When Constraints Bind

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Abstract

We create proxies for constrained supply of lendable shares by combining unique data on loan fees, stock lending activity, and failures to deliver to examine how contrarian short-sale strategies are affected by constraints. Constraints affect roughly one-third of the cross- section of stocks and result in a significant reduction in the contrarian response of short sellers to past returns. When short sellers' contrarian strategies are constrained, the market is significantly less efficient. Furthermore, the previously documented relation between short selling activity and future returns breaks down for the most constrained stocks.

Short sales have been the focus of recent regulatory action worldwide. More than a dozen stock markets around the world have in one way or another made short selling more costly either during or since the financial crisis of 2008. The actions range from requiring short sellers to borrow the stocks they want to sell short in advance of executing a short-sale to temporarily banning short sales for certain groups of stocks or the entire market. These regulatory actions are a response to concerns raised by issuers, politicians, regulators and media commentators that the decline in stock prices in 2008 was somehow directly related to short sales. In other words, the popular view is that short sales exacerbates downward spirals in the market, or even worse cause these downward spirals to occur.

In stark contrast to the popular view, several academic studies have shown that short sellers play a very important role in financial markets by detecting and correcting market overreaction. For example, Diether, Lee, and Werner (2009b) study daily short selling data for NYSE and Nasdaq stocks and find that short sellers are contrarian traders in that they increase their shorting activity after price increases. Moreover, their trades are followed by significant price declines over the following week (see also Boehmer, Jones, and Zhang (2008)). This evidence is consistent with short sellers trading on short-term overreaction of stock prices. Other evidence suggesting that short sellers trade on overvaluation is presented by Cao, Dhaliwal, and Kolasinski (2006) who find that short interest is high for firms with high accruals and by Karpoff and Lou (2008) who find that short interest is high in the period leading up to Securities and Exchange Commission (SEC) enforcement actions against firms for misrepresentation.

Whether or not short sellers are able to act on a deviation of market price from fundamental value depends on their ability to borrow shares. If a short seller is unable to locate shares to borrow, the supply of lendable shares is obviously constrained. However, even when lendable shares are available, the loan fee may be too high for it to be worthwhile to execute a profitable short sale. In either case, a short seller's ability to implement a short-sale strategy based on past returns will be limited and as a result a deviation from fundamental value is likely to persist longer. In other words, a market with more constrained supply is likely to be less efficient.

Unfortunately, the supply of lendable shares is not publicly observable so it is unclear how large a problem constrained supply is for market efficiency. We attempt to shed light on this issue by creating proxies for constrained supply of lendable shares based on unique data on loan fees, stock lending activity, and failures to deliver. We define the supply of lendable shares as constrained when the contrarian response of short sellers is significantly attenuated. Furthermore, we consider a constraint fully binding when short sellers no longer respond on average to past returns.

We first determine how often short sellers are constrained based on a large sample of Nasdaq- and NYSE-listed stocks during the first ten months of 2005. We then examine whether stocks with binding constraints are less efficient. Specifically, we examine price delay (Hou and Moskowitz (2004)) for constrained versus unconstrained stocks. Finally, we examine whether the previously documented relation between shorting activity and future returns (Boehmer, Jones, and Zhang (2008) Diether, Lee, and Werner (2009b)) is different for constrained stocks.

Several studies document a relation between monthly short interest and future returns (see Asquith and Meulbroek (1996) and Desai, Ramesh, Thiagarajan, and Balachandran (2002), Figlewski and Webb (1993), Figlewski (1981), Asquith, Pathak, and Ritter (2005), and Dechow, Hutton, Meulbroek, and Sloan (2001)). That is, when short interest increases significantly, future abnormal returns at the monthly horizon are negative. However, most studies fail to recognize that short interest is the market clearing result of the interaction of the supply of lendable shares and the demand for borrowing where the market clearing price is the borrowing cost (the loan fee). Without observing the loan fees, a researcher cannot identify whether an observed increase in short interest is the result of an increase in supply (lower fees) or an increase in demand (higher fees).

By using unique loan fee and stock lending data from a large institution, Cohen, Diether, and Malloy (2007) are able to separate increases in supply from increases in demand.[1] They show that it is particularly an increase in *demand* for shorting activity that is associated with negative future

[1] See D'Avolio (2002), Jones and Lamont (2002), Geczy, Musto, and Reed (2002), Ofek and Richardson (2003), Reed (2002), Ofek, Richardson, and Whitelaw (2004), Diether (2008) and Mitchell, Pulvino, and Stafford (2002) for examples of other studies that use direct measures of shorting costs.

returns. In this paper, we use loan fee data from the same source to create a proxy for when the *supply* of additional lendable shares is limited. We estimate the distribution of loan fees based on past data to focus on supply of lendable shares. Our goal is not necessarily to identify the stocks with the smallest supply of shares, but rather stocks for which lending tends to become difficult or expensive when demand for additional lendable shares spikes (i.e., the supply curve is relatively steep). We use the stock specific distribution of loan fees to empirically determine the level of past loan fees that indicate constrained supply.

One drawback with our loan fee data is that it does not cover all stocks and it is not available for the most recent time period. Moreover, it is proprietary data that is not readily available to other researchers. Therefore, we also use our detailed loan fee data to estimate how loan fees relate to stock and market characteristics. Our second measure of constrained supply is based on these predicted loan fees.

Naked short-selling has recently received considerable attention due to regulatory action by the SEC. If shares are very expensive or hard to borrow, a short sale may result in a failure to deliver or a naked short sale. Naked short selling occurs when a short seller is permitted by their broker to execute a sale but the broker does not succeed in borrowing the shares in time for settlement (T+3). This creates a failure to deliver shares from the seller's brokerage account to the brokerage account of the buyer at the Depository Trust Company (DTC). On July 15, 2008, the SEC issued an emergency order to enhance investor protections against naked short selling for a group of nineteen financial stocks. The emergency rule implied that short sellers in the nineteen financial stocks were required to pre-borrow shares instead of simply satisfying the less stringent locate requirements that generally applied at that time for short sales pursuant to Regulation SHO (RegSHO). On October 17, 2008, the SEC clamped down even more on naked short selling by adopting RegSHO Rule 204T which effectively prohibits naked short selling for all US listed stocks, and this rule was made permanent on July 31, 2009.

There are many different reasons why fails to deliver occur, including logistic reasons such as frictions associated with the delivery of paper stock certificates. Boni (2006) and Evans, Geczy, Musto, and Reed (2006) have also found that equity and option market makers sometimes strategically fail to deliver shares when loan fees are high. Market makers enjoy special exemptions from the RegSHO locate requirements (and these market participants were ultimately also exempted from the pre-borrow requirement of the emergency rule). Therefore, constrained supply of lendable shares should not affect their trading strategies significantly. By contrast, other short sellers during our sample period have to abide by the RegSHO locate requirements and we conjecture that they are therefore more likely to be significantly affected by constrained supply of lendable shares. Thus our third measure of constrained supply is based on fails to deliver.

A commonly used proxy for short sale constraints in the literature is low institutional ownership (e.g., Asquith, Pathak, and Ritter (2005), and Nagel (2005)). Since institutions are important stock lenders, stocks with low institutional ownership probably have low lendable supply of shares. However, we want to identify stocks where lendable supply is limited in the sense that a typical spike or increase in demand makes shorting much more expensive or difficult. It is quite possible that there are stocks which are of little interest to institutional investors both on the long and the short side. For these stocks supply might not be limited in the sense that there may still be enough shares to borrow to satisfy short term increases in demand. Thus, we would like to investigate empirically whether or not institutional ownership is a good proxy for short-sale constraints.

Our various measures of constraints may capture different aspects of how frictions affect short-sale strategies. While we find that our proxies all are significant individually, we also create a composite proxy for constraints. We compute a composite constraint measure as the sum of normalized variables based on past loan fees, imputed fees, and failures to deliver.

For each of our measures we test at what point (if any) the contrarian response of short sellers becomes significantly attenuated and at what point (if any) the contrarian response is completely eliminated. We consider the lendable supply constrained when the response is significantly attenuated because it is the point where there is evidence of a significant change in the behavior of short sellers. Furthermore, we consider a constraint fully binding when short sellers no long respond on average to past returns.

We combine our measures of constrained supply of lendable shares with daily measures of short selling activity created from intraday data on short sales that became available to academics to examine the impact of RegSHO on financial markets. We find that as our proxies increase, the response of short selling activity to past returns both for Nasdaq and NYSE stocks declines. These results show that for a large cross section of stocks the behavior of short sellers is significantly affected by short sell constraints as defined by our proxies. In fact, short selling is significantly affected for roughly one-third of the stocks in the sample. However, not until the constraints reach extremely high levels is the contrarian response eliminated. Only for stocks in the 99^{th} percentile are frictions high enough to eliminate contrarian short-sale strategies completely. The evidence for institutional ownership is mixed. Constraints as proxied by institutional ownership significantly affect short-sale strategies for Nasdaq stocks, but do not significantly affect contrarian short-sale strategies in NYSE stocks.

Overall, our results suggest that constraints do affect contrarian short-sale strategies. A significant reduction in the contrarian response is common but the response is only completely eliminated for a small number of stocks. In both cases limited supply reduces the ability of short sellers to trade based on what they perceive is a positive deviation of market price compared to fundamental value. This effect is more dramatic when the constraint binds (i.e. when the contrarian response is completely eliminated) but is important whenever the constraint significantly affects behavior.

In the rest of the paper, we examine how constrained short selling affects the relation between short sales and prices. We first examine the relation between constraints and market efficiency. As pointed out by Miller (1977), when short sellers are constrained, market prices are more likely to exceed fundamental value. In other words, the market is likely to be less efficient for stocks where short sellers face significant constraints. At the heart of an efficient market is the notion that prices incorporate relevant information quickly. Consistent with this hypothesis, we find that price delays are significantly higher and large in magnitude for stocks with constrained supply of lendable shares.

Second, we examine how these constraints affect the link between shorting activity and returns.

The previous literature (e.g., Boehmer, Jones, and Zhang (2008) and Diether, Lee, and Werner (2009b)) has examined the relationship between short selling activity and future returns by first sorting stocks into portfolios based on short-selling activity, and then examining the returns to a strategy of buying the stocks with low shorting activity and selling the stocks with high shorting activity. Implicitly, this assumes that shorting activity is low by choice and not because short-sellers are constrained due to limited supply of lendable shares.

If short sellers are constrained, market prices are more likely to exceed fundamentals (Miller (1977)). Thus short sellers could in theory generate larger profits if they are able to pursue strategies in stocks with constrained lendable supply. Second, if short-sellers are constrained, we cannot determine whether low short-selling activity is caused by low demand from short-sellers or low supply of lendable shares. If low short sales are caused by low demand, we predict that future returns should be positive. By contrast, if low short-selling activity is caused by constrained supply, we predict that future returns should be negative. For both these reasons, the link between low short-selling activity and future returns is likely weaker when short sellers face significant constraints. Consistent with this hypothesis, we find that the previously documented relation between short selling activity and future returns is different for the most constrained stocks. Specifically, for the most constrained stocks, average abnormal returns are actually negative for stocks that are lightly shorted (although a large return spread does still exist between lightly and heavily shorted stocks).

