitivity of the fund to the sentiment index for each fund in the sample. This approach allows me to directly measure the interaction between short selling activity, sentiment and the valuation of the closed-end funds. The variable description appendix contains the details of data sources and variable definition and construction.

[14] I include the dividend ratios, however the period and fund fixed effects make this variable redundant.

D Results

D.1 Failure-to-deliver and the Premium to NAV

The Arellano-Bond dynamic panel relies on the first-differences to eliminate unobserved fund-specific effects and then uses lagged level and difference values of the endogenous variables as instruments for subsequent first-differences. The necessity for lagged levels of the endogenous variables reduces the sample size from 297 to 168 funds.

Table III reports the results of regressing the premium to NAV on the failure-to-deliver variables and fund specific control variables. The fund, period fixed effects and lag premium render most controls insignificant. Size and the beta are the only significant coefficients. With regards to the valuation effect of the failure-to-deliver variables, funds with uncovered short sale positions trade at a 2.63% premium, as can be seen from the first specification in Table III. The relation between the continuous failure-to-deliver variable and the premium (column 2) is also statistically and economically significant. Funds with uncovered short sale position equal to 1% of their shares outstanding have a 3.05% higher premium to NAV. The average failure position as a fraction of shares outstanding is 0.05%, with a standard deviation of 0.03%. Economically, a one standard deviation increase in failure translates into an increase in premium of 0.09%.

[Table III about here]

The results in Table III are robust to the estimation technique used. The results using fixed effects, the between estimator and pooled OLS with period effects are reported in IV. Additionally, I test the GMM results for robustness with respect to reductions in the instrument set by presenting the results using 1 lag, collapsing the instrument count, using a two-step estimation, estimating in differences and levels. These alternative estimations produce results that are very similar to the results in Table III.

The results are robust to alternative failure measurements, panel B Table IV. First I calculate the average relative failure position in the week leading up to the last trading day of the month. The results are even stronger, a 1% increase in failure relative to the shares outstanding increases the premium with 9.12%. Similarly if I measure failure as the average monthly failure position relative to shares outstanding. In the third and fourth column of panel B, the number of days in which the threshold level of fails is reached throughout the last week leading up to the last trading day of the month and the number of days in which the threshold level of fails is reached throughout the month. The reporting of the threshold level of fails increases the premium with 0.33 per day during the last trading week of the month and 0.09% for each occurrence during the month. In the last column failure is measured in changes and a 1% increase in failure increases the premium with 2.30%.

An important concern is that of endogeneity. The use of lagged values of failure as instruments mitigates some of these concerns. Nonetheless, I also attempt to mitigate these concerns with instrumental-variables (IV) regressions, treating failure-to-deliver and premium as endogenous variables. Although it is difficult to obtain truly exogenous instruments, I use the total number of lending agents (intermediaries) as reported to Data Explorers, as instrument.[15] The validity of this measure as an instrument requires that the number of intermediaries not impact the fund premium except through its effect on failure-to-deliver. Empirically, the number of lending agents correlates with the failure-to-deliver variable, but it does not relate to the premium to NAV.[16] Agents typically include asset managers, custodians, specialist securities lending agents and brokers. A priori it is unlikely that lending agents decide on facilitating security lending on the basis of the existence of a premium to NAV for closed-end funds. Providing lending services requires set-up costs, rooted relationships with the industrys largest lenders and investment in inventory. Usually investment banks have long-established lending programs, making entering or exiting the loan intermediation market on the basis of temporary valuation unlikely.

As can be seen in the column 10 of Table IV, using the total number of lending agents as an instrument, I still find a positive and significant relation between failure and the premium to NAV. To rule out that the premium and failure are endogenous, in that premium funds stocks attract short-sellers, thus increasing short sale quantity and the likelihood of a failure-to-deliver to occur, I also include loan quantity as control variable. As can be seen in the last column, the results are also robust to the inclusion of loan quantity as additional control variable.

[Table IV about here]

[15] I look at the total number of lending agents for each fund, not the number of custodians with open transactions. The decision to make inventory available is likely endogenous to the lending fee and in turn the premium.

[16] To test whether the instrument affect failure-to-deliver and premium, I run the following two panel data regressions:

$$Failure_{it} = \alpha_i + \beta_1 ln(\#Agents)_{it} + \gamma' x_{it} + \delta_t + \epsilon_{it} \tag{3}$$

$$Premium_{it} = \alpha_i + \beta_1 ln(\#Agents)_{it} + \gamma' x_{it} + \delta_t + \epsilon_{it} \tag{4}$$

where $Failure_{it}$ is the quantity of reported fails as a fraction of shares outstanding at the end of the month, for fund i at time t. $Premium_{it}$ is the premium to NAV, for fund i at time t. δ_t are period-specific time dummies. x is the same vector of control variables. I also include fund fixed effects to control for any time-invariant unobservable influences. I find that the number of lending agents does not have a statistically significant effect on the premium at even the 10% but is strongly related to failure-to-deliver variable at a 1% significance level.

The economic magnitude of the premium associated with a failure seems large, but considering that stocks on special can have large fees it is possible for a failure to lead to a premium of above 2%. D'Avolio (2002) shows that the aggregate market is easy to borrow during April 2000 till September 2001. The value-weighted cost to borrow the sample loan portfolio is 25 basis points per annum, however 1% of stocks (roughly seven per month) on loan become extremely special, demanding negative rebate rates (i.e., loan fees in excess of the risk-free rate). Kolasinski et al. (2010) corroborate that the difficulty of finding shares leads to an increase in borrowing costs and therefore failures are expected to lead to these exceptional 1% cases.

Table 4 of D'Avolio (2002) provides a partial list of those negative rebate stocks and their highest measured loan fee in the loan database. The fees that short sellers pay for these stocks are 79% per annum for CNH Global, 63% for General Motors, and 55% for Krispy Kreme. While not a lot of stocks are on special, when they are the fee can be substantial, especially considering that during that time period the average fee is only 25 basis points.

Considering the reported special fees by D'Avolio (2002), if a fee of 70% lasts for 5 days the premium could be as large as 1.05%, at a discount rate of 10%. For the fee to lead to a premium of at least 2,5% a loan fee of at least 67% needs to last 30 days. A fee of 35% can lead to a 1.30% premium if it last for a month or 0.53% if it last for only 5 days. This excludes the security lending income earned on re-investing cash collateral.

Since 2007, securities lending revenue and loan volumes have reached new highs. Average loan spreads widened from 20-30 basis points in 2005-2006, to over 60 basis points in 2008. The business of securities lending became lucrative business for funds with large portfolios of stocks. Dimensional Advisors for example earned $182 million in net lending revenue for the fiscal year 2008. The resulting performance enhancement ranged from 0.04% for US Large Company Portfolio to 0.66% for Japanese Small Company Portfolio. Kaplan et al. (2010) estimate the total revenue from lending out the full potential of all high fee stocks for a money manager, based on an implementation of a lending experiment during 2008-2009, to be about 1.5 to 2%. Based on their first phase (September 5 to 18, 2008) results, they estimate lending revenue to add between 2.78% to 4.64% per year with median fees ranging from 83 to 129 basis points.

Aggarwal et al. (2011) find that during 2005-2009 the maximum annualized fee is 19.25% and the average number of days for which stocks are on loan is 16 days. Given these numbers it could explain a 0.6% premium, a quarter of the observed premium.

The premise of this paper is that failure-to-deliver lead to a deviation from the intrinsic value due to loss of information and capitalization of future lending gains. So the premium need not be fully explained by future lending profits, all though these back of the envelop calculation show that if the fee is large enough the reported premiums are possible.

D.2 Lending Expectation

Failure leads to an increased premium to NAV, if future lending profits are capitalized into prices then the premium associated with the occurrence of a failure should be related to future lending profits, as measured by future short sale fees and loan quantity.

In Table V are the transition probabilities of the change in fee score over time of closed-end funds with no reported failures vis-à-vis funds with a reported threshold level of fails. The fee classification is expressed in undisclosed fee buckets 0-6, where 0 represents no fee, a fee score of 1 is relatively cheap, while 6 is the most expensive category. Of the closed-end funds with no reported failures 94.90% has no fee, against 94.65% of funds with reported failures. Funds with reported failures are more likely to fall in the higher fee categories. 6.96 of the funds with a reported failure have a high fee of 5 or 6 against 3.9% of funds with no failures. They are also much more likely to shift from a low fee classification into a high fee category, and stay in the high fee category. Funds with reported failures appear to have higher fees.