Our study proceeds as follows. We summarize our hypotheses in Section I, and describe the data and our proxies for constraints in Section II. In Section III we examine how short-selling relates to past returns for stocks that are constrained and unconstrained using proxies based on past loan fees, imputed loan fees, past fails to deliver, and institutional ownership. In section IV we examine the relation between low lendable supply and price delay. Section V is devoted to examining the effect of limited supply of lendable shares on return predictability. Section VI concludes.

I. Hypotheses

Our hypotheses can be summarized as follows:

- Short sellers are on average contrarian traders that trade on short-term overreaction of market price from fundamental value.
- If the supply of lendable shares is unconstrained, short sales increase (decrease) following positive (negative) returns.
- If the supply of lendable shares is constrained, the response of short selling to past positive returns will be attenuated. If the constraint binds completely then short selling will not respond at all to past returns.
- If the supply of lendable shares is constrained, the market is less efficient.
- If the supply of lendable shares is unconstrained, high (low) short sales predict future negative (positive) returns.
- If the supply of lendable shares is constrained, high short sales indicate high demand and thus predict negative returns.
- If the supply of lendable shares is constrained, low short sales may indicate either low demand (predict positive returns) or low supply (predict negative returns). This tends to weaken the predictive power of low short sales.

II. Data and Sample Characteristics

A. Data Description

This study focuses on NYSE and Nasdaq-listed stocks. We define our universe as all NYSE and Nasdaq stocks that appear in CRSP with share code 10 or 11 (common stock). In most of the tests, the sample period is January 2, 2005 to October 31, 2005. This sample period represents the intersection of our constraint proxy that is based on past loan fees from our stock lending sample and the intraday short-selling activity data produced by Reg SHO.

We use a proprietary database of stock lending contracts from a large institutional investor during the period of September 1999 to August 2005. We do not name the institution because of a confidentiality agreement. However, the institution is an active lender and is particularly active in the small-cap lending market. The database contains daily contract level short-selling data. For each contract-day we have the following variables: loan fees, rebate rates, shares on loan, collateral amount, rate of return on the collateral account, estimated income from each loan, and broker firm name. We exclude contracts that cannot be matched with daily return data from CRSP. During the period of September 1, 1999 to August 31, 2005 we identify 119,827 contracts for NYSE listed stocks and 197,489 for Nasdaq listed stocks.

The loan fee is our measure of the cost of shorting throughout the paper.[2] The loan fee is equal to the difference between the interest earned in the collateral account and the rebate rate. The rebate rate is the portion of the collateral account interest rate that the short-seller receives back. Every contract-day observation has a potentially unique loan fee even for contract-day observations involving the same stock. Loan fees for contracts that borrow the same stock on the same day are almost always very similar and are frequently identical. Following Cohen, Diether, and Malloy (2007) we use the loan fee of the largest contract in our tests.

For many tests we combine our lending sample data with short-selling activity data produced by Reg SHO. On June 23, 2004, the SEC adopted Regulation SHO to establish uniform locate and delivery requirements, create uniform marking requirements for sales of all equity securities, and to establish a procedure to temporarily suspend the price-tests for a set of pilot securities during the period May 2, 2005 to April 28, 2006 in order to examine the effectiveness and necessity of short-sale price-tests.[3] At the same time, the SEC mandated that all Self Regulatory Organizations (SROs) make tick-data on short-sales publicly available starting January 2, 2005. The

[2]See D'Avolio (2002), Jones and Lamont (2002), and Duffie, Garleanu, and Pedersen (2002) for further details on the mechanics of the equity lending market.

[3]On July 6, 2007 all short-sale price tests were suspended by the SEC. Diether, Lee, and Werner (2009a) for more information on the effects short-sale price tests on market quality.

SHO-mandated data includes the ticker, price, volume, time, and listing market for all short-sales. We download intraday data from all SROs that report short-sales and calculate daily short-selling measures. Specifically, we compute the total number of shares sold short.

We combine our other data with SEC daily stock level data on fails to deliver. We download this data from the SEC website.[4] The data are currently available from the second quarter of 2004 to the second quarter of 2011. The data primarily report the total number of fails to deliver as "recorded in the National Securities Clearing Corporation's (NSCC) Continuous Net Settlement (CNS) system aggregated over all NSCC members when that security has a balance of total fails to deliver of at least 10,000 shares as of a particular settlement date."[5] Fails to deliver are only reported if the aggregate net balance as of a particular settlement date is greater than 10,000 shares. Also, the reported fails represent a cumulative amount of fails. Thus reported fails on a particular day are the sum of both new and existing fails.

Finally, we combine our short-sale contract data, daily short-selling activity data and fails-to-deliver data with a variety of other data sources. We draw data on returns, prices, shares outstanding, volume, and other items from CRSP, book equity from COMPUSTAT, quarterly institutional holding data from CDA/Spectrum, and analyst coverage and forecasts from Thompson Financial. Finally, we compute daily buy order imbalances using the Lee and Ready (1991) algorithm, and daily effective spreads from TAQ.

For the baseline tests our sample period is January 2, 2005 to October 31, 2005. Our loan fee data end in August of 2005 but our past loan fee based constraint proxy uses a back window of t-125 to t-43. This allows us to extend our sample period to the end of October. We require that a stock can be borrowed from our lender. Specifically, we only include stocks if lagged quarterly ownership by our lender is greater than 0.1% of shares outstanding or if the stock has been borrowed from our lender in the past 6 months. We only include stocks with a price greater than $1 as

[4]http://www.sec.gov/foia/docs/failsdata.htm

[5]http://www.sec.gov/foia/docs/failsdata.htm. If fails exceed 10,000 shares and at least of on-half of one percent of the issuer's total shares outstanding for more than five consecutive settlement days, the stock will appear on the RegSHO mandated "threshold list." This is another indication that the supply of lendable shares is constrained. We examine the effect of securities being on the "threshold list" on short sales in the Appendix.

of the end of December 2004 and for our regressions and portfolios we further restrict the sample to only include an observation if lagged price is greater than \$5. We exclude stock-days where there is zero volume reported by CRSP.[6]

B. Summary Statistics

Table I presents summary statistics for a pooled sample of lending contracts from September 1999 to August 2005. Panel A presents summary statistics for contracts involving stocks listed on the NYSE. The loan fee in the table refers to the loan fee on the first day of the contract expressed per annum. The average (median) loan fee for NYSE listed stocks is 1.64% (0.16%) per annum and for Nasdaq listed stocks the average (median) loan fee is 3.74% (3.08%) per annum. Additionally 22% of the contracts for NYSE listed stocks have negative rebate rates (loan fee greater than the collateral account interest rate) while 54% of Nasdaq stocks have negative rebate rates. Thus borrowing costs are typically higher for Nasdaq stocks in our sample.

The higher fees are understandable given the difference in stock characteristics between the NYSE and Nasdaq listed stocks. The median market-cap on the first day of the contract is 1,352 million for NYSE stocks and only 164 million for Nasdaq stocks. The median market-cap for Nasdaq securities also reveals the small-cap lending tilt of our lender. The contract size (in dollars) for NYSE listed stocks is typically much larger. The median contract size is \$241,237 for NYSE stocks and \$40,098 for Nasdaq stocks. However, the typical contract length is similar for both exchanges. The median contract length is 6 days for NYSE stocks and 8 days for Nasdaq listed stocks.

Table II presents summary stock characteristics and short-selling activity statistics for our baseline sample (January 2, 2005 to October 10, 2005). We normalize across stocks by defining the relative amount of short-selling (*relss*) as the daily number of shares sold short for a stock day divided by the total number of shares traded in the stock during the same day. We then compute the time series average of each variable over the available sample period for each stock. Table II

[6]Following Diether, Lee, and Werner (2009b) we set short-sales equal to volume in the few instances where short-sales exceed reported volume.

reports the cross-sectional summary statistics of those averages.

Median (average) *relss* is 24.09% (23.91%) for NYSE listed stocks and the median (average) *relss* is 31.23% (29.74%) for Nasdaq listed stocks. The restriction that our lender must have shares available for lending has little affect on average *relss*. For both exchanges, when we lift the ownership restriction, average and median relss (computed but not tabulated) are very similar to the average and median reported for the restricted sample. The medians and averages are also very similar to those reported by Diether, Lee, and Werner (2009a) using a slightly larger cross section and longer sample period. For NYSE listed stocks the ownership restriction appears to produce relatively small differences in the cross sectional stock characteristics. For example, median market-cap is $1,614 million in the restricted sample and $1,736 million if we remove the lending availability restriction. For Nasdaq stocks the restricted sample is also quite similar to the unrestricted sample. The one exception is institutional ownership. In the restricted sample, median ownership is 49% but in the unrestricted sample median ownership is only 40%. Still, we conclude that the lending restriction does not have a large effect on the cross-sectional characteristics of the samples.

C. Loan Fees

Our first measure of short-sale constraints is based on loan fees in the recent past. Loan fees, of course, contain information about both lending supply and lending demand. We want to capture whether lending supply is sometimes limited for a stock, so we need to proxy for the lending capacity relative to demand in a particular stock during our period. We create our proxy for lending capacity by computing the highest observed daily loan fee for a stock from day t-125 to t-43 (fee_{max}).[7] We then form dummy variables based on fee_{max} cutoffs: $fee_{max} \approx$ general borrowing rate (gb), $gb < fee_{max} \leq 1\%$, $1\% < fee_{max} \leq 4\%$, $4\% < fee_{max} \leq 7\%$, and $fee_{max} > 7\%$. Some stocks are not on loan at all during the maximum loan fee calculation. If this is the case we assume the loan fee was at the general borrowing rate. This rate is between 0.05% and 0.20% per annum

[7] The results are robust to using different back windows to compute the maximum fee. For example, computing the back window from t-84 to t-22 yields very similar results.

in our sample. About 7% (14%), 2% (8%), and 0.5% (1%) of the sample is captured by a fee_{max} greater than 1%, 4%, and 7% for NYSE (Nasdaq) stocks.

Our fee_{max} measure should correlated with the extent to which lendable supply has been limited relative to spikes in demand over the last 6 months. We believe that lending capacity is relatively slow-moving, and we therefore estimate it over a relatively long window, day t-125 to t-43. We skip the first two months of past lending fee data to mitigate the extent to which information about recent shorting demand is picked up by our measure.

D. Failures to Deliver

Our second measure of constrained supply is based on past failures to deliver. Fails-to-deliver, like loan fees, potentially contain information about both shorting demand and supply. We try to capture if lending supply is sometimes limiting by using the same strategy we employed with loan fees. We estimate our measure over a relatively long window: t-125 to t-43. We skip the most recent past two months of data to hopefully mitigate how much information about recent shorting demand our measure is picking up. We create our proxy for lending capacity by computing the highest observed fails to deliver on a given day as a fraction of shares outstanding for a stock from day t-125 to t-43: $fails_{max}$. We create dummy variables based on daily percentile cutoffs by exchange of maximum past fails to deliver.

E. Imputed Loan Fees

One drawback with our loan fee data is that it does not cover all stocks. Moreover, it is proprietary data that is not readily available to other researchers. Therefore, we also use our detailed loan fee data to estimate a model for predicting loan fees based on stock characteristics. This model can be used to impute loan fees outside our sample both in the cross-section and the time series. Our third measure of constrained supply is based on the imputed loan fee data. Our goal is not to identify the lendable supply curve, but rather to identify the important characteristics that are correlated with high loan fees. Stocks with these characteristics are more likely to have limited lendable supply.