[Table V about here]

To test whether failure-to-deliver positively predicts an increase in lending lending fee, I first estimate the following daily generalized ordered logistic regression considering the 6 fee categories:

$$g(PR(Fee_{it+n} \leq | \, x)) = \alpha_i + \beta * FailID_{it} + \beta' z_{it} + \epsilon_{it+n} \qquad i = 1, \cdots, 6 \tag{5}$$

where Fee_{it+n} is value weighted fee classification expressed in undisclosed fee bucket i, which runs from 1-6 in the following n days. $\alpha_{1 \cdots 6}$ are k intercept parameters, and $FAIL_{it}$ is the occurrence of failure-to-deliver. z_{it} is the vector of control variables. D'Avolio (2002) finds that the likelihood of higher short sale fees decreases with size, but increases with differences of opinion. He uses institutional ownership as a proxy for supply and finds that it decreases the likelihood of higher fees. I include the inventory quantity as a percentage of shares outstanding as a more direct measure of supply. An additional benefit is that inventory is also measured daily, while institutional ownership is only available at a quarterly frequency. The vector of explanatory variables also includes fund characteristics such as size and turnover as a measure of differences of opinions. In addition, the specification includes systematic risk and volatility to control for short selling motivated by hedging.[17]. The unknown parameters β are estimated by maximum likelihood. ϵ is assumed to have a standard logistic distribution, i.e $g(\epsilon_{it+n}) = \frac{1}{1+e^{-\epsilon_{it+1}}}$.

Table VI reports the marginal effects of the generalized ordered logit results of the fee score on the occurrence of a failure for the following day and panel B for the following 5, 30,60 and 90 days.[18] The marginal effect is the change in the predicted probability associated with changes in the short sale constraints.

The first column represents the likelihood of having a fee, while the remaining are probabilities of a particular fee score conditional on having a fee. A reported failure increases the likelihood of having a fee by 1.44%. Conditional on having a fee a failure occurrence reduces the likelihood of having a low fee classification by 24.80% and it increases the odds of ending up in a high fee category. The occurrence of a failure makes it 12.30% more likely that the fund will have the highest fee score in the following day. As can be seen in panel B, the results persist for at least 90 days, although at t+90 the likelihood of having a fee is significantly reduced.

[Table VI about here]

The expected future revenue associated with the potential to lend the asset is not only a function of the lending fee, but also the lending frequency. Subsequently, I run predictive regressions to test whether failures-to-deliver lead to an increase in lending frequency. I estimate the following daily panel regression:

$$Loan_{it+n} = \alpha_i + \beta'_{it} FailID_{it} + \beta'_{it} z_{it} + \epsilon_{it+n} \tag{6}$$

where $Loan_{it+1}$ is the future loan quantity relative to shares outstanding, for fund i in the following

[17]The addition of the controls rejects the the parallel lines assumption, which is the requirement that the β's be the same for each value of the categories, only the α's differ across the categories and the regression lines are parallel. To overcome this limitation I use a generalized ordered logit, which is less restrictive than the parallel-lines model but more parsimonious and interpretable than a non-ordinal method such as multinomial logistic regression. I refer to Williams (2006) for more information on the generalized ordered model.

[18]The signs of the estimated coefficients are cumulative probabilities. In order to be able to derive more information from the estimated coefficients I calculate the derivatives of the six probabilities at the sample means of the independent variables.

n days $t{+}n$. $FailID_{it}$ is the corresponding constraint variable; loan quantity, demand shift (DOUT), utilization and failure-to-deliver. The vector of explanatory variables, z_{it}, includes fund characteristics such as size, past 12-month return, and turnover as a measure of differences of opinions. These controls reflect findings of Dechow et al. (2001), Asquith et al. (2005) and Boehmer et al. (2010) that short interest is related to market capitalization and momentum. Karpoff and Lou (2010) find that short interest increases with share turnover and institutional ownership. Since a daily frequency institutional ownership is not available, I therefore include inventory as a supply variable. In addition, the specification includes systematic risk and volatility to control for short selling motivated by hedging as in Huszár and Qian (2010). The results are reported in Table VII.

Failure-to-deliver predicts an increase in short sale quantity in the following days up to even two months. Funds with a reported failure experience an increase of 0.42% in short sales the following day. The fact that failures lead to an increase in short sale quantity indicates that the failure premium cannot be attributed to a short squeeze. A short squeeze leads to a forced coverage of the short sale position leading to a reduction not an increase in the number of borrowed shares. Funds with reported failures trade at a premium with respect to funds with no failures and the failure premium is related to future lending fee and loan quantity.

[Table VII about here]

D.3 Interaction Effect

To illustrate that search frictions play a role in prices and that the price inflation cannot solely be attributed to a reduction in the information content of prices, I rerun the GMM specification, with an interaction effect between the occurrence of a failure variable and inventory. The availability of inventory from beneficial owners should lower the bargaining power of lenders and decrease lending fees.[19] To test this premise, I interact the failure proxy with three inventory measures in the following regression specification.

[19]Inventory at the occurrence of a constraint can best be interpreted as a reduction in bargaining power in extracting higher fees from lenders. Alternatively, inventory might also indirectly relax the binding nature of the constraints. Inventory can, a priori, mitigate the occurrence of a constraint, but it is not clear that once a constraint is in place, inventory would relax the binding nature of the constraint. The latter is a more indirect effect than the former.

$$Prem_{it} = \alpha_i + \beta_1 FailID_{it} + \beta_2 I_{it} * FailID_{it} + \beta_3 I_{it} + \gamma' x_{it} + \beta_4 Prem_{it-1} + \beta_5 Prem_{it-2} + \delta_t + \epsilon_{it} \quad (7)$$

where $Prem_{it}$ is the premium to NAV, for fund i at time t. I_{it} is the interaction variable. δ_t are period-specific time dummies. The first interaction variable is the available inventory quantity from beneficial owners relative to the shares outstanding. The second represents the number of inventory accounts held by beneficial owners and the third is the number of active lending agents. Since the interactions are also assumed to be endogenous, I set a lag limit of two and collapse the instrument count as suggested by Roodman (2008) to reduce the risk of overfitting the endogenous variables.

As shown in the first specification in Table VIII, a reported failure leads to 2.70% increase in NAV premiums. The interaction term, however, is not statistically significant though of the correct sign. However, in the collapsed specification, the availability of inventory reduces this premium by 0.35% for every 1% of inventory. When allowing for a larger instrument set, the coefficient on the interaction variable is statistically significant, thus larger inventories reduce the bargaining power of lenders. The number of active agents significantly reduces the premium associated with failures, both in the collapsed as using the full instrument set. An additional active agent reduces the premium by 0.91%. The number of active agents give rise to a stronger effect, since more lending agents equates to lower bargaining power or increased possibility of lender expropriation. In fact, Kolasinski et al. (2010) and Saffi and Sturgess (2009) find that inventory and especially, concentrated ownership lead to an increase in lending fees.

As additional support for the fee capitalization hypothesis, I interact failure-to-deliver with a period indicator variable set to one for the 2006-2007 period.

During 2006 and 2007, the average fee and total return from lending shares was considerably lower. According to Data Explorers, the average total return from security lending increased from 20 bp in 2006-2007 to 1.1% in 2008. If lending fees do play a role in pricing, their effects should be less pronounced in the 2006-2007 period. As can be seen from the fourth specification, the interaction term of failure and the low fee indicator is indeed negative. A failure in 2008 is associated with a 1.72% lower premium. The fact that the coefficient of the failure indicator variable is larger in the fifth specification can be attributed to the higher reported threshold quantity. Data prior to September 16, 2008 include only securities with a balance of total fails-to-deliver of at least 10,000 shares as of a particular settlement date whereas data on or after this date include all securities with a balance of total fails-to-deliver as of a particular settlement date.

-Insert Table VIII-

Finally, for expected future revenue associated with the potential to lend the asset to be capitalized in prices, institutional investors need to be willing to pay a premium associated with lending fees. To measure whether the occurrence of a failure would trigger the interest of institutional investors and lead to increased institutional ownership I look at how the occurrence of a failure in the past month affects the change in institutional ownership. In the last column of Table VIII you can see that the occurrence of a failure leads to a 0.13% increase in institutional ownership, consistent with a failure triggering the interest of institutional investors.

The premise of the paper is that failure-to-deliver lead to a deviation from the intrinsic value due to loss of information and capitalization of future lending gains. Consistent with the premise, the failure premium is related to future lending fee and loan quantity, and it decreases with availability of inventory and active lending agents. The premium associated with a failure is less pronounced during the low fee period and triggers institutional investor interest. The combination of effects suggests that failure-to-deliver premium cannot solely be driven by a reduction in the information content of prices. To explore this latter premise, I contrast the pricing of the premium associated with a failure-to-deliver to the pricing of other forms of short sale constraints.

IV Other Short Sale Constraint Measures

In this paper, I test the hypothesis that security prices are biased when short sales constraints exist. For one short sale constraints restrict information but also because future lending expectations play a pricing role. To test that I take advantage of the cross-sectional variation of short sale constraints.