To identify the determinants of loan fees we run pooled regressions of month end loan fees on past stock characteristics. The results of these regressions are reported in Table III. Standard errors take into account clustering by calendar month because of concerns about cross-correlation. The time period is September 1999 to December 2004. Once again we restrict the sample to only include stocks that are available from our lender.[8] We also run separate regressions for NYSE and Nasdaq listed securities.

We include the following stock level variables in the regressions: $\log(ME)$, $\log(B/M)$, r_{-1}, $r_{-12,-2}$, $instown$, $\log(disp)$, $\log(price)$, $price < 5$, $log(tv)$, σ, $log(1+alyst)$, $shint$, $r_{f,-1}$, $r_{M,-1}$, and $r_{M,-12,-2}$. ME is market cap from month $t-1$. B/M is book to market ratio defined as in Fama and French (1993). r_{-1} is the return from month $t-1$. $r_{-12,-2}$ is the return from month $t-12$ to $t-2$. $instown$ is institutional ownership from the end of the previous quarter measured as a fraction of shares outstanding. $disp$ is average dispersion from $t-3$ to $t-1$ where dispersion is the standard deviation of one year ahead analyst earnings forecasts divided by the absolute value of the mean of the forecasts. $price$ is the stock price from $t-1$. σ is the standard deviation of daily returns during the past 12 months. $alyst$ is the number of analyst covering the stock in month $t-1$. $shint$ is lagged short interest ($t-1$) as a fraction of shares outstanding. $r_{f,-1}$ is the one-month T-Bill rate for month $t-1$. [9] $r_{M,-1}$ and $r_{M,-12,-2}$ are the lagged return on the market portfolio and the eleven month return on the market portfolio, $t-12$ to $t-2$.[10]

In the first regression we only include $\log(ME)$, $\log(B/M)$, r_{-1}, $r_{-12,-1}$, and $r_{f,-1}$. All of the coefficients are significant for NYSE listed stocks except for logged book to market and all but the coefficient on one month lagged returns are significant for Nasdaq stocks. Loan fees are higher for small-cap stocks, growth stocks, and stocks with poor past returns. The previous literature (Diether, Malloy, and Scherbina (2002), Asquith, Pathak, and Ritter (2005), and Nagel (2005)) has suggested that both institutional ownership and analyst dispersion should be related to short-selling constraints. Thus we augment our base regression with institutional ownership ($instown$)

[8]We do not use a lagged price restriction in these regressions because we wish to explore the determinants of loan fees and be able to potentially predict loan fees for the widest possible cross-section.

[9]Replacing the monthly treasury bill rate with LIBOR produces very similar results.

[10]We also ran regressions that included the TERM premium, but it was not significant.

and logged dispersion in analyst forecast ($\log(disp)$). We find that both are significantly related to loan fees and the signs of the coefficients are consistent with the hypotheses proposed by the previous literature. Institutional ownership seems to be much more important for Nasdaq listed stocks. The coefficient is about three times bigger for the Nasdaq regressions. This difference may be attributable in part to the greater cross-sectional variation in institutional ownership for Nasdaq stocks. The positive and significant coefficient on dispersion in analyst forecasts is interesting because it directly links analyst dispersion with short-sale constraints which is central to the hypothesis proposed by Diether, Malloy, and Scherbina (2002) to explain the link between analyst dispersion and future returns.

One drawback of dispersion in analyst forecasts is that it narrows the sample because one needs at least two analysts covering a stock to estimate dispersion. We want to apply our predicted loan fees as widely as possible thus we explore alternate variables. Lagged price is significantly negatively related to fees and seems to capture some of the same information about loan fees as dispersion. Analyst dispersion is no longer significant when logged lagged price is included in the regression. Thus we drop analyst dispersion from our later specifications. We form our final regression by adding a dummy for stock prices below \$5, logged turnover ($\log(tv)$), volatility (σ), the log of 1 + the number of analysts that cover a stock ($\log(1+alyst)$), short interest (*shint*), and past market returns ($r_{M,-1}$ and $r_{M,-12,-2}$). We find in the full specification that loan fees are significantly positively related to past share turnover and volatility and significantly negatively related to the number of analysts. Moreover, loan fees are significantly positively related to short interest, negatively (albeit not significantly) related to past market return, but significantly positively related to market momentum over the past eleven months. All of the coefficients are at least significant at the 10% level in the full specification for both Nasdaq and NYSE listed stocks. The R^2 for the full regression is 0.179 for NYSE listed stocks and 0.185 for Nasdaq listed stocks. Thus there is a lot of unexplained variation but these stock characteristics do seem to capture an important component of loan fees.

Our third measure of constrained supply is based on imputed loan fees. We use the regression coefficients from columns 4 and 8 of Table III to predict loan fees out of sample (every month) for all the stocks in our base sample. We create dummy variables based on the daily percentile cutoffs by exchange of imputed loan fee.

III. Short-Sale Constraints and Trading Activity

Diether, Lee, and Werner (2009b) find strong evidence that short-sellers increase their trading activity when past returns are high. Thus short-sellers act contrarian on average. That paper does not take into account that short sellers may be constrained, and the effect of past returns on short selling may therefore have been underestimated. In practice, short-sellers may be unable or unwilling to respond to past returns if locating shares is difficult or borrowing costs are high. If short sellers can only partially implement contrarian positions or are entirely unable to take contrarian positions because of short-sale constraints, mispricing, all else equal, is more likely to occur.

In this section we examine how short-sale constraints affect the ability of short sellers to take short positions in response to movements in prices. Specifically, we examine the effect of short-sale constraints on the ability of short sellers to increase their short selling activity in response to positive past returns using constraint proxies: fee_{max}, $fails_{max}$, and $impute$. We also examine whether institutional ownership affects contrarian short sale strategies after positive returns. Finally, we investigate the effect of constraints on short-sale strategies more broadly using a composite measure.

To examine the effect of constrained lending supply on short-selling activity in response to past returns we run pooled regressions of daily stock level relative short-selling (*relss*) on past returns, our proxies for constraints, past returns interacted with our proxies for constraints, and control variables. We run the regressions separately for Nasdaq and NYSE listed stocks. The sample period is January 17, 2005 to October 31, 2005. We add the restriction that the price as of day $t-6$ must be at least $5. The regressions include calendar day dummies, and the standard errors take into account clustering by calendar date and clustering by stock (Thompson (2009)). We cluster the standard errors by both date and stock because of concerns about both serial correlation and cross-correlation. We estimate the following regression:

$$relss_{it} = \sum_t \phi_t I_t^d + \sum_{j,j\neq 1} \alpha_j I_j^c + \sum_j \beta_j^+ r_{i,-5,-1}^+ I_j^c + \sum_j \beta_j^- r_{i,-5,-1}^- I_j^c + \gamma X_{i,t-6} + \varepsilon_{it} \tag{1}$$

Relative short-selling is measured as of day t for stock i; $relss_{it}$. I_t^d is a indicator variable that equals one on day t (calendar day fixed effects). I_j^c is an indicator variable that equals one if stock i on day t belongs to the jth constraint level for constraint measure c. We interact the constraint dummy variables with past returns. $r_{-5,-1}$ is the return from $t-5, t-1$. We split returns based on whether returns are positive or negative. $r_{-5,-1}^+$ ($r_{-5,-1}^-$) equals $|r_{-5,-1}|$ if the return is positive (negative) and zero otherwise. We split returns into their positive and negative components because according to our hypotheses, short-sellers should respond differently to positive returns than negative returns for constrained stocks. Note, the constraint-return interaction slope coefficients are defined as total effects and not incremental effects. However, we also report the incremental effects in our tables.

We include the following control variables ($X_{i,t-6}$) in the regression specifications: $relss_{t-6,t-1}$, $\log(ME)$, $log(B/M)$, $r_{-125,-6}$, $spread_{-10,-6}$, $oimb_{-10,-6}$, and $\sigma_{-10,-6}$. $relss_{-10,-6}$ is average daily relss from $t-10$ to $t-6$. $\log(ME)$ is logged market-cap as of day $t-6$. $log(B/M)$ is logged book to market ratio defined as in Fama and French (1993). $r_{-125,-6}$ is the return from $t-125$ to $t-6$. $spread_{-10,-6}$ is average daily effective spread from $t-10$ to $t-6$. $oimb_{-10,-6}$ is daily order imbalance from $t-10$ to $t-6$ where daily order imbalance is computed as daily buys minus sells scaled by daily volume. Buys and sells are defined as in Lee and Ready (1991). $\sigma_{-10,-6}$ is the average daily volatility from $t-10$ to $t-6$ where volatility is measured as the difference in the high and low price on day t divided by the high price: $(high-low)/high$. $tv_{-10,-6}$ is average daily share turnover of a stock from day $t-10$ to day $t-6$.

A. *Loan Fees, Fails to Deliver, and Imputed Fees*

Table IV, Panel A, presents the results of estimating equation (1) with the first proxy for constraints, fee_{max}, for NYSE and Nasdaq listed stocks. The regression includes all the controls mentioned above but the coefficients are not reported. Instead, we focus on the effect of constraints on the ability of short-sellers to respond to positive past returns and therefore only report the slope coefficient (β_j^+) of the fee_{max} based dummy variables interacted with positive past returns.

We find (like Diether, Lee, and Werner (2009b)) that short-sellers react strongly to past returns. The slope coefficients (β_j) are significant and positive for all fee_{max} cutoffs less than or equal to 7%. The magnitude of the slope coefficient for NYSE (Nasdaq) ranges from a highly significant 0.384 (0.224) when fee_{max} is the general borrowing rate to an insignificant -0.024 (0.050) when fees exceeds 7%. Thus one percent return leads to an increase of 0.384% (0.224%) in relative short selling volume ($relss$) for stocks at the general borrowing rate but virtually no change in relative short selling volume for stocks in the highest fee_{max} category.

The slope coefficients are not monotonically declining in fees for NYSE stocks, but the slope coefficients generally decline as fees increase for Nasdaq stocks. We also test for the difference in slope coefficients, and find that $\beta_{>7}^+$ is significantly lower than β_{gb}^+ and the difference is -0.408 for NYSE stocks and -0.174 for Nasdaq stocks with t-statistics -4.30 and -2.76 respectively. For Nasdaq, but not for NYSE stocks, the slope coefficients are significantly lower for loan fees in excess of 1% than for loan fees at the general borrowing rate.

In sum, we find that the short-sale constraints as proxied for by past loan fees do significantly affect the behavior of short sellers. For NYSE stocks, the effect is only large and significant for fee_{max} greater than 7%. This corresponds to the top percentile of stocks listed on the NYSE. For Nasdaq the effect is large and significant for loan fees greater than 1%. This corresponds to about 14% of the observations. As a result, constricted lendable supply affects the behavior of short-sellers and limits the ability of short sellers to act on a perceived deviation of market price from fundamental value for some stocks.

Our second measure of constrained supply of lendable shares is based on fails to deliver. The results are reported in Table IV, Panel B. The regressions and controls are identical to the specifications we used previously in Table IV Panel A, and we now report the slope coefficients $\beta +_j$ where j refers to daily percentile cutoffs based on $fails_{max}$.

Based on fails to deliver as a proxy for constrained supply, the slope coefficients are generally (but not monotonically) declining in the constraint. For NYSE stocks, the slope coefficient $\beta_{<20}$ is a highly significant 0.505. Contrarian behavior is significantly affected starting with the second quintile for NYSE stocks. In the top 10% of NYSE stocks, the magnitude of the response to past returns is cut in half and in the 99^{th} percentile it is small (0.10) and insignificant. The slopes for Nasdaq stocks range from a highly significant 0.227 for the lowest quintile of fails to an insignificant slope of 0.07 for the 99^{th} percentile. The differences in slopes is statistically significant for the top 10% of stocks sorted by fails to deliver.

Our third measure of constrained lending supply is imputed loan fees. The results are reported in Table IV, Panel C. The regressions and controls are identical to the specifications we used previously[11] Table IV Panel A, and we now report the slope coefficients $\beta +_j$ where j refers to daily percentile cutoffs based on $impute$.

The results are very similar to those for fails in Panel B, except that the ability of short sellers to act contrarian after positive past returns is now monotonically declining in imputed fees. The slope coefficients range from a highly significant 0.602 (0.293) for NYSE (Nasdaq) stocks with imputed fees in the lowest quintile to an insignificant 0.080 (0.106) for stocks in NYSE (Nasdaq) stocks in the 99^{th} percentile. The differences in slope coefficients are statistically significant for imputed fees above the 40^{th} percentile on NYSE and above the 80^{th} percentile on Nasdaq.

Thus, even using our imputed loan fee measure of short-sale constraints we find that constraints make it more difficult for short-sellers to pursue a contrarian strategy following positive returns. And, as before, it takes extremely high levels of constraints (99^{th} percentile) for the constraints to be high enough to completely wipe out the contrarian response of short sellers.

[11] The $impute$ measure is formed in part based on market-cap, B/M, and one year past returns. We use those variables as controls in these regressions. Thus we are over controlling in these specifications. When we drop market-cap, B/M, and the momentum controls the results get a little stronger. For example, the Nasdaq slope interaction for the 99^{th} percentile is only an 0.021 instead of 0.106.

B. Alternative Measure of Constraints

We next consider institutional ownership (*instown*) as a proxy for constrained lendable supply. Low institutional ownership has been used in the literature to proxy for constrained short selling (see, for example, Asquith, Pathak, and Ritter (2005) and Nagel (2005)). We measure institutional ownership as a fraction of shares outstanding at the end of the last quarter and create a set of dummy variables based on the percentiles of institutional ownership.

In Table V, we report the results from estimating equation (1) with institutional ownership as our proxy for short-sale constraints. The table reports the slope coefficients for institutional ownership based dummy variables interacted with positive past returns. The regressions and controls are identical to the specifications we used previously in Table IV, and we report the slope coefficients $\beta+_j$ where j refers to daily percentile cutoffs based on *instown*.

For NYSE stocks, all the estimated slope coefficients are positive and highly significant. Clearly, short sellers in NYSE stocks are able to increase short selling following positive past returns regardless of very low institutional ownership (a typical stock in the 1^{1st} percentile for NYSE stocks has institutional ownership around 9%). Moreover, there is no significant difference in any of the slope coefficients. For Nasdaq stocks, short sellers respond significantly to past positive returns for institutional ownership higher than the 10^{th} percentile. However, they do not execute contrarian strategies following positive returns when institutional ownership falls below the 10^{th} percentile (a typical stock in the 10^{th} percentile for Nasdaq stocks has ownership around 12%). The differences in slopes for the last two columns are negative and statistically significant.

As NYSE traders' ability to reduce short sales in response to negative past returns are unaffected by the level of institutional ownership, we conclude that institutional ownership does not appear to be a good proxy for short sale constraints for NYSE stocks. By contrast, very low levels of institutional ownership appears to be a reasonable alternative proxy for short sale constraints for Nasdaq stocks.

C. Composite Constraint Measure

The measures we have introduced so far are all proxies for restricted supply of lendable shares. A natural question to ask is the extent to which these measures overlap. Panel A of Table VI presents pooled correlation by exchange for fee_{max}, $fails_{max}$, and $impute$. In each case the the correlation is positive. For example, fee_{max} has a correlation of 0.40 with $fails_{max}$ and 0.48 with $impute$ for NYSE stocks. This suggests that while there is significant overlap between our measures, they do potentially capture different aspects of constrained supply of lendable shares. To ensure that we get the broadest possible measure of such constraints, and to economize on table space, we create a composite measure of constraints. This measure, *composite*, is the sum of normalized fee_{max}, $fails_{max}$, and $impute$. Each variable is normalized on a daily basis by exchange to a mean of zero and a standard deviation of 1.

Panel B of Table VI report pooled summary statistics of short-selling activity (*relss*) across various composite constraint measure percentiles. For NYSE stocks short selling activity (*relss*) is fairly similar across the different percentile categories but increasing across the constraint percentile categories until the 99^{th} percentile. Activity in the 99^{th} percentile is the same as the [20,40) percentile category. The pattern is more dramatic for Nasdaq stocks. Short-selling activity doesn't monotonically decrease across the percentile categories, but stocks in the 99^{th} percentile have median activity less than half that of those in the bottom 20% (33% versus 16% percent). Stocks in the [90,99] percentile category have median activity 9 percentage points lower.

We do not have any specific prediction about the relation between short-selling activity and our constraint measure. Our constraint measure is meant to finds stocks where it is expensive or difficult to significantly increase short selling activity (i.e., where abnormal activity is expensive). Still, it is intuitive that our measure should be negatively correlated with short-selling activity. This may be another indication that binding constraints are a much larger issue for Nasdaq stocks and that constraints only bind for a relatively small cross-section of NYSE stocks.

We repeat the pooled regression analysis in equation (1) with the measure of short-sale constraints based on our *composite* constraint measure. In Table VII Panels A and B we report the estimated slope coefficients from positive past returns (β_j^+) and the slope coefficients from negative past returns (β_j^-). As before, we suppress reporting of the estimated coefficients from the remaining control variables.

We turn to analyzing how the composite constraint affects short sellers' ability to respond to positive past returns in Panel A. While short-sellers on both markets are strongly contrarian they find it increasingly difficult to respond to positive past returns as the composite constraint becomes tighter. The slope coefficients for the top percentile on both markets, $\beta_{>99}^+$, are not significantly different from zero which means that short sellers no longer act contrarian with respect to positive past returns. Moreover, the coefficients decline (virtually) monotonically as we move from lower to higher percentiles of the composite constraint both for NYSE and Nasdaq stocks. The differences in the slope coefficients for higher percentiles of constraints are significantly different from the slope of the first quintile for the 2nd quintile and above for NYSE stocks and for the top decile among Nasdaq stocks.

Panel B of Table VII reports the effect of the composite constraint on short sellers' ability to respond to *negative* past returns. Diether, Lee, and Werner (2009b) find that short sellers are contrarian also following negative past returns. In other words, they reduce their short selling activity significantly following negative returns. We do not expect the contrarian pattern to change on the negative side because constraints do not affect short sellers' ability to reduce activity following negative returns.

The results show that the estimated slope coefficients for all percentiles of the composite constraint are negative and significant both for NYSE and Nasdaq. The estimated slope coefficients both for NYSE and Nasdaq look like they first decline when constraints tighten, and then start increasing again. However, none of these differences are statistically significant. As a result, we conclude that traders' desire to reduce their short selling following negative returns is not significantly affected by our composite constraint measure.

For completeness, we run regressions that interact the composite based dummy variable with contemporaneous returns instead of past returns. The estimated slope coefficients for positive contemporaneous returns are reported in Table VIII. A couple of things are worth noting. First, short sales increase significantly in positive past returns for all percentiles of the composite constraint aside from the 99^{th} percentile on the Nasdaq exchange. Second, the magnitude of the coefficients are generally much larger for contemporaneous than for past positive returns. For example, $\beta^{+}_{<20}$ is 2.014 (1.016) compared to a $\beta^{+}_{>99}$ of 0.495 (0.078) for NYSE (Nasdaq). Third, the slope coefficients are monotonically declining in the percentiles of the composite constraint and all the differences in slopes are highly significant and large in magnitude. For both NYSE and Nasdaq stocks by the third quintile of constraints the magnitude of the slope coefficient has been reduced by almost half. As a result we conclude that constraints do affect short sellers' ability to respond even to contemporaneous positive returns and for high constraint levels the reduction in contrarian behavior is dramatic (although there is still some contrarian response).

We conclude that our *composite* measure works well in capturing limited supply of lendable shares. Constraints as captured by our measure clearly affect the strategies of NYSE and Nasdaq short sellers. The results suggest that constraints do effect the cross section of stocks and this has potential implications for the likelihood of mispricing. However, only for extremely high levels of the composite constraint do short sellers become completely unresponsive to past returns and not act as contrarians on average.

IV. Efficiency

Our results so far suggest that our proxies for constraints work quite well in detecting when the supply of lendable shares is limited. Limited supply reduces the ability of short sellers to trade based on what they perceive is a deviation of market price from fundamental value. If short sellers help correct deviations of prices from fundamental value, prices will be less efficient when short sellers are constrained. At the heart of an efficient market is the notion that prices incorporate relevant information quickly. If short-sale constraints reduce efficiency, then constrained stocks should incorporate new information more slowly than unconstrained stocks. We test for this by examining the relation between our constraint measure and price delay (Hou and Moskowitz (2004)).

In a given month for a given stock we compute price delay by regressing daily stock returns over a two month window (t to $t+42$) on contemporaneous market returns, lagged market returns, and lagged own stock returns:

$$r_{i,t} = \alpha + \beta r_{M,t} + \sum_{j=1}^{2} \delta_{-j} r_{M,t-j} + + \sum_{j=1}^{2} \gamma_{-j} r_{i.t-j} + \varepsilon_{i,t} \tag{2}$$

$$Delay = 1 - \frac{R^2_{\delta_{\forall j}=0, \gamma_{\forall j}=0}}{R^2} \tag{3}$$

More efficient stocks should have less price delay. In other words, stale information contained in past own stock returns and past market returns should explain less of the variation in today's return.

We test whether constrained stocks have bigger price delays by running pooled monthly regressions of price delay on past short-sale constraint proxies, other stock level control variables, and monthly fixed effects. We include the same stock level control variables as in our previous empirical tests. Specifically we include controls for past short selling activity ($relss_{-10,-6}$), five day past returns ($r_{-5,-1}$), six month past returns ($r_{-125,-6}$), lagged market cap, lagged book to market, effective spread ($spread_{-10,-6}$), order imbalance ($oimb_{-10,-6}$), volatility ($\sigma_{-16-,-6}$), and share turnover ($tv_{-10,-6}$). Note, that since price delay is measured over a two month window there will be some serial correlation in the dependent variable for our pooled monthly regressions. There is also likely some potential cross-correlation. Consequently, we adjust standard errors by double clustering by both month and stock (Thompson (2009).

Table IX reports the results of these regressions for our different constraint measures. Note, that all of these coefficients are reported as marginal differences relative to the base category (the least constrained group of stocks). We find that constrained stocks have significantly higher price delay for every constraint measure. The coefficients are also large in magnitude. For example, Panel A shows that NYSE (Nasdaq) stocks in the highest fee_{max} category have an average price delay measure that is over 11 (10) percentage points higher than stocks in the lowest fee_{max} category. These represent large increases since price delay for the lowest fee_{max} category is 29% for NYSE stocks and 36% for Nasdaq stocks.