I focus on the constraints that have been found to lead to overvaluation. Several studies confirm that stocks with high short interest, short quantity relative to shares outstanding, experience low subsequent returns.[20]

[20] Figlewski (1981), Senchank and Starks (1993), Aitken et al. (1998), Dechow et al. (2001), Asquith et al. (2005), Desai

The first additional measure of short sale constraints will be a proxy for short sale quantity, namely number of borrowed securities a fraction of shares outstanding. According to estimates of Ringgenberg (2010) the mean (median) correlation between loan quantity from Data Explorers and semi-monthly short interest from Compustat is 0.70 (0.78).

$$Loan_{i,t} = \left(\frac{\#borrowedsecurities_{i,t}}{shrout_{i,t}} \right) \tag{8}$$

Cohen et al. (2007) identify demand shifts using price-quantity pairs and find shorting demand to be an important predictor of future stock returns. Stocks that have experienced at least an outward demand shift (DOUT), have seen both their loan fees and their loan quantities rise. According to their findings, following a demand shift, stocks have a negative abnormal return of 2.98% in the following month.

The second measure therefore follows the methodology proposed by Cohen et al. (2007) to identify demand shifts using price-quantity pairs. Funds that experienced an outward demand shift (DOUT), see a rise in both their loan fees and their loan quantities.

$$DOUT_{i,t} = \begin{cases} 1 & \text{if } \Delta Feescore > 0 \text{ and } \Delta ShortSaleQuantity > 0 \\ 0 & \text{if } \Delta Feescore \leq 0 \text{ or } \Delta ShortSaleQuantity \leq 0 \end{cases} \tag{9}$$

I use the fee score as price variable. This is the value weighted average of all applicable loan fees weighted by loan value. The fee classification is expressed in undisclosed fee buckets 0-6, where 0 represents no fee, a fee score of 1 is relatively cheap, while 6 is the most expensive category.

The final measure is short utilization, which is the value of assets on loan from beneficial owners (beneficial owner value on loan) relative to the total lendable asset value (beneficial owner inventory value).

$$Utilization_{i,t} = \left(\frac{valueonloan_{i,t}}{inventoryvalue_{i,t}} \right) \tag{10}$$

The regression specification for the relation between short sales constraints and the premium to

et al. (2002), Aitken et al. (1998), Angel et al. (1998), Diether, Werner and Lee (2009), Boehmer et al. (2008*b*) and Boehmer et al. (2010)

NAV is as follows:

$$Prem_{it} = \alpha_i + \beta_1 CONST_{it} + \gamma' x_{it} + \beta_2 Prem_{it-1} + \beta_3 Prem_{it-2} + \delta_t + \epsilon_{it} \tag{11}$$

where $Prem_{it}$ is the premium to NAV, for fund i at time t. The premium is calculated as the price over net asset value P/NAV-1. x is the vector of control variables and $CONST_{it}$ is the corresponding constraint variable; failure-to-deliver and subsequently short sale quantity, demand shift (DOUT), and utilization. δ_t are period-specific time dummies. Kolasinski et al. (2010) examine the shape of the share loan supply curve and show that the average loan supply schedule is non-monotonic and that supply curves tend to become steep at high levels of short sale quantity. To account for this non-monotonicity, funds are ranked high if they are assigned to the highest tercile in terms of utilization and short sale quantity. The Arellano-Bond test for autocorrelation again dictates a lag length of two.

The results in table IX show that the relation between demand shifts and NAV premiums and the loan quantity and premiums is not statistically significant. High level of borrowed securities, as measured as the fund belonging to the highest tercile, lead to a 1.01% increase in premium. Utilization, in turn, has a significant relation to the NAV premium of closed-end funds. For every increase in utilization of 10%, the premium increases by 0.17%. Funds with high utilization levels, belonging to the top tercile, trade at a 0.76% premium, although this is not significant except when collapsing the instrument count. The premium associated with failures is economically significantly higher than that associated with other forms of short sale constraints. I standardize the continuous variables to facilitate comparison. A one standard deviation increase in failure raises the premium by 0.52%, while a one standard deviation increase in utilization leads to a 0.33% premium. The occurrence of a failure causes a 2.63% premium, while high relative loan positions, lead to increases of 1.01%.

-Insert Table IX -

The analysis reveals large pricing differences for the various short sale constraints. One plausible explanation for these differences is that each constraint gives rise to different lending expectation and that the lending profits increase the premium as reported by Duffie et al. (2002). Both D'Avolio (2002) and Boehme et al. (2006) use proprietary lending data to show that shorting demand is related to the cost of lending and find that stocks with high levels of short interest have high lending fees. Kolasinski et al. (2010) document that an increase in demand triples the abnormally high lending fees for stocks with high short sale demand. The lending profit, in turn, might explain the premium for high short sale funds.

Alternative explanations for the large cross-sectional differences in the prices of the various forms of constraints do not seem to hold. The short sale constraints can differ in terms of risk of shorting, recall risk or arbitrage risk. When controlling for arbitrage risk in the general specifications by including sentiment, replication and noise proxies, the results persist. Although intuitively, recall risk should lead to a lower premium (risk premium), I find that the constraint that would be subject to recall risk as failure-to-deliver is not associated with lower premiums. In the following analysis, I explore the dynamic relation of the various constraints and future lending profits in more depth.

A VAR Analysis

The premise is that the short sale constraints give rise to different lending expectations and are therefore priced differently. If future lending plays a role in pricing, I expect the differences in premiums across the constraints to be related to the variation in the relation between the constraints and future short sale fee's and loan quantity. To jointly explain the response of future short sale fee, and loan quantity to the presence of the various constraints, I use a panel vector autoregression approach (VAR).[21] This is a multivariate simultaneous equation system that treats all variables as endogenous, while allowing for unobserved fund heterogeneity.

First, to capture the fee development as a function of shocks to the short sale constraints, I specify a first-order VAR model as follows:

$$y_{it} = \Upsilon_0 + \Upsilon_1 y_{it-1} + f_i + d_t + \epsilon_{it} \tag{12}$$

where y_{it} is a vector including premium to NAV, fee score and one of the respective constraint variables: loan quantity, demand shift (DOUT), utilization or failure-to-deliver. f_i introduces fund fixed effects and d_t period-specific time dummies. The particular ordering of the specification is important. The variables that appear earlier in the system are assumed to be more exogenous while the later ones are assumed to be more endogenous. I also assume that the constraints are endogenous to the premium and the fee score in the short run.

[21] The estimation is implemented with the PVAR routine by Inessa Love. See Love and Zicchino (2006) for computational details.

I will focus on the impulse-response functions. Theses functions describe the reaction of the premium, short sale fees, and loan quantity to the innovations in the constraints, while holding all other shocks at zero. Figure 1 illustrates the response of the premium to the respective short sale constraint shock. The premium to NAV shows an immediate reduction in response to a demand shift shock and this persists for 6 months. A demand shock is accompanied by a reduction in fee score that persists up to two months and subsequently reverts. The premium to NAV increases following an innovation in short sale, fee, utilization and failure-to-deliver.

The second graph depicts the impulse-response functions with the reaction of the fee score to the innovations in constraints. The response of the fee score to a shock in failure-to-deliver reduces the fee score at immediate horizons, but raises it in the following months. As depicted in panel B, an innovation in fee score in turn, has a negative influence on utilization and DOUT, but a positive influence on failure-to-deliver. Higher fees increase the likelihood of a failure-to-deliver. In line with Evans, Geczy, Musto and Reed's (2009) findings, short sellers strategically fail to deliver shares when borrowing costs are high although the results also show that failures, in turn, increase future lending fees. A demand shock has a negative influence on future short sale fees, while shocks to utilization and failure-to-deliver positively influence future lending fees.

The third graph in 1 shows the impulse responses to illustrate the differing influences of the short sale constraints on loan quantity and inventory. A demand and utilization shock translates into an immediate reduction in short sales, as measured by the number of borrowed securities. In contrast, failure-to-deliver innovations increase in lending frequency in the short run. The impulse-response analysis illustrates that a demand shock has a negative influence on future short sales. Demand shocks reduce future loan quantity and fees and therefore future lending gains and prices. Utilization predicts a reduction in loan quantity. Failure-to-deliver, in turn, leads to a short run increase in loan quantity, holding all other influences constant.

-Insert Table 1-

The predictive regressions and the impulse-response functions show that the various short sale constraints give rise to different future lending expectation in terms of lending fees and loan quantity. DOUT predicts a reduction in fees and loan quantity, high utilization forecasts an increase in fees, but a reduction in future loan quantity and loan quantity and failure-to-deliver lead to a persistent increase in fees. The differences in the pricing of the constraints line up with future lending outlook. The fact that lending expectation mirrors pricing is consistent with the premise that lending revenue plays a role in pricing.

Intuitively, the information restriction hypothesis on its own cannot account for the large pricing differences across the constraints. The variation in short sale constraints pricing is consistent with the variation in lending expectation.

B Economic Significance

To gauge the economic significance of the short sale constraints in influencing the pricing of closed-end funds, I present variance decompositions. Table X shows the% of the variation in the row variable explained by a shock to the column variable, accumulated over time. The variance decomposition indicates the amount of information each variable contributes to the other variables in the VAR model. I report the accumulated effect for 1 month to 1 year. Demand shifts (DOUT) only account for 0.4% of the total variation in premium 1 year ahead, while utilization explains 0.14% of the variation. Loan quantity and failure-to-deliver account for 25.91% and 17.74% respectively of the variation 6 months ahead, which accumulates to 87.43% for loan quantity and 31.56% for failure-to-deliver for a horizon of a year. Loan quantity explains a large fraction of the variation at the expense of the fee score, which accounts for about 20% of the variation in the other specifications. Short sale constraints are economically significant in explaining the variation in premium.