The results for the composite constraint measure are similar. Stocks in the 99^{th} percentile for NYSE (Nasdaq) stocks have an average price delay that is 9.5 (7.7) percentage points higher than the lowest composite quintile. We also find that price delays are significantly higher for a much larger cross section of Nasdaq stocks. Using the composite measure, the top quintile of Nasdaq stocks have significantly more price delay but only the top 1% of NYSE stocks do.

The results from the regressions indicate that price delay is significantly larger for constrained stocks, even after controling for stock characteristics. This suggests that constrained stocks are less efficient. Our explanation for this lower efficiency is that short sellers are limited in their ability to correct deviations from fundamental value in constrained stocks.

V. Predictability

Our proxies for constraints appear to be able to detect when the lendable supply of shares is limited. As we have noted previously, limited supply reduces the ability of short sellers to trade based on what they perceive is a deviation of market price from fundamental value. In turn, this will potentially affect any link between short selling activity and future returns. For example, Boehmer, Jones, and Zhang (2008) and Diether, Lee, and Werner (2009b)) find that high (low) short selling activity is associated with significant abnormal negative (positive) future returns both for NYSE and Nasdaq stocks.

The presence of short-sale constraints may have several consequences. First, as pointed out by Miller (1977), when short sellers are constrained, market prices are more likely to exceed fundamentals. This means that short sellers could in theory generate larger profits if they were able to pursue contrarian strategies in stocks with constrained lendable supply. Second, if short-sellers are constrained, we cannot determine whether low short-selling activity is caused by low demand from short-sellers or low supply of lendable shares. If low short sales are caused by low demand, we predict that future returns should be positive. By contrast, if low short-selling activity is caused by low supply, we predict that future returns should be negative. For both these reasons, the link between short-selling activity and future returns is likely weaker or no longer positive when short-selling activity is low for constrained stocks. Additionally, some our previous results suggest that a wider cross section Nasdaq stocks is constrained than NYSE stocks. Thus we expect these patterns to show up more strongly among Nasdaq stocks (particularly given that there are data constraints for forming short selling portfolios within very extreme constraint levels).

The previous literature (e.g., Boehmer, Jones, and Zhang (2008) and Diether, Lee, and Werner (2009b)) has examined the relation between short selling activity and future returns by first sorting stocks into portfolios based on short-selling activity, and then examining the returns to a strategy of buying the stocks with low shorting activity and selling the stocks with high shorting activity. Implicitly, this assumes that shorting activity is low by choice and not because short-sellers are constrained due to limited supply of lendable shares. As discussed above, in practice we cannot distinguish the two so we do not know whether the resulting bias in future returns is positive or negative for the low short sale portfolio. In addition, the return on the low short-selling portfolio is potentially biased upward due to the Miller (1977) effect. If the positive bias of future returns (due to overreaction) outweighs the negative bias (due to misinterpreting low short sales as low demand) when short sales are low, it may translate into larger abnormal returns to the low-high short-sale portfolios.

In Table X, we conduct a two-way portfolio sort of short selling activity and constraints.[12] Specifically, we first sort stocks each day (t) into quintiles based on *relss*, and independently sort into different buckets based on the composite constraint measure. Finally, we form equal-weight portfolios for the stocks in each bin for NYSE and Nasdaq stocks respectively. We examine the returns of all these portfolios from $t+1$ to $t+5$. We then compute size and book-to-market adjusted returns based on the 25 value-weight portfolios (Fama and French (1993)) for each portfolio.[13] The

[12]Table X reports results for portfolios but return predictability regressions yield results similar in magnitude. Specifically, we also run pool regressions of 5 day subsequent average returns on short-selling constraints, past market-cap, past book to market, 5 day past returns, 6 month past returns, and day fixed effects (the standard errors are clustered by stock and by date).

[13]Specifically, On the last day of June of year 2004 and 2005 we sort NYSE stocks by their market equity (ME). We also sort NYSE stocks independently by their book to market ratio. We use the ME and B/M breakpoints to allocate all stocks into the appropriate ME deciles and ME and B/M quintiles. We then form 25 size-B/M portfolios using all common stock on CRSP will lagged price greater than or equal to 5 dollars. The B/M ratio in June of year t is

results are reported in Table X.

The first column in Table X reports the results for equal-weight portfolios sorted by short selling activity, *relss*, only (note, the table reports average daily abnormal returns for all columns). The return traders would obtain if they could go long the portfolio of low *relss* stocks and short the portfolio of high *relss* stocks is a highly significant 0.043% per day (T-statistic of 3.47) for NYSE stocks and a significant 0.049% (T-statistic of 2.366) for Nasdaq stocks. Compounding to a monthly returns the spread portfolio delivers average abnormal returns of 0.9% and 1.0% per month. In summary, short selling activity predicts future returns in this sample.

Columns 2-3, 4-5, and 6-7 show *relss*/composite constraint portfolio average abnormal returns. In column 2, we form *relss* portfolios excluding stocks in the highest constraint quintile and in column 3 we form *relss* portfolios just using the top quintile. Columns 4 and 5 is formed analogously using the top decile of the composite constraints and columns 6 and 7 are formed analogously only using stocks in the top 5% of the composite measure.

There is not much evidence that return predictability is different for stocks with high composite constraint measure among NYSE stocks. The average abnormal return for Low-High is 0.043% per day excluding the 5% most constrained and 0.041% for the top 5% most constrained stocks (although the spread is not significant). More importantly, the average abnormal return on the low portfolio is lower for the most constrained stocks, but the magnitude is not that large and it is insignificant: 0.019% verse 0.028% per day day (a little over 20 basis points per month).

On the other hand, the results are much stronger for Nasdaq stocks particularly when examining the top 5% most constrained stocks. Interestingly, the Low-High spread for the most constrained stocks is actually quite a bit bigger than for the unconstrained stocks: 0.080% vs 0.050% per day (a difference of over 60 basis points per month). However, the average spread return for the most constrained stocks is not significant and neither is the difference between the two spreads. There is a dramatic difference between the low *relss* quintile for the most constrained stocks. Among the top 5% most constrained stocks, average abnormal returns are negative (-0.043% per day or

comprised of the book equity (B) for the fiscal year ending in calendar year $t-1$, and market equity (M) from end of December of $t-1$. The portfolios are rebalanced annually.

-0.9% per month). The difference between the average abnormal returns on the low *relss* portfolios between constrained and unconstrained is 0.085% per day (about 1.8% per month). We conjectured earlier that the signal is likely most muddled for the low portfolio as it is most subject to opposing effects. The results are consistent with this hypothesis. However, we note that the differences between constrained and unconstrained low *relss* portfolios are not statistically significant (t-stat = 1.19).

In summary, we do find evidence that the relation between short-selling activity and returns is different for the most constrained stocks. Specifically, for the most constrained stocks, average abnormal returns are actually negative for stocks that are lightly shorted. Thus the previously documented relation between short selling activity and future returns breaks down for the most constrained stocks.

VI. Conclusion

In this paper we examine how constrained lending supply affects high-frequency short-sale strategies. Our results show that when the supply of lendable shares is constrained based on our proxies, the positive relation between past returns and future short selling is reduced significantly. This effect is significant both for Nasdaq and NYSE listed stocks using all three of our primary proxies. It is also highly significant for our *composite* proxy for limited supply of lendable shares. We find that as much as one-third of the cross-section experiences a significant reduction in the contrarian response of short sellers. This has potentially important implications because if short sellers are unable to fully implement their contrarian positions because of short-sale constraints, mispricing, all else equal, becomes more likely.

We also find that when the constraint level is very high the contrarian relation between past returns and short selling is completely eliminated. We find that the effect in only the top 1% of stocks listed on the NYSE or Nasdaq. Thus constraints only seem to completely eliminate contrarian short sale strategies for a small number of stocks on both exchanges.

Furthermore, we find that constrained stocks are less efficient than unconstrained stocks.

Specifically, we find that price delays are significantly higher for stocks with limited lendable supply. This effect is large, with delay being as much as 10% higher for the most constrained stocks (the top 1%). In other words, when constraints make it difficult for short sellers to trade on short-term overreaction, the market price deviates from fundamental value more often and for longer periods of time.

Finally, we do find evidence that the relation between short-selling activity and returns is different for the most constraint stocks. Specifically, for the most constrained stocks, average abnormal returns are actually negative for stocks that are lightly shorted. Thus the previously documented relation between short selling activity and future returns breaks down for the most constrained stocks.

Taken together, our results emphasize that short sellers play an important role in equity markets. They show that when constraints make it costly for short sellers to trade on short-term overreaction market prices are less efficient.

Appendix

We also examine whether short sales are affected by the more stringent rules that apply after a stock has spent a significant period on one of the exchange's "threshold list." A security is placed on the threshold list if it has significant fails to deliver (more than 10,000 shares and at least one-half of one percent of the issuer's total shares outstanding) for more than five consecutive settlement days. Short sellers in stocks on these threshold lists are subject to tightened delivery requirements. Specifically, if a stock is on the threshold list for 13 consecutive settlement days, broker-dealers are required to close-out the position and are also prohibited from further short sales without pre-borrowing the shares.

Threshold lists were downloaded from NYSE's and Nasdaq's websites. The threshold list has been available from the beginning of January (2005) and was enacted as part of RegSHO. Table A1 reports summary statistics as of the first day a stock is published on the list. A stock is included in our sample if it was published on the list between January 6, 2005 and August 31, 2005 and if the stocks is available from our lender. Note that there are only 43 different NYSE stocks in our threshold sample. As a result, we focus our empirical analysis of threshold lists on Nasdaq stocks.

The median time a stock spends on the list is 15 trading days for NYSE stocks and 12 days for Nasdaq stocks. The averages are much higher because a few of the stocks stay on the list for a very long time. All of these stocks were initially listed during the first 8 months of 2005 but several stocks did not get off the list until 2006 and one stock did not make it off the list until 2007.

At the time a stock appears on the threshold list, median *relss* is 22% for Nasdaq stocks which is about 9% percentage points lower than for the entire sample. The median market-cap of the Nasdaq stocks at the time of listing is only 110 million which is less than half the size of the typical stock in the entire sample. Thus the Nasdaq threshold sample is skewed toward smaller stocks. The summary statistics also show a link between being published on the threshold list and loan fees. The average loan fee on the day of listing is 4.16% and the average maximum loan fee from t-125 to t-43 is 4.94% per annum.

To proxy for constrained short selling, we define three dummy variables based on threshold list information. The first is a dummy that equals one if a stock is on the list on day t: *thresh*. The second dummy equals one if the stock has currently been listed 13 consecutive days or less: $thresh_{\leq 13}$. The last dummy equals one if a stock has currently been listed more than 13 consecutive days: $thresh_{>13}$. Recall that the tightened delivery requirements come into effect when a stock has been on the list more than 13 days. We therefore expect that short selling is particularly constrained for stocks which have been on the threshold list more than 13 days.

To examine the effect of threshold listing and the post 13 day restrictions on short-selling activity we estimate equation (1) with three dummy variables to capture constraints based on the threshol list. The first is a dummy that equals one if a stock is on the list on day t: *thresh*. The second dummy equals one if the stock has currently been listed 13 consecutive days or less: $thresh_{\leq 13}$. The last dummy equals one if a stock has currently been listed more than 13 consecutive days: $thresh_{>13}$.

The results are in Table A2. The slope coefficient when the security is on the threshold list, β^{+}_{thresh} is 0.161 which is lower, but not significantly different from the slope for the rest of the sample (0.221). In the last part of Panel B we use separate dummies for stocks that have been on the threshold list more than 13 days, $\beta^{+}_{thresh>13}$. The slope coefficients show that the response of short sales to past returns at 0.126 is lower that for those not on the list at 0.221. However, the difference of -0.095 is not statistically significant.

Taken together, these results suggest that being on the threshold list even for those stocks that remain on the list 13 days when more stringent locate and delivery requirements are enforced only has a small hand in constraining short sellers' contrarian strategies following positive returns. In other words, we find only weak evidence that being on a threshold list affects contrarian short-sale strategies.

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Table I
Summary Statistics: Short-Sale Contracts

This table presents pooled summary statistics for short-sale contracts. Loan Fee is the interest rate per annum that the short-seller pays to the lender. The rebate rate is the interest rate from the collateral account that is rebated back to the short-seller. The loan fee plus the rebate rate equals that interest rate earned off of the short-sale collateral. Contract size is the number of shares borrowed by the short-seller multiplied the price. Contract length is the number of trading day the shares were on loan. Price is the closing stock price on the first day of the short-sale. ME is the market-cap of the shorted stocks on the first day of the contract. B/M is lagged book to market ratio computed as in Fama and French (1993). *instown* is lagged quarterly institutional ownership as a fraction of shares outstanding. The time period is September 1, 1999 to August 31, 2005.

	NYSE Contracts (N=119,827)		Nasdaq Contracts (N=197,489)	
	Mean	Median	Mean	Median
Loan Fee	1.64	0.16	3.74	3.08
Rebate Rate < 0%	0.22	0.00	0.54	1.00
Contract Size ($)	1,221,497.21	241,237.00	300,504.41	40,098.00
Contract Length (days)	27.30	6.00	33.36	8.00
Price	24.70	19.25	11.88	7.00
ME (millions)	7,999.63	1,352.43	1,546.48	163.82
B/M	1.11	0.72	0.65	0.34
instown	65.36	69.66	37.25	28.44

Table II
Summary Statistics: Stock Characteristics

This table presents cross-sectional summary statistics. *relss* is the number of shorted shares divided by traded shares per day (in percent) averaged over the sample period. *price* is the share price of a stock averaged over the sample period. *ME* is average lagged market-cap (in millions). B/M is average lagged book to market equity as defined in Fama and French (1993). *instown* is average lagged quarterly institutional ownership as a fraction of shares outstanding. *spread* is the effective spread (in %) averaged over the sample period for each stock. *oimb* is buy order imbalance of a stock averaged over the sample period (in %) and is computed as daily buys minus sells scaled by daily volume. Buys and sells are defined as in Lee and Ready (1991). σ is the difference in the high and low price divided by the high price ($(high - low)/high$) averaged over the sample period. $tv_{-5,-1}$ is average daily share turnover of a stock for day $t-5$ to day -1 averaged over the sample period. The sample only includes NYSE and Nasdaq stocks with CRSP share code 10 or 11 and with a price greater than or equal to $1 at the end of year 2004. The time period is January 3, 2005 to October 31, 2005.

	NYSE Stocks			Nasdaq Stocks		
	Stocks	Mean	Median	Stocks	Mean	Median
relss	1,313	23.91	24.09	2,145	29.74	31.23
fails	1,313	0.04	0.00	2,145	0.06	0.00
price	1,313	33.19	29.41	2,145	17.17	13.28
ME	1,313	7,960.19	1,614.31	2,145	1,259.56	249.73
B/M	1,272	0.64	0.55	2,096	0.51	0.43
instown	1,313	73.32	78.43	2,145	50.70	49.13
shint	1,313	4.17	2.75	2,145	3.84	2.22
spread	1,313	11.33	5.71	2,145	50.30	25.20
oimb	1,313	8.04	8.02	2,145	-1.22	-0.94
σ	1,313	2.42	2.23	2,145	3.83	3.50
tv	1,313	0.74	0.59	2,145	0.85	0.57

Table III
Panel Regressions: Monthly Loan Fees and Stock Characteristics

We regress end of month loan fee (fee) on past stock characteristics. ME is market cap from month $t-1$. B/M is lagged book to market ratio defined as in Fama and French (1993). r_{-1} is the return in month $t-1$. $r_{-12,-2}$ is the return from month $t-12$ to $t-2$. $instown$ is institutional ownership from the end of the previous quarter measured as a fraction of shares outstanding. $disp$ is average dispersion from $t-3$ to $t-1$ where dispersion is the standard deviation of one year ahead analyst earnings forecasts divided by the absolute value of the mean of the forecasts. $price$ is the stock price from month $t-1$. tv is average daily share turnover during the past 12 months. σ is the standard deviation of daily returns during the past 12 months. $alyst$ is the number of analyst covering the stock in month $t-1$. $shint$ is short interest as a fraction of the shares outstanding from month $t-1$. $r_{f,-1}$ is the lagged monthly t-bill rate. $r_{M,-1}$ and $r_{M,-12,-2}$ are the lagged return on the market portfolio and the eleven month return on the market portfolio ($t-12$ to $t-2$). The sample only includes NYSE (Nasdaq) stocks with CRSP share code 10 or 11 and stocks where the lender shares available to lend. The regressions include standard errors that take into account clustering by calendar date. The time period is September, 1999 to December 30, 2004. T-statistics are in parenthesis.

	NYSE Stocks				Nasdaq Stocks			
$\log(ME)$	-0.054	-0.032	-0.017	0.007	-0.185	-0.076	-0.021	0.034
	(-16.97)	(-10.98)	(-6.03)	(2.26)	(-15.16)	(-13.35)	(-4.42)	(5.79)
$\log(B/M)$	-0.009	-0.006	-0.013	-0.014	-0.239	-0.136	-0.146	-0.088
	(-1.87)	(-0.93)	(-2.09)	(-3.05)	(-11.20)	(-7.43)	(-7.95)	(-7.73)
r_{-1}	-0.353	-0.314	-0.265	-0.256	-0.154	-0.324	-0.204	-0.137
	(-6.22)	(-6.16)	(-5.42)	(-5.08)	(-1.70)	(-3.66)	(-2.40)	(-2.43)
$r_{-12,-2}$	-0.252	-0.197	-0.163	-0.125	-0.134	-0.214	-0.132	-0.154
	(-10.36)	(-10.39)	(-9.45)	(-7.36)	(-4.28)	(-7.19)	(-4.77)	(-7.19)
$instown$		-0.164	-0.128	-0.462		-0.490	-0.392	-1.208
		(-8.67)	(-7.22)	(-16.63)		(-12.36)	(-9.56)	(-20.15)
$\log(disp)$		0.011	0.002			0.028	-0.001	
		(2.43)	(0.56)			(4.09)	(-0.13)	
$\log(price)$			-0.066	0.001			-0.182	-0.110
			(-9.32)	(0.06)			(-10.26)	(-8.30)
$price < 5$				0.313				0.082
				(10.18)				(4.37)
$log(tv)$				0.051				0.169
				(4.87)				(12.06)
σ				2.913				3.953
				(3.30)				(8.35)
$log(1+alyst)$				-0.066				-0.196
				(-12.67)				(-19.35)
$shint$				5.007				7.468
				(10.95)				(10.85)
$r_{f,-1}$	22.178	15.049	16.436	41.435	82.356	58.800	74.845	78.550
	(3.44)	(2.53)	(2.78)	(7.93)	(7.68)	(6.26)	(8.88)	(9.34)
$r_{M,-1}$				-0.329				-0.450
				(-1.92)				(-1.64)
$r_{M,-12,-2}$				0.194				0.668
				(3.09)				(9.30)
Intercept	0.519	0.514	0.546	0.494	1.070	0.866	0.830	1.539
	(16.86)	(13.58)	(14.18)	(5.29)	(13.93)	(12.94)	(13.14)	(13.63)
R^2	0.062	0.056	0.058	0.179	0.074	0.101	0.108	0.185

Table IV
Short Selling Activity, Past Returns, and Constraints

We regress stock level shorting activity ($relss_t$) on past returns, short-sale constraint proxies, other stock level control variables, and day fixed effects. $relss_t$ is the number of shorted shares divided by traded shares on day t. $r_{-5,-1}$ is the return from $t-5$ to $t-1$. $r^+_{-5,-1}$ ($r^-_{-5,-1}$) equals $|r_{-5,-1}|$ if the return is positive (negative) and zero otherwise. fee_{max} is the maximum loan fee from $t-125$ to $t-43$. We form dummy variables based on fee_{max} cutoffs. Note, that gb = general borrowing rate. $fails_{max}$ is maximum daily fails as a fraction of shares outstanding during $t-125$ to $t-43$. $impute$ is the predicted loan fee. We form dummy variables based on percentile cutoffs for $fails_{max}$, and $impute$. The dummy variables are interacted them with $r^+_{-5,-1}$ and $r^-_{-5,-1}$). We run separate regressions for each constraint proxy by exchange. The control variables are $relss_{-10,-6}$, ME, B/M, $r_{-125,-6}$, $spread_{-10,-6}$, $oimb_{-10,-6}$, $\sigma_{-10,-6}$, and $tv_{-10,-6}$. $relss_{-10,-6}$ is average daily relss from $t-10$ to $t-6$. ME is market-cap from day $t-6$. B/M is book to market ratio defined as in Fama and French (1993). $r_{-125,-6}$ is the return from $t-125$ to $t-6$. $spread_{-10,-6}$ is average daily effective spread from $t-10$ to $t-6$. $oimb_{-10,-6}$ is daily order imbalance from $t-10$ to $t-6$. Order imbalance is computed as daily buys minus sells scaled by daily volume (as in Lee and Ready (1991)). $\sigma_{-10,-6}$ is the average daily volatility from $t-10$ to $t-6$ where volatility is $(P_{high}-P_{low})/P_{high}$. $tv_{-10,-6}$ is average daily share turnover from day $t-10$ to day -6. We only includes NYSE (Nasdaq) stocks with CRSP share code 10 or 11, stocks with lagged price greater than \$5, and stocks available to be borrowed from the lender. The regressions include calendar day dummies, and the standard errors take into account clustering by calendar date and stock (Thompson (2009)). The time period is January 17, 2005 to October 31, 2005. T-statistics are in parenthesis.