According to Chopra et al. (1993), the variation in closed-end fund discount is related to investor sentiment. In panel B, I also report the variance decomposition including sentiment as opposed to the constraint variables. While sentiment explains almost 12% of the total variation in premium 1 month ahead, this reduces to 8% for a 6-month horizon. In the short-run, sentiment has an economically significant influence but in the long-run short sale constraints explain a significant part of the variation in the premium to NAV.

-Insert Table X-

V Portfolio Analysis

The capitalization of future lending profits has important implications for future common equity stock returns. Future lending expectations and information restriction capacity vary across the constraints that impede short selling and thus stocks with low future returns can be identified by pinpointing stocks with particular short sale constraints. In this section, I perform a calendar time portfolio analysis on all the common equity stocks in the Data Explorers data. Due to the limited time series available, I study daily and weekly portfolio returns to maintain statistical validity of the results.[22]

Each day (week), I sort the common equity stocks into a portfolio based on the short sale constraint considered. After assigning funds to the portfolios, I calculate the value weighted return over the subsequent day (week). The one and four-factor alpha are calculated using the market and factor returns available in French's data library. The four-factor alpha controls for the market, size, value, and momentum factor returns.

The prediction, following the intuition as discussed by Miller (1977), is that when constraints inhibit the market's ability to impound relevant information, future returns decrease as the correction of the bias sets in. However, if short sale constraints also represent an increase in future lending profits, the correction caused by the bias will be attenuated.

Consistent with this hypothesis, the portfolio of reported failures and the portfolio of high short sales have the lowest underperformance, while the high fee portfolios and demand shifts lead to the highest reduction in prices. These results, presented in Table XI, cannot be explained by differential exposure to risk factors. The four-factor alpha of the highest loan portfolio is -0.15% lower in the following day than that of the low short sale portfolio. Similarly, I observe a -0.51% return in the following day for stocks that experience a demand shift. There is a 34 bp difference in performance between stocks which have experienced a demand shift and stocks which have not. Utilization follows the ranking of producing the subsequent largest discrepancy in performance, with the highest utilization portfolio underperforming the lowest by 14 bp. There is a monotonically decreasing relation between returns and fees; the higher the fees, the lower the following day's performance. Finally, the return difference for failure-to-locate shares is only 8 bp.

[22]Note that I am not presenting a viable portfolio strategy, as first the data is not publicly available and second, daily horizon portfolios are not practical for re-balancing reasons. The sole purpose of this analysis is to illustrate the differential returns associated with the various short sale constraints.

-Insert Table XI-

In Table XII, I extend the horizon to a week. Here again, demand shifts and utilization show the lowest abnormal returns. Stocks that have experienced a demand shift during the week, earn a -0.45% lower excess return in the following week. The results are consistent with Cohen et al. (2007), who find that shorting demand is an important predictor of future stock returns. Demand shifts measure the extent of overpricing but do not lead to an increase in future loan quantity and loan fees, and as such the correction of the overpricing is the largest as compared to the other short sale constraints.

-Insert Table XII-

The negative abnormal returns for those constraints that represent an increase in future lending profits, are lower than the abnormal returns of the constraints that only lead to a restriction of negative information. The largest corrections are for those constraints that do not lead to future lending profits. Both the difference in prices of the various constraints as well as the return analysis suggest that information restriction capacity is not the only dimension on which these constraints differ. The findings are consistent with future lending profits being capitalized into prices.

VI Conclusion

By lending shares to short sellers, institutional investors benefit by generating lending revenue. In this paper, I show that the expectation of lending profits increases the premium of closed-end funds to NAV. To determine whether investors are willing to pay a premium associated with lending fees, I look at how prices behave following a failure-to-deliver in the equity lending market. The search for a counter-party is the mechanism in Duffie et al. (2002) that affects asset values. Failure-to-deliver represents situations in which it is difficult to locate securities available for lending, leading to high bargaining power for the lender and prospective increases in lending profits. High prospective lending gains, in turn, translate into higher prices.

The results show that closed-end funds with reported failures trade at a 2.63% premium. A 1% of shares outstanding uncovered short sale position leads to a 3.05% increase in premium to NAV. The results are robust to variations in failure measurement, to alternative estimation techniques and to endogeneity concerns.The failure premium is related to future loan quantity and price and is decreasing in the level of inventory and the number of active lending agents, consistent with lower bargaining power of lenders when demanding higher future lending fees. As additional support for the fee capitalization hypothesis, I also find that the premium associated with a failure is less pronounced during the low fee period and leads to increased institutional ownership.

The premium associated with failures is economically and statistically significantly higher than the premium associated with other forms of short sale constraints. The empirical pattern in the pricing of the various measures of constraints appear to be related to the reduced lending profit expectation that arises from the other short sale constraint measures. The short sale constraints exhibit dynamic lending patterns consistent with the pricing.

The results from this study imply that short selling constraints can cause prices to deviate from the intrinsic value due to the loss of information *and* the capitalization of future lending gains.

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Appendix Variable Description

Fund Characteristic Variables	**Definition**
Noise Beta	Following Gemmill and Thomas (2002), noise beta is the individual fund sensitivity to the value-weighted average discount of the funds in the sample.
Replication Risk	Following Pontiff (1996), replication risk is the residual error from a regression of NAV returns on the CRSP value weighted index
Size (MCAP)	Price*shares outstanding from the CRSP monthly file.
Turnover	Volume over shares outstanding
Spread	Spread is the difference between the closing bid and ask quotes for a security over the security price
Amihud illiquidity	Amihud illiquidity measure is calculated as the daily average of absolute value of return divided by dollar volume for asset i in a month in logs
Systematic risk (Beta)	Systematic risk was calculated on a rolling window basis of 25 months with respect to the CRSP value weighted index
Standard deviation (stdev)	Volatility, measured as the standard deviation of the monthly returns over 20 months
Past 12m ret	Average returns over 12 months. Price information from CRSP
Institutional Ownership	Compilation of the holdings of institutional investors from 13-f filings
Premium	Premium to Net Asset Value is calculated as the price over NAV: ((P/NAV)-1). The Closed-end fund NAV information comes from CRSP (general equity funds only).

Stock Market Sentiment	**Definition**
Stock Market Sentiment	To correct for sentiment influences in the deviations from NAV, I calculate for each closed-end fund in the sample the sensitivity of the fund to the sentiment index. The betas with respect to the sentiment index are estimated on the basis of rolling window regressions of 20 months. The Stock market sentiment index is constructed as the first principal component of four sentiment proxies following Baker and Wurgler (2007), dividend premium, the number and first-day return on IPOs and the equity share in new issues. I use the monthly data as used and described in Baker and Wurgler (2007), I exclude the closed-end fund aggregate premium and update the data until December 2008. The dividend premium is defined following Baker and Wurgler (2004) as the log difference in the value weighted average market to book of payers and the value weighted market to book of nonpayers. The updates were obtained from Compustat. IPO volume and first-day returns and updates are from Jay Ritters website. Issue information was obtained from SDC. Lagged one year NYSE turnover from NYSE Factbook, detrended using past five-year average. The sentiment variables were orthogonalized wrt macro variables to remove the influence of economic fundamentals. I regress, using a 50 month rolling window, each proxy on macro variables; changes in industrial production, employment and the NBER recession indicator. The macro variables I obtained from econstat.com and the NBER website. Long run S&P stock data were obtained from Shillers website. The correlation of the sentiment index with that of Baker and Wurgler (2007) over 1969-2005 is 0.74.

(Continue on next page)

Short Sale Variables	Definition
Loan	The quantity of borrowed securities as a percentage of shares outstanding
Utilization	The value of assets on loan from beneficial owners relative to the lendable asset value.
Fee Score	Fee score is the value weighted average fee score over 30 days. 0 represents no fee, a fee score of 1 is relatively cheap, while 6 is the most expensive category.
DOUT	Indicator variable equal to 1 in the advent of a demand shift. Demand shift identification follows the methodology proposed by Cohen et al. (2007).
Failure	Total fails-to-deliver, represents the aggregate net balance of shares that failed to be delivered as of settlement date. Data obtained from the Federal Reserve website: http://www.sec.gov/foia/docs/failsdata.htm
FailID	Indicator variable equal to 1 when a share failed to be delivered.
Inventory	The available inventory quantity from beneficial owners as a percentage of shares outstanding.
Inventory Accounts	Total number of inventory accounts. Separate count for each row of inventory held by each underlying beneficial owner or fund that owns the security.
Active Agents	Number of custodians with open transactions.
Inactive Agents	Number of custodians and lending agents with inventory but without open transactions.

Table I

Closed End fund descriptive Statistics

Panel A contains Mean Monthly Net Asset Value statistics for the closed-end fund sample. Premium is calculated as (price/nav)-1. Sample period September 2006 to December 2008. Panel B reports aggregate NAV statistics for the funds trading above (premium) or below (discount) their NAV value, in a particular month during the year. Panel C shows the test of equality of the means ($t-$test) and medians (Wilcoxon) for premium and discount funds. Failure represents the aggregate net balance of shares that failed to be delivered as of settlement date at the end of the month relative to shares outstanding and the number of failures is the frequency of reported failures relative to the total number of months. Panel B shows loan descriptive statistics for the closed end fund and common equity sample. Loan is the total quantity of borrowed securities as a percentage of the shares outstanding. Inventory is the available inventory quantity from beneficial owners as a percentage of the number of outstanding shares. Utilization is the value of assets on loan from beneficial owners divided by the total lendable assets. Fee score is the value weighted average fee score over 30 days. 0 represents no fee, a fee score of 1 is relatively cheap, while 6 is the most expensive category. The description of the rest of the variables are in the appendix.

Panel A Descriptive Statistics per year						
	Year	Obs	Mean	Stdev	Min	Max
Premium	2006	575	-2.20%	9.57%	-29.90%	50.76%
N=297	2007	1407	-4.08%	9.61%	-38.82%	84.11%
	2008	1885	-7.38%	10.45%	-48.84%	48.45%
	2006-2008	3642	-5.38%	10.22%	-48.84%	84.11%

Panel B: # Obs per year			
	Year	Obs	N
# Premium Funds	2006	177	53
	2007	312	76
	2008	299	81
# Discount Funds	2006	398	99
	2007	1095	201
	2008	1586	265

Panel C: Comparison Premium Discount Funds					
	Discount	Premium	Difference	Diff. of means t-test (p-value)	Wilcoxon test (p-value)
Size (thousands)	417,431	462,807	-45,376	(0.04)**	(0.07)*
Turnover	72.88%	76.81%	-3.93%	(0.24)	(0.00)***
Institutional Own	15.43%	5.75%	9.67%	(0.00)***	(0.00)***
Premium	-9.43%	9.27%	-18.70%	(0.00)***	(0.00)***
Loan	0.36%	0.36%	0.00%	(0.95)	(0.00)***
Inventory	1.57%	0.57%	1.00%	(0.00)***	(0.00)***
Utilization	6.77%	8.68%	-1.90%	(0.02)**	(0.29)
Fee Score	3.48	4.51	-1.04	(0.06)*	(0.00)***
# Failure	15.59%	45.94%	-30.35%	(0.00)***	(0.00)***
Failure	0.04%	0.11%	-0.08%	(0.00)***	(0.00)***
N	284	122			

Table II

Failure Descriptive Statistics

Mean end of the month failure statistics for the sample period July 2006-December 2008. The sample consists of all equity closed end funds (share code=14) and common equity stocks (share code=10, 11) in the Data Explorers data. Failure represents the aggregate net balance of shares that failed to be delivered as of settlement date at the end of the month relative to shares outstanding and the number of failures is the frequency of reported failures relative to the total number of months. Panel B shows loan descriptive statistics for the closed end fund and common equity sample. Loan is the total quantity of borrowed securities as a percentage of the shares outstanding. Inventory is the available inventory quantity from beneficial owners as a percentage of the number of outstanding shares. Utilization is the value of assets on loan from beneficial owners divided by the total lendable assets. Fee score is the value weighted average fee score over 30 days. 0 represents no fee, a fee score of 1 is relatively cheap, while 6 is the most expensive category. Panel C shows the test of equality of mean ($t-$test) and medians (Wilcoxon) for funds with reported failures and funds without.

Panel A: Failure Descriptive Statistics Closed end and Common Equity

		Closed end funds		Common Equity	
		# Failures	Failure	# Failures	Failure
Sample period (2006-2008)	Mean	21.77%	0.05%	14.69%	0.37%
	Stdev	10.70%	0.03%	8.47%	0.09%
	Min	0.00%	0.00%	0.00%	0.25%
	Max	50.00%	0.12%	25.49%	0.52%
Mean per year	2006	20.00%	0.03%	0.95%	0.53%
	2007	25.52%	0.07%	16.57%	0.33%
	2008	19.81%	0.04%	17.84%	0.39%

Panel B: Loan Descriptive Statistics Closed end and Common Equity

Sample period (2006-2008)		Loan	Inventory	Utilization	Fee Score
	Closed end funds	0.36%	1.33%	7.18%	3.65
	Common Equity	4.55%	14.38%	22.85%	3.13

Panel C: Comparison Funds with reported Failures and funds without

	Funds with Failures	Funds without Failures	Difference	Diff. of means t-test (p-value)	Wilcoxon test (p-value)
Size (thousands)	489,705	409,113	80,592	(0.00)***	(0.00)***
Turnover	79.48%	72.06%	7.42%	(0.01)**	(0.41)
Institutional Own	10.83%	14.13%	-3.30%	(0.00)***	(0.00)***
Premium	1.23%	-7.19%	8.42%	(0.00)***	(0.00)***
Loan	0.58%	0.30%	0.28%	(0.00)***	(0.00)***
Inventory	1.02%	1.46%	-0.43%	(0.00)***	(0.00)***
Utilization	12.53%	5.67%	6.86%	(0.00)***	(0.00)***
Fee Score	4.33	3.65	0.68	(0.00)***	(0.01)**
N	202	283			

Table III

Failures and Premium

Panel regression of premium to NAV on failure-to-deliver, fund specific control variables and period dummies. Results are reported in percentages. Period dummies are not reported. Panel data are U.S. equity closed-end funds (share code=14) followed from June 2006 to December 2008. The model is estimated using Arellano-Bond (1991) system dynamic panel model (GMM), t statistics clustered by fund in parenthesis. The Arellano-Bond test for autocorrelation and difference-in-Sargan/Hansen tests for the validity of instruments p-values are reported. The details of data sources and variable definitions are in the appendix.

Variables	(1) Premium	(2) Premium
FailID	2.63***	
	(5.10)	
Failure		3.05**
		(2.46)
Control Variables		
Size	0.01**	0.01**
	(2.29)	(2.29)
Turnover	0.00	0.00
	(-0.11)	(-0.54)
Noise Beta	0.14*	0.12
	(1.90)	(1.44)
Replication	-0.27	-0.26
	(-0.59)	(-0.58)
Beta Sentiment	2.94	0.59
	(0.70)	(0.13)
Stdev	-0.01	0.05
	(-0.06)	(0.58)
Past 12M return	-0.04	-0.04
	(-1.10)	(-1.23)
Beta	0.86*	0.79*
	(1.86)	(1.69)
Institutional Own	0.02	0.02
	(0.66)	(0.47)
Amihud	0.00	0.00
	(1.13)	(0.47)
Spread	-0.03	0.01
	(-0.18)	(0.05)
Lagged Dependent variable		
Premium (t-1)	0.71***	0.72***
	(12.30)	(12.15)
Premium (t-2)	0.23***	0.23***
	(3.85)	(4.00)
Constant	-0.13***	-0.17***
	(-4.00)	(-4.72)
Tests		
AR(1)	0.00	0.00
AR(2)	0.17	0.28
Sargan	0.00	0.00
Hansen	0.25	0.18
Difference-in-Hansen	0.37	0.20
Obs	1466	1466
# Funds	168	168
# Instruments	131	131
Fixed Effects	Yes	Yes
Period Effects	Yes	Yes

Robust $t-$statistics in parentheses

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table IV

Sensitivity Estimation

Panel regression of premium to NAV on failure-to-deliver variables, fund specific control variables and period dummies. The results are reported in percentages. Controls, period dummies and lagged dependent variable (3) not reported. t-statistics clustered by fund in parenthesis. The second specification reports the dynamic panel-data estimates using 1 lag. The third specification invokes the collapse option to restrict the instrument count and reduce the risk of overfitting the data. The fourth specification perform the two-step system GMM, with the finite sample correction of Windmeijer. The following two rows report the GMM estimation in levels and differences respectively. The following three rows report the two-way fixed effects regression results, the between estimator and a pooled OLS regression with fund clustered standard errors. The final two rows report the GMM estimation using the log of the number of lending agents as an instrument and including the loan quantity as control. In Panel B are the dynamic regression results using alternative failure measurements. The weekly average failure measure the average failure threshold level relative to shares outstanding over the week prior to the NAV date. The monthly average failure is the average failure threshold level relative to shares outstanding over the month prior to the NAV date. The weekly and monthly # of fails are the number of days with a reported threshold level of failures during the respectively week or month prior to the NAV. The details of data sources and variable definitions are in the appendix.