	Panel A: fee_{max} / past positive return interaction				
	β^+_{gb}	$\beta^+_{gb,1\%}$	$\beta^+_{1\%,4\%}$	$\beta^+_{4\%,7\%}$	$\beta^+_{>7}$
			NYSE Stocks		
Est. Slope Coef.: β^+_j	0.384	0.411	0.317	0.472	-0.024
	(10.44)	(13.56)	(3.76)	(4.61)	(-0.27)
Differences: $\beta^+_{b,1\%}-\beta^+_j$		0.027	-0.067	0.088	-0.408
		(0.59)	(-0.74)	(0.82)	(-4.30)
			Nasdaq Stocks		
Slope Coef.: β^+_j	0.224	0.271	0.092	0.117	0.050
	(10.82)	(12.82)	(1.92)	(3.11)	(0.86)
Differences: $\beta^+_{b,1\%}-\beta^+_j$		0.046	-0.132	-0.107	-0.174
		(1.62)	(-2.51)	(-2.52)	(-2.76)

	Panel B: $fail_{max}$ / past positive return interaction						
	$\beta^+_{\leq 20}$	$\beta^+_{20,40}$	$\beta^+_{40,60}$	$\beta^+_{60,80}$	$\beta^+_{80,90}$	$\beta^+_{90,99}$	$\beta^+_{>99}$
				NYSE Stocks			
Est. Slope Coef.: β^+_j	0.505	0.471	0.355	0.357	0.393	0.267	0.100
	(10.35)	(10.11)	(7.51)	(8.44)	(6.83)	(5.47)	(0.93)
Differences: $\beta^+_{0,20}-\beta^+_j$		-0.034	-0.150	-0.148	-0.112	-0.238	-0.405
		(-0.51)	(-2.37)	(-2.33)	(-1.55)	(-3.53)	(-3.37)
				Nasdaq Stocks			
Est. Slope Coef.: β^+_j	0.227	0.255	0.244	0.247	0.163	0.131	0.070
	(7.39)	(5.32)	(8.09)	(9.41)	(4.45)	(3.77)	(1.37)
Differences: $\beta^+_{0,20}-\beta^+_j$		0.027	0.016	0.020	-0.064	-0.096	-0.157
		(0.49)	(0.38)	(0.50)	(-1.33)	(-2.02)	(-2.56)

Panel C: *impute* / past positive return interaction	$\beta^+_{\leq 20}$	$\beta^+_{20,40}$	$\beta^+_{40,60}$	$\beta^+_{60,80}$	$\beta^+_{80,90}$	$\beta^+_{90,99}$	$\beta^+_{>99}$
NYSE Stocks							
Est. Slope Coef.: β^+_j	0.602	0.510	0.465	0.307	0.248	0.240	0.080
	(13.18)	(12.00)	(9.29)	(7.06)	(4.91)	(4.35)	(1.14)
Differences: $\beta^+_{0,20} - \beta^+_j$		-0.092	-0.138	-0.295	-0.354	-0.363	-0.522
		(-1.57)	(-2.14)	(-4.93)	(-5.28)	(-5.21)	(-6.26)
Nasdaq Stocks							
Est. Slope Coef.: β^+_j	0.293	0.239	0.234	0.231	0.163	0.122	0.106
	(6.99)	(7.24)	(7.82)	(7.83)	(4.35)	(4.10)	(1.33)
Differences: $\beta^+_{0,20} - \beta^+_j$		-0.054	-0.059	-0.062	-0.131	-0.171	-0.187
		(-1.06)	(-1.17)	(-1.24)	(-2.32)	(-3.31)	(-2.10)

Table V

Short Selling Activity, Past Returns, and Institutional Ownership

We regress stock level shorting activity ($relss_t$) on past returns, institutional onwership, other stock level control variables, and day fixed effects. $relss_t$ is the number of shorted shares divided by traded shares on day t. $r_{-5,-1}$ is the return from $t-5$ to $t-1$. $r^+_{-5,-1}$ ($r^-_{-5,-1}$) equals $|r_{-5,-1}|$ if the return is positive (negative) and zero otherwise. *instown* is lagged institutional ownership as a fraction of shares outstanding. We form dummy variables based on daily percentile cutoffs for *instown*. The dummy variables are interacted with $r^+_{-5,-1}$ and $r^-_{-5,-1}$). We run separate regressions for each exchange. The control variables are $relss_{-10,-6}$, ME, B/M, $r_{-125,-6}$, $spread_{-10,-6}$, $oimb_{-10,-6}$, $\sigma_{-10,-6}$, and $tv_{-10,-6}$. $relss_{-10,-6}$ is average daily relss from $t-10$ to $t-6$. ME is market-cap from day $t-6$. B/M is book to market ratio defined as in Fama and French (1993). $r_{-125,-6}$ is the return from $t-125$ to $t-6$. $spread_{-10,-6}$ is average daily effective spread from $t-10$ to $t-6$. $oimb_{-10,-6}$ is daily order imbalance from $t-10$ to $t-6$. Order imbalance is computed as daily buys minus sells scaled by daily volume (as in Lee and Ready (1991)). $\sigma_{-10,-6}$ is the average daily volatility from $t-10$ to $t-6$ where volatility is $(P_{high}-P_{low})/P_{high}$. $tv_{-10,-6}$ is average daily share turnover from day $t-10$ to day -6. The sample only includes NYSE (Nasdaq) stocks with CRSP share code 10 or 11, stocks with lagged price greater than \$5, and stocks available to be borrowed from the lender. The regressions include calendar day dummies, and the standard errors take into account clustering by calendar date and stock (Thompson (2009)). The time period is January 17, 2005 to October 31, 2005. T-statistics are in parenthesis.

	Panel A: *instown* / past positive return interaction						
	$\beta^+_{\geq 80}$	$\beta^+_{60,80}$	$\beta^+_{40,60}$	$\beta^+_{20,40}$	$\beta^+_{10,20}$	$\beta^+_{1,10}$	$\beta^+_{<1}$
	NYSE Stocks						
Est. Slope Coef.: β^+_j	0.364	0.422	0.410	0.446	0.316	0.354	0.324
	(7.98)	(8.89)	(8.95)	(8.85)	(5.14)	(5.90)	(3.84)
Differences: $\beta^+_{\geq 80}-\beta^+_j$		0.059	0.046	0.082	-0.048	-0.010	-0.040
		(0.97)	(0.73)	(1.25)	(-0.64)	(-0.13)	(-0.40)
	Nasdaq Stocks						
Est. Slope Coef.: β^+_j	0.214	0.210	0.229	0.260	0.249	0.098	0.012
	(6.67)	(6.52)	(7.84)	(8.05)	(5.07)	(2.23)	(0.17)
Differences: $\beta^+_{\geq 80}-\beta^+_j$		-0.003	0.016	0.046	0.036	-0.115	-0.202
		(-0.08)	(0.36)	(1.02)	(0.61)	(-2.11)	(-2.61)

Table VI
Composite Constraint Measure

In panel A we report a pooled correlation matrix of the variables we use to construct the composite constraint measure: fee_{max}, $fail_{max}$ and $impute$. fee_{max} is the maximum loan fee from $t-125$ to $t-43$. $fails_{max}$ is the maximum daily fails / shares outstanding during $t-125$ to $t-43$. $impute$ is the predicted loan fee. In panel B we report pooled summary statistics of short-selling activity ($relss$) across various composite constraint measure percentiles. The composite measure is the sum of normalized fee_{max}, $fails_{max}$, and $impute$. Each variable is normalized on a daily basis by exchange to a mean of zero and a standard deviation of 1. $relss_t$ is day t shorted shares divided by traded shares. Composite measure percentiles are computed each calender day. The sample only includes NYSE (Nasdaq) stocks with CRSP share code 10 or 11, stocks with lagged price greater than \$1, and stocks available to be borrowed from the lender. The time period is January 3, 2005 to October 31, 2005.

Panel A: Correlation of Inidividual Constraint Measures			
	fee_{max}	$fail_{max}$	$impute$
NYSE Stocks			
fee_{max}	1.00		
$fail_{max}$	0.40	1.00	
$impute$	0.48	0.29	1.00
Nasdaq Stocks			
fee_{max}	1.00		
$fail_{max}$	0.28	1.00	
$impute$	0.47	0.34	1.00

Panel B: Composite Constraint Measure Percentiles and $relss$							
	≤ 20	$[20,40)$	$[40,60)$	$[60,80)$	$[80,90)$	$[90,99)$	≥ 99
NYSE Stocks							
Mean	0.22	0.24	0.25	0.26	0.26	0.28	0.24
Median	0.21	0.22	0.24	0.25	0.25	0.27	0.22
Nasdaq Stocks							
Mean	0.33	0.33	0.32	0.28	0.29	0.24	0.19
Median	0.33	0.32	0.31	0.29	0.30	0.24	0.16

Table VII
Short Selling Activity, Past Returns, and a Composite Constraint Measure

We regress stock level shorting activity ($relss_t$) on past returns, a composite constraint measure, stock level control variables, and day fixed effects. $relss_t$ is day t shorted shares divided by traded shares. $r_{-5,-1}$ is the return from $t-5$ to $t-1$. $r^+_{-5,-1}$ ($r^-_{-5,-1}$) equals $|r_{-5,-1}|$ if the return is positive (negative) and zero otherwise. We form dummy variables based on daily percentiles of the composite constraint measure. These dummy variables are interacted with $r^+_{-5,-1}$ ($r^-_{-5,-1}$). The composite measure is the sum of normalized fee_{max}, $fails_{max}$, and $impute$. Each variable is normalized on a daily basis by exchange to a mean of zero and a standard deviation of 1. fee_{max} is the maximum loan fee from $t-125$ to $t-43$, $fails_{max}$ is the maximum daily fails / shares outstanding during $t-125$ to $t-43$, and $impute$ is the predicted loan fee. The control variables are $relss_{-10,-6}$, ME, B/M, $r_{-125,-6}$, $spread_{-10,-6}$, $oimb_{-10,-6}$, $\sigma_{-10,-6}$, and $tv_{-10,-6}$. $relss_{-10,-6}$ is average daily relss from $t-10$ to $t-6$. ME is market-cap from day $t-6$. B/M is book to market ratio. $r_{-125,-6}$ is the return from $t-125$ to $t-6$. $spread_{-10,-6}$ is average daily effective spread from $t-10$ to $t-6$. $oimb_{-10,-6}$ is daily order imbalance from $t-10$ to $t-6$. $\sigma_{-10,-6}$ is the average daily volatility $((price_{high}-price_{low})/price_{high}$ from $t-10$ to $t-6$. $tv_{-10,-6}$ is average daily share turnover from day $t-10$ to day -6. The sample only includes NYSE (Nasdaq) stocks with CRSP share code 10 or 11, stocks with lagged price greater than \$5, and stocks available to be borrowed from the lender. The regressions include calendar day dummies, and the standard errors take into account clustering by calendar date and by stock (Thompson (2009)). The time period is January 17, 2005 to October 31, 2005. T-statistics are in parenthesis.