Panel A: Robustness Estimation

	Maximum Lag 2	Collapse	(Windmeijer) Two Step	Level	Arellano Bond Differences	Fixed Effects	Between Estimator	OLS	IV # Agents	IV with loan
FailID	2.67***	2.40***	2.64***	2.67***	1.03**	3.08***	1.54***	7.71***	2.42***	2.92**
	(6.07)	(5.31)	(5.61)	(6.07)	(2.42)	(6.59)	(4.82)	(6.80)	(4.03)	(2.51)
Failure	2.90**	5.79***	2.88**	2.90**	3.29**	6.99***	23.58**	11.22***	2.95**	2.42***
	(2.59)	(2.75)	(2.49)	(2.59)	(2.12)	(3.86)	(1.97)	(3.97)	(2.41)	(4.10)

Panel B: Alternative Failure Measures

	(1) Premium	(2) Premium	(3) Premium	(4) Premium	(5) Change in Premium
Weekly Average Failure	9.12***				
	(4.29)				
Monthly Average Failure		9.58***			
		(3.58)			
Weekly # Fails			0.33***		
			(3.45)		
Monthly # Fails				0.09***	
				(4.43)	
Change in Failure					2.30**
					(2.05)

Robust $t-$statistics in parentheses
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table V

Failure and Fee Score

The table reports transition probabilities in percentages of the change in Fee score over time for funds without reported failures and funds with reported failures. Fee score is the value weighted average fee score over 30 days. 0 represents no fee, a fee score of 1 is relatively cheap, while 6 is the most expensive category.

	Transition Probabilities							
FailID =0				Fee score				
Fee score	0	1	2	3	4	5	6	Total
0 (no fee)	94.90	2.21	0.34	0.35	0.60	0.58	1.02	100
1 (cheap)	23.55	73.08	1.10	0.38	0.37	0.67	0.83	100
2	27.55	12.16	50.97	3.36	3.88	0.65	1.42	100
3	19.79	2.11	5.19	67.05	3.17	1.54	1.15	100
4	18.77	1.00	0.65	1.55	70.79	5.14	2.10	100
5	18.54	1.78	0.42	1.03	4.40	69.01	4.82	100
6 (expensive)	16.19	0.87	0.33	0.45	0.52	2.34	79.30	100
Total	79.94	7.60	0.95	1.28	2.46	2.59	5.19	100
FailID =1								
				Fee score				
Fee score	0	1	2	3	4	5	6	Total
0 (no fee)	94.65	1.44	0.22	0.23	0.76	0.86	1.84	100
1 (cheap)	13.16	83.32	0.92	0.17	0.42	1.17	0.84	100
2	20.69	8.28	64.14	3.45	1.38	0.00	2.07	100
3	15.19	1.90	4.43	69.62	6.96	0.00	1.90	100
4	15.56	0.68	0.34	1.37	76.75	2.74	2.56	100
5	14.89	1.40	0.42	0.56	3.93	74.72	4.07	100
6 (expensive)	14.12	0.61	0.12	0.43	0.55	1.84	82.32	100
Total	73.42	7.24	0.87	0.98	3.57	4.18	9.74	100

Table VI

Predictive Fee score Ordered Logit

The table reports the marginal effects of the generalized Ordered Logit regression of the occurrence of a failure on fee score, controls and year-month fixed effects. The marginal effects are calculated as the derivatives of the six probabilities at the sample means of the independent variables and represent the change in the predicted probability associated with a discrete change of the failure dummy variable from 0 to 1. t-statistics are reported in brackets and are calculated using fund clustered standard errors. The details of data sources and variable definitions are in the appendix.

Panel A: Marginal effects of the generalized Ordered Logit regression (t+1)							
	Fee vs No Fee	Fee Score= 1	Fee Score= 2	Fee Score= 3	Fee Score= 4	Fee Score= 5	Fee Score= 6
	(t+1)	(t+1)	(t+1)	(t+1)	(t+1)	(t+1)	(t+1)
FailID	1.44***	-24.80***	1.78*	0.56	5.07***	5.03***	12.30***
	(2.68)	(-6.78)	(1.96)	(0.77)	(2.64)	(4.19)	(4.32)
Size	0.01	-0.04	0.02***	0.00	0.01	0.01*	-0.01
	(0.98)	(-1.24)	(2.68)	(0.64)	(1.06)	(1.90)	(-0.88)
Div rate	-0.00	-0.01	0.00	-0.00	-0.01**	0.01**	0.02*
	(-0.50)	(-0.58)	(0.24)	(-0.09)	(-2.04)	(2.40)	(1.73)
Turnover	0.28	-8.24***	2.36***	1.84**	-0.35	1.67	2.72*
	(0.48)	(-3.07)	(2.86)	(2.47)	(-0.37)	(1.39)	(1.94)
Stdev	-0.23***	-2.11***	0.39**	0.45***	-0.56**	0.79***	1.03***
	(-3.18)	(-3.75)	(1.98)	(2.99)	(-2.00)	(3.92)	(4.94)
Beta	-1.27***	-1.45	1.28*	-0.55	1.73***	-0.51	-0.50
	(-3.54)	(-0.75)	(1.75)	(-1.36)	(2.60)	(-0.87)	(-0.55)
Inventory	0.32**	1.24	1.15***	-0.08	0.24	-0.85**	-1.69***
	(2.00)	(1.09)	(2.70)	(-0.34)	(0.71)	(-2.49)	(-2.88)
Panel B: Long Horizon (t+n days)							
	(t+5)	(t+5)	(t+5)	(t+5)	(t+5)	(t+5)	(t+5)
FailID	1.64***	-21.80***	1.21	1.23	0.44	3.94***	15.00***
	(3.19)	(-6.09)	(1.32)	(1.57)	(0.34)	(3.18)	(5.52)
FailID	(t+30)	(t+30)	(t+30)	(t+30)	(t+30)	(t+30)	(t+30)
	1.82***	-18.90***	1.47*	0.41	2.88**	3.50***	10.60***
	(3.57)	(-4.85)	(1.80)	(0.48)	(2.36)	(2.60)	(3.95)
FailID	(t+60)	(t+60)	(t+60)	(t+60)	(t+60)	(t+60)	(t+60)
	1.60***	-16.60***	-0.47	1.99**	3.03***	3.10***	8.99***
	(3.25)	(-4.64)	(-0.49)	(2.26)	(3.31)	(2.66)	(3.29)
	(t+90)	(t+90)	(t+90)	(t+90)	(t+90)	(t+90)	(t+90)
FailID	-5.30	-18.80***	-0.69	-1.51**	1.80	3.81***	15.41***
	(-14.45)***	(-10.15)	(-0.93)	(-2.37)	(1.61)	(3.21)	(9.42)

Robust $t-$statistics in parentheses

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Table VII

Predictive Loan Quantity Regression

Predictive regression of the occurrence of a failure on loan quantity over shares outstanding, including controls and month-year fixed effects. The results are reported in percentages. $t-$statistics are reported in brackets and are calculated using fund clustered standard errors. The details of data sources and variable definitions are in the appendix.

	(1) Loan (t+1)	(2) Loan (t+5)	(3) Loan (t+30)	(4) Loan (t+60)	(5) Loan (t+90)
FailID	0.42***	0.42***	0.35***	0.27**	0.18
	(3.18)	(3.11)	(2.62)	(2.07)	(1.35)
Size	0.00	0.00	0.00	0.00	0.00
	(1.00)	(0.99)	(1.11)	(1.00)	(0.89)
Div rate	0.00***	0.00***	0.00***	0.00***	0.00***
	(3.52)	(3.53)	(3.47)	(3.30)	(3.36)
Turnover	0.33***	0.35***	0.33***	0.31***	0.28***
	(5.19)	(5.39)	(4.95)	(4.01)	(3.85)
Stdev	-0.01	-0.01	-0.01	0.01	0.02**
	(-0.84)	(-1.44)	(-0.96)	(1.29)	(2.19)
Beta	0.04	0.05	0.01	-0.04	-0.03
	(0.99)	(1.08)	(0.15)	(-0.87)	(-0.79)
Inventory	0.30***	0.29***	0.28***	0.26***	0.24***
	(9.76)	(9.75)	(9.51)	(8.36)	(7.15)
Past 12m ret	0.03**	0.02**	0.02**	0.00	0.01
	(2.54)	(2.12)	(2.34)	(0.12)	(0.90)
Constant	-0.99*	-0.96*	-0.86	-0.69	-0.58
	(-1.92)	(-1.87)	(-1.65)	(-1.22)	(-0.97)
Observations	94167	94163	94138	94108	94078
R-squared	0.56	0.55	0.48	0.41	0.35

Robust $t-$statistics in parentheses

*** $p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table VIII

Interaction Failure

Interaction effects. The specification includes the failure-to-deliver variable, fixed effects, the controls, lagged (2) dependent variables and period dummies. Results are reported in percentages. Period dummies, lagged dependent variables and controls are not reported. The first interacting inventory variable is the available inventory quantity from beneficial owners relative to the shares outstanding. The second variable represents the number of inventory accounts held by beneficial owners and the third variable is the number of active lending agents. The details of data sources and variable definitions are in the appendix. The model is estimated using Arellano-Bond (1991) system dynamic panel model (GMM), $t-$statistics clustered by fund in parenthesis. The Arellano-Bond test for autocorrelation and difference-in-Sargan/Hansen tests for the validity of instruments p-values are reported. The last regression of the change in institutional ownership on the lagged occurrence of a failure is estimated using standard period and fund fixed effects.

Variables	(1) Premium (%)	(2) Premium (%)	(3) Premium (%)	(4) Premium (%)	(5) Change Institutional Own (%)
FailID	2.70***	2.87***	2.96***	3.44***	
	(5.17)	(4.96)	(5.85)	(4.41)	
Inventory	0.33				
	(0.79)				
FailID*Inventory	-0.31				
	(-1.08)				
FailID*Inventory Accounts		-0.17			
		(-1.53)			
Inventory		0.21***			
		(3.07)			
FailID*Active Agents			-0.91**		
			(-1.99)		
Active Agents			-0.43		
			(-0.68)		
FailID*Lowfee				-2.10**	
				(-2.39)	
Low Fee				3.09***	
				(3.12)	
FailID (t-1)					0.13**
					(2.32)
Tests					
AR(1)	0.00	0.00	0.00	0.00	
AR(2)	0.21	0.28	0.32	0.22	
Sargan	0.18	0.22	0.03	0.31	
Hansen	0.57	0.51	0.64	0.57	
Difference-in-Hansen	0.48	0.79	0.90	0.75	
Obs	1466	1466	1466	1466	994
# Funds	168	168	168	168	138
# Instruments	40	40	40	40	
Fixed Effects	Yes	Yes	Yes	Yes	Yes
Period Effects	Yes	Yes	Yes	Yes	Yes

Robust $t-$statistics in parentheses

*** $p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table IX

Short Sale Constraints and Premium

Panel regression of premium to NAV on short sale constraints, fund specific control variables and period dummies. Results are reported in percentages. Period dummies are not reported. Panel data are U.S. equity closed-end funds (sharecode=14) followed from June 2006 to December 2008. Funds are ranked high if they are assigned to the highest tercile in terms of utilization and short sale quantity. The details of data sources and variable definitions are in the appendix. The model is estimated using Arellano-Bond (1991) system dynamic panel model (GMM). The Arellano-Bond test for autocorrelation and difference-in-Sargan/Hansen tests for the validity of instruments p-values are reported. The $t-$statistics clustered by fund are reported in parenthesis.

Variables	(1) Premium (%)	(2) Premium (%)	(3) Premium (%)	(4) Premium (%)	(5) Premium (%)	(6) Premium (%)	(7) Premium (%)
FailID	2.63***						
	(5.10)						
Failure		3.05**					
		(2.46)					
Loan			0.00				
			(0.00)				
High Loan				1.01**			
				(2.00)			
Utilization					0.02*		
					(1.66)		
High Util						0.76	
						(1.32)	
DOUT							-1.01
							(-1.14)
Controls							
Size	0.01**	0.01**	0.01***	0.01**	0.01***	0.01**	0.01***
	(2.29)	(2.29)	(2.61)	(2.48)	(2.67)	(2.27)	(2.72)
Turnover	-0.00	-0.00	-0.00	-0.00	-0.00	-0.00	0.00
	(-0.11)	(-0.54)	(-0.11)	(-0.12)	(-0.11)	(-0.09)	(0.26)
Noise Beta	0.14*	0.12	0.15**	0.17**	0.15**	0.15**	0.16**
	(1.90)	(1.44)	(2.21)	(2.36)	(2.12)	(2.19)	(2.22)
Replication	-0.27	-0.26	-0.23	-0.25	-0.26	-0.26	-0.23
	(-0.59)	(-0.58)	(-0.53)	(-0.55)	(-0.57)	(-0.58)	(-0.53)

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Table IX – continued from previous page

Beta Sentiment	2.94	0.60	3.06	2.92	2.64	3.69	3.58
	(0.70)	(0.13)	(0.70)	(0.71)	(0.61)	(0.87)	(0.83)
Stdev	-0.01	0.05	0.02	0.01	0.02	0.02	0.01
	(-0.06)	(0.58)	(0.26)	(0.07)	(0.25)	(0.19)	(0.12)
Past 12M return	-0.04	-0.04	-0.06	-0.06	-0.06	-0.06	-0.06
	(-1.10)	(-1.23)	(-1.51)	(-1.42)	(-1.54)	(-1.58)	(-1.45)
Beta	0.86*	0.79*	0.76*	0.63	0.67	0.67	0.67
	(1.86)	(1.69)	(1.68)	(1.26)	(1.36)	(1.36)	(1.37)
Institutional Own	0.02	0.02	0.01	0.01	0.01	0.01	0.01
	(0.66)	(0.47)	(0.44)	(0.25)	(0.35)	(0.20)	(0.27)
Amihud	0.00	0.00	0.00	0.00	0.00	0.00	0.00
	(1.13)	(0.47)	(0.94)	(0.92)	(1.08)	(0.99)	(1.18)
Spread	-0.03	0.01	0.03	0.05	0.05	0.05	0.03
	(-0.18)	(0.05)	(0.20)	(0.31)	(0.31)	(0.31)	(0.18)
Lagged Dependent variable							
Premium (t-1)	0.71***	0.72***	0.73***	0.72***	0.73***	0.73***	0.73***
	(12.30)	(12.15)	(13.03)	(12.43)	(12.22)	(12.58)	(12.60)
Premium (t-2)	0.23***	0.23***	0.23***	0.22***	0.23***	0.23***	0.22***
	(3.85)	(4.00)	(3.78)	(3.50)	(3.56)	(3.64)	(3.54)
Constant	-0.13***	-0.18***	-0.17***	-0.17***	-0.17***	-0.16***	-0.18***
	(-4.00)	(-4.72)	(-4.67)	(-4.61)	(-4.63)	(-4.02)	(-4.62)
Tests							
AR(1)	0.00	0.00	0.00	0.00	0.00	0.00	0.00
AR(2)	0.17	0.28	0.32	0.42	0.33	0.33	0.38
Sargan	0.00	0.00	0.00	0.00	0.00	0.00	0.00
Hansen	0.25	0.18	0.13	0.32	0.16	0.13	0.37
Difference-in-Hansen	0.37	0.20	0.10	0.42	0.37	0.32	0.11
Obs	1466	1466	1466	1466	1466	1466	1466
# Funds	168	168	168	168	168	168	168
# Instruments	131	131	131	131	131	131	126
Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Period Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

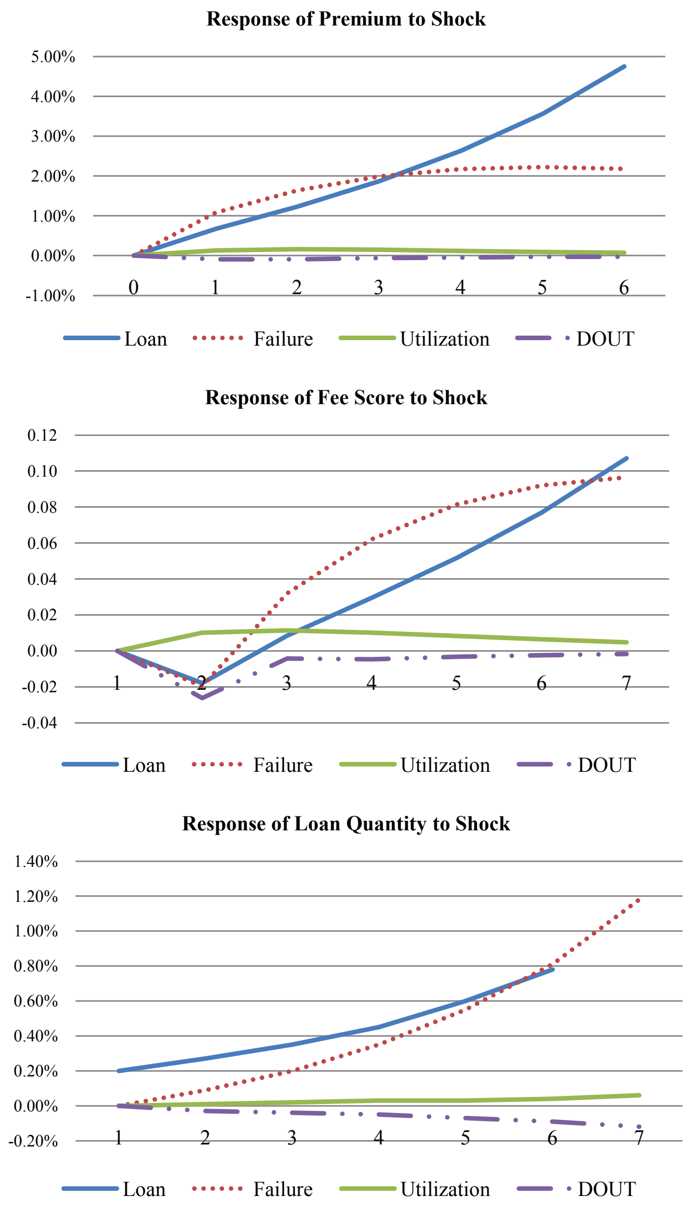

Figure 1

Impulse Response Function Premium, Fee Score and Loan Quantity

Impulse-response functions describing the reaction of the premium to NAV, fee score and loan quantity to a one standard deviation innovation in the constraints: DOUT, Loan, Utilization and Failure-to-deliver. The impulse-response functions follow from a first-order VAR model specification, including premium to NAV, fee score, and one of the respective constraint variables and fund and period-specific fixed effects. Fixed effects are removed using Helmert transformation (See Arellano and Bover (1995)). Estimation is by GMM with untransformed variables used as instruments for Helmert-transformed variables. Variables are time-demeaned for the period-specific effects.

Table X

Variance Decomposition

The variance decompositions resulting from the first-order vector autoregression, including premium to NAV, fee score, and one of the respective constraint variables and fund and period-specific fixed effects. The table reports the percent of variation in the row variable explained by column variable. The variance decompositions show the magnitude of the total effect.

Panel A: Variance Decomposition Short Sale Constraints												
	Months	Premium	Fee score	DOUT	Months	Premium	Fee score	DOUT	Months	Premium	Fee score	DOUT
Premium	1	100.00%	0.00%	0.00%	6	78.27%	21.70%	0.03%	12	77.88%	22.08%	0.04%
Fee score	1	5.73%	94.27%	0.00%	6	9.10%	90.87%	0.02%	12	9.20%	90.77%	0.02%
DOUT	1	0.17%	2.02%	97.81%	6	1.10%	2.29%	96.61%	12	1.13%	2.31%	96.56%
		Premium	Fee score	Util		Premium	Fee score	Util		Premium	Fee score	Util
Premium	1	100.00%	0.00%	0.00%	6	78.88%	20.99%	0.13%	12	78.53%	21.33%	0.14%
Fee score	1	5.82%	94.18%	0.00%	6	9.24%	90.75%	0.01%	12	9.34%	90.64%	0.02%
Util	1	3.31%	0.20%	96.49%	6	4.47%	6.45%	89.08%	12	4.58%	6.49%	88.93%
		Premium	Fee score	Loan		Premium	Fee score	Short		Premium	Fee score	Loan
Premium	1	100.00%	0.00%	0.00%	6	59.70%	14.39%	25.91%	12	10.57%	2.01%	87.43%
Fee score	1	6.34%	93.66%	0.00%	6	9.78%	89.91%	0.31%	12	9.34%	78.32%	12.33%
Loan	1	1.45%	0.00%	98.55%	6	3.93%	0.32%	95.76%	12	4.36%	0.41%	95.23%
		Premium	Fee score	Failure		Premium	Fee score	Failure		Premium	Fee score	Failure
Premium	1	100.00%	0.00%	0.00%	6	61.76%	20.51%	17.74%	12	50.73%	17.71%	31.56%
Fee score	1	6.73%	93.27%	0.00%	6	10.45%	88.91%	0.64%	12	10.34%	87.60%	2.06%
Failure	1	35.99%	0.20%	63.82%	6	9.88%	6.52%	83.60%	12	9.32%	5.11%	85.57%
Panel B: Variance Decomposition Sentiment												
		Premium	Fee score	Sentiment		Premium	Fee score	Sentiment		Premium	Fee score	Sentiment
Premium	1	100.00%	0.00%	0.00%	6	84.57%	15.16%	0.26%	12	84.32%	15.38%	0.30%
Fee score	1	6.57%	93.43%	0.00%	6	11.49%	88.09%	0.42%	12	11.60%	87.98%	0.43%
Sentiment	1	11.69%	0.81%	87.50%	6	7.33%	12.95%	79.72%	12	7.75%	12.74%	79.51%

Table XI

Daily Portfolio Analysis

Portfolio Analysis of the common equity sample in the Data Explorers data. Each day I sort the common equity stocks into a portfolio based on the short sale constraint considered. After assigning funds to the portfolios, I calculate the value weighted return over the subsequent day. The one and four-factor alpha are calculated using the market and factor returns available in French's data library. The four-factor alpha controls for the market, size, value, and momentum factor returns. Funds are classified according to whether a demand shift (DOUT=1), failure-to-deliver (FailID=1) or high fee (Fee score>= 4) has taken place. Funds are classified as ranking high if they are assigned to the highest tercile in terms of utilization and loan quantity. The number of stocks represents the count of stocks classified as falling into the respective category during the sample period June 2006-December 2008.

								Four-Factor Loadings							
		Raw Return	One Factor Alpha	t−stat	Four Factor Alpha	t−stat	# Stocks	MKT	t−stat	SMB	t−stat	HML	t−stat	UMD	t−stat
Loan	Low	-0.12%	-0.09%***	-3.41	-0.10%***	3.59	9045	0.91***	50.17	0.00	0.02	-0.10*	1.93	0.10	2.99
	Medium	-0.20%	-0.17%***	-6.55	-0.17%***	-6.53	9982	0.94***	52.55	0.14***	3.45	-0.10**	-2.02	-0.02	-0.56
	High	-0.30%	-0.26%***	-7.38	-0.25%***	-8.67	7453	1.06***	54.83	0.65***	15.23	0.04	0.82	-0.22	-6.39
	Difference	-0.18%	-0.17%***		-0.15%***										
	t−stat		-4.33		-5.02										
Util	Low	-0.14%	-0.11%***	-4.66	-0.12%***	-4.85	9461	0.91***	55.64	0.03	0.76	-0.17***	-3.78	0.06	2.02
	Medium	-0.24%	-0.21%***	-7.30	-0.21%***	-7.38	10117	0.99***	51.94	0.26***	6.14	-0.02	-0.28	-0.07	-1.96
	High	-0.31%	-0.27%***	-7.60	-0.26%***	-8.61	9064	1.04***	51.06	0.60***	13.37	0.00	0.05	-0.22	-6.10
	Difference	-0.17%	-0.16%**		-0.14%***										
	t−stat		-4.71		-5.74										
Failure	Failid=0	-0.17%	-0.14%***	-7.16	-0.14%***	-7.41	7497	0.99***	77.89	0.17***	5.95	-0.12***	-3.45	0.02	0.84
	Failid=1	-0.25%	-0.22%***	-4.38	-0.21%***	-4.33	6670	0.89***	26.01	0.24***	3.20	0.02	0.19	-0.12*	-1.87
	Difference	-0.08%	-0.08%**		-0.08%*										
	t−stat		-2.04		-1.94										
DOUT	DOUT=0	-0.20%	-0.17%***	-7.01	-0.17%***	-7.06	14139	0.96***	59.36	0.20***	5.51	-0.08*	-1.73	-0.02	-0.85
	DOUT=1	-0.53%	-0.51%**	-2.02	-0.51%**	-2.02	560	0.71***	11.95	0.35**	2.69	0.09	0.53	0.08	0.74
	Difference	-0.33%	-0.34%		-0.34%										
	t−stat		-4.00		-4.03										
Fee Score	1	-0.28%	-0.27%***	-5.18	-0.27%***	-5.17	4197	0.61***	17.10	0.07	0.94	0.05	0.49	0.02	0.27
	2	-0.19%	-0.17%	-1.68	-0.17%*	-1.70	2277	0.79***	11.64	0.16	1.09	-0.42**	-2.17	0.12	0.97
	3	-0.30%	-0.28%***	-3.79	-0.28%***	-3.88	2047	0.73***	14.49	0.24**	2.21	0.01	0.06	0.20**	2.21
	4	-0.21%	-0.20%***	-3.10	-0.20%***	-3.15	2504	0.55***	12.49	0.05	0.55	0.01	0.09	0.11	1.38
	5	-0.38%	-0.36%***	-6.43	-0.37%***	-6.46	2831	0.55***	14.05	-0.06	0.72	0.15	1.35	0.02	0.31
	6	-0.37%	-0.36%***	-6.20	-0.35%***	-6.16	2618	0.63***	15.97	-0.07	0.79	0.00	0.03	-0.07	-0.99
	Difference	-0.09%	-0.09%		-0.09%										
	t−stat		-1.32		-1.28										

$***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Table XII

Weekly Portfolio Analysis

Portfolio Analysis of the common equity sample in the Data Explorers data. Each week I sort the common equity stocks into a portfolio based on the short sale constraint considered. After assigning funds to the portfolios, I calculate the value weighted return over the subsequent week. Funds are classified according to whether a demand shift (DOUT=1), failure-to-deliver (FailID=1) or high fee (Fee score>= 4) has taken place. Funds are classified as ranking high if they are assigned to the highest tercile in terms of utilization and loan quantity. The four-factor alpha is calculated using the market and factor returns available in French's data library.

	Horizon: Week		
	Raw Return	Four-Factor Alpha	$t-$stat
High Loan	-0.49%	-0.28%***	-3.38
High Util	-0.51%	-0.31%***	-3.77
Failure	-0.45%	-0.27%***	-3.88
DOUT	-0.63%	-0.45%**	-2.16
Special	-0.49%	-0.40%	-1.45

***$p < 0.01$, **$p < 0.05$, *$p < 0.1$