	Panel A: Constraint / past positive return ($r^+_{-5,-1}$) interaction						
	$\beta^+_{\le 20}$	$\beta^+_{20,40}$	$\beta^+_{40,60}$	$\beta^+_{60,80}$	$\beta^+_{80,90}$	$\beta^+_{90,99}$	$\beta^+_{>99}$
	NYSE Stocks						
Est. Slope Coef.: β^+_j	0.598	0.484	0.441	0.306	0.231	0.294	0.052
	(12.55)	(12.10)	(10.06)	(7.31)	(4.36)	(5.29)	(0.66)
Differences: $\beta^+_{0,20}-\beta^+_j$		-0.114	-0.157	-0.292	-0.367	-0.304	-0.546
		(-1.94)	(-2.59)	(-4.79)	(-5.33)	(-4.23)	(-6.03)
	Nasdaq Stocks						
Est. Slope Coef.: β^+_j	0.293	0.212	0.274	0.226	0.181	0.122	0.014
	(6.81)	(6.27)	(9.61)	(8.78)	(4.25)	(3.60)	(0.24)
Differences: $\beta^+_{0,20}-\beta^+_j$		-0.080	-0.019	-0.067	-0.112	-0.171	-0.278
	(0.00)	(-1.49)	(-0.37)	(-1.36)	(-1.83)	(-3.19)	(-3.84)

	Panel B: Constraint / past negative return ($r^-_{-5,-1}$) interaction						
	$\beta^-_{\le 20}$	$\beta^-_{20,40}$	$\beta^-_{40,60}$	$\beta^-_{60,80}$	$\beta^-_{80,90}$	$\beta^-_{90,99}$	$\beta^-_{>99}$
	NYSE Stocks						
Est. Slope Coef.: β^-_j	-0.443	-0.464	-0.364	-0.377	-0.416	-0.325	-0.351
	(-9.37)	(-10.31)	(-8.38)	(-8.27)	(-8.17)	(-6.42)	(-3.85)
Differences: $\beta^-_{0,20}-\beta^-_j$		-0.021	0.080	0.066	0.027	0.119	0.092
		(-0.36)	(1.31)	(1.04)	(0.39)	(1.73)	(0.91)
	Nasdaq Stocks						
Est. Slope Coef.: β^-_j	-0.183	-0.205	-0.191	-0.197	-0.236	-0.258	-0.406
	(-4.33)	(-5.92)	(-5.28)	(-7.10)	(-5.86)	(-7.74)	(-4.85)
Differences: $\beta^-_{0,20}-\beta^-_j$		-0.022	-0.009	-0.014	-0.053	-0.075	-0.224
		(-0.40)	(-0.16)	(-0.28)	(-0.91)	(-1.39)	(-2.35)

Table VIII
Short Selling Activity, Contemporaneous Returns, and a Composite Constraint Measure

We regress stock level shorting activity ($relss_t$) on contemporaneous returns, a composite constraint measure, stock level control variables, and day fixed effects. $relss_t$ is day t shorted shares divided by traded shares. r_0 is the return on day t. r_0^+ (r_0^-) equals $|r_0|$ if the return is positive (negative) and zero otherwise. We form dummy variables based on daily percentiles of the composite constraint measure. The dummies are interacted them with r_0^+ and r_0^-. The composite measure is the sum of normalized fee_{max}, $fails_{max}$, and $impute$. Each variable is normalized on a daily basis by exchange to a mean of zero and a standard deviation of 1. fee_{max} is the maximum loan fee from $t-125$ to $t-43$, $fails_{max}$ is the maximum daily fails / shares outstanding during $t-125$ to $t-43$, and $impute$ is the predicted loan fee. The control variables are $relss_{-10,-6}$, ME, B/M, $r_{-125,-6}$, $spread_{-10,-6}$, $oimb_{-10,-6}$, $\sigma_{-10,-6}$, and $tv_{-10,-6}$. $relss_{-10,-6}$ is average daily relss from $t-10$ to $t-6$. ME is market-cap from day $t-6$. B/M is book to market ratio. $r_{-125,-6}$ is the return from $t-125$ to $t-6$. $spread_{-10,-6}$ is average daily effective spread from $t-10$ to $t-6$. $oimb_{-10,-6}$ is daily order imbalance from $t-10$ to $t-6$. $\sigma_{-10,-6}$ is the average daily volatility $((price_{high} - price_{low})/price_{high}$ from $t-10$ to $t-6$. $tv_{-10,-6}$ is average daily share turnover from day $t-10$ to day -6. The sample only includes NYSE (Nasdaq) stocks with CRSP share code 10 or 11, stocks with lagged price greater than \$5, and stocks available to be borrowed from the lender. The regressions include calendar day dummies, and the standard errors take into account clustering by calendar date and by stock (Thompson (2009)). The time period is January 17, 2005 to October 31, 2005. T-statistics are in parenthesis.

	Constraint / contemporaneous return (r_0^+) interaction						
	$\beta^+_{\leq 20}$	$\beta^+_{20,40}$	$\beta^+_{40,60}$	$\beta^+_{60,80}$	$\beta^+_{80,90}$	$\beta^+_{90,99}$	$\beta^+_{>99}$
	NYSE Stocks						
Est. Slope Coef.: β_j^+	2.014	1.902	1.573	1.177	0.895	0.793	0.495
	(19.48)	(21.81)	(18.66)	(14.25)	(7.39)	(8.56)	(2.07)
Differences: $\beta^+_{0,20} - \beta_j^+$		-0.111	-0.441	-0.836	-1.118	-1.221	-1.518
	(0.00)	(-1.06)	(-3.61)	(-6.92)	(-7.44)	(-8.96)	(-5.78)
	Nasdaq Stocks						
Est. Slope Coef.: β_j^+	1.016	0.827	1.015	0.635	0.573	0.333	0.078
	(12.21)	(10.18)	(14.40)	(15.23)	(9.13)	(5.57)	(0.90)
Differences: $\beta^+_{0,20} - \beta_j^+$		-0.189	-0.001	-0.381	-0.443	-0.683	-0.939
	(0.00)	(-1.69)	(-0.01)	(-4.22)	(-4.46)	(-6.43)	(-7.94)

Table IX
Pooled Monthly Regressions: Price Delay and Constraints

We regress price delay on past short-sale constraint proxies (fee_{max}, $fails_{max}$, $impute$, and $composite$), other stock level control variables, and month fixed effects. At the end of each month we run the following regression for all stocks in the sample:

$$r_{i,t} = \alpha + \beta r_{M,t} + \sum_{j=1}^{2} \delta_{-j} r_{M,t-j} + \sum_{j=1}^{2} \gamma_{-j} r_{i.t-j} + \varepsilon_{i,t}$$

The regression is run using daily data from to t to $t+41$. The price daily variable is computed as the following:

$$Delay = 1 - \frac{R^2_{\delta_{\forall j}=0,\gamma_{\forall j}=0}}{R^2}$$

fee_{max} is the maximum loan fee from $t-125$ to $t-43$. We form dummy variables based on fee_{max} cutoffs. Note, that gb = general borrowing rate. $fails_{max}$ is maximum daily fails as a fraction of shares outstanding during $t-125$ to $t-43$. $impute$ is the predicted loan fee. The composite measure is the sum of normalized fee_{max}, $fails_{max}$, and $impute$. Each variable is normalized on a daily basis by exchange to a mean of zero and a standard deviation of 1. We form dummy variables based on percentile cutoffs for $fails_{max}$, $impute$, and $composite$. We run separate regression for each constraint proxy. The control variables are $r_{-5,-1}$, $relss_{-10,-6}$, ME, B/M, $r_{-125,-6}$, $spread_{-10,-6}$, $oimb_{-10,-6}$, $\sigma_{-10,-6}$, and $tv_{-10,-6}$. $r_{-5,-1}$ is the return from day $t-5$ to $t-1$. ME is market-cap from day $t-6$. B/M is book to market ratio defined as in Fama and French (1993). $r_{-125,-6}$ is the return from $t-125$ to $t-6$. $spread_{-10,-6}$ is average daily effective spread from $t-10$ to $t-6$. $oimb_{-10,-6}$ is daily order imbalance from $t-10$ to $t-6$. Order imbalance is computed as daily buys minus sells scaled by daily volume (as in Lee and Ready (1991)). $\sigma_{-10,-6}$ is the average daily volatility from $t-10$ to $t-6$ where volatility is $(P_{high} - P_{low})/P_{high}$. $tv_{-10,-6}$ is average daily share turnover from day $t-10$ to day -6. The sample only includes NYSE (Nasdaq) stocks with CRSP share code 10 or 11, stocks with lagged price greater than \$5, and stocks available to be borrowed from the lender. The regressions include calendar day dummies, and the standard errors take into account clustering by calendar date by stock (Thompson (2009)). The time period is January, 2005 to October 2005. T-statistics are in parenthesis.

Panel A: fee_{max} bin dummy variable coefficients

	$fee_{max}^{gb,1\%}$	$fee_{max}^{1\%,4\%}$	$fee_{max}^{4\%,7\%}$	$fee_{max}^{>7\%}$
		NYSE Stocks		
Estimate	0.036	0.040	0.067	0.111
	(3.79)	(2.53)	(2.26)	(2.72)
		Nasdaq Stocks		
Estimate	0.005	0.035	0.096	0.098
	(0.54)	(2.96)	(7.03)	(3.54)

Panel B: $fail_{max}$ dummy variable coefficients

	$fail_{max}^{20,40}$	$fail_{max}^{40,60}$	$fail_{max}^{60,80}$	$fail_{max}^{80,90}$	$fail_{max}^{90,99}$	$fail_{max}^{>99}$
			NYSE Stocks			
Estimate	0.011	0.008	0.010	0.017	0.046	0.137
	(0.82)	(0.59)	(0.73)	(0.90)	(2.53)	(3.86)
			Nasdaq Stocks			
Estimate	0.015	0.010	0.026	0.066	0.066	0.056
	(0.76)	(0.87)	(2.53)	(4.54)	(3.95)	(2.42)

Panel C: *impute* dummy variable coefficients						
	$impute^{20,40}$	$impute^{40,60}$	$impute^{60,80}$	$impute^{80,90}$	$impute^{90,99}$	$impute^{>99}$
NYSE Stocks						
Estimate	-0.020	-0.015	-0.013	-0.014	0.003	0.095
T-stat	(-1.84)	(-1.34)	(-1.15)	(-0.99)	(0.21)	(2.62)
Nasdaq Stocks						
Estimate	-0.012	0.007	0.014	0.043	0.053	0.068
T-stat	(-1.05)	(0.45)	(0.77)	(3.10)	(2.94)	(3.10)

Panel D: *composite* dummy coefficients						
	$composite^{20,40}$	$composite^{40,60}$	$composite^{60,80}$	$composite^{80,90}$	$composite^{90,99}$	$composite^{>99}$
NYSE Stocks						
Estimate	-0.028	-0.010	-0.023	-0.012	0.022	0.095
T-stat	(-3.02)	(-0.89)	(-1.65)	(-0.85)	(1.29)	(2.47)
Nasdaq Stocks						
Estimate	-0.009	0.016	0.019	0.044	0.098	0.077
T-stat	(-0.77)	(0.91)	(1.23)	(2.88)	(5.46)	(2.18)

Table X

Daily relss/composite Constraint Equal Weight Portfolios

The table reports average abnormal returns for portfolios sorted by short-selling activity and the composite constraint. In day t we compute *relss* quintiles using all NYSE (Nasdaq) stocks available to be borrowed from our lender and with a closing price on day t at least equal to \$5.00. We also sort the stocks based on the composite constraint variable. We then form portfolios based on the intersection of thsee sorts. We compute the return on the portfolios from day $t+1$ to $t+5$. *relss* is the number of shorted shares divided by traded shares on day t. The composite measure is the sum of normalized fee_{max}, $fails_{max}$, and $impute$. Each variable is normalized on a daily basis by exchange to a mean of zero and a standard deviation of 1. fee_{max} is the maximum loan fee from $t-125$ to $t-43$, $fails_{max}$ is the maximum daily fails / shares outstanding during $t-125$ to $t-43$, and $impute$ is the predicted loan fee. Abnormal returns are computed by characteristically adjusting returns using 25 value weight size-BE/ME portfolios computed as in Fama and French (1993). The time period is January 3, 2005 to October 30, 2005. The t-statistics are adjusted for autocorrelation using the Newey-West (1987) procedure with lag=5.

Panel A: NYSE Stocks (Average Abnormal Returns)

relss quintiles	All Stocks	Excluding Top 20%	Top 20%	Excluding Top 10%	Top 10%	Excluding Top 5%	Top 5%
low	0.029	0.031	0.011	0.028	0.031	0.028	0.019
2	0.018	0.019	0.009	0.020	-0.006	0.019	-0.029
3	0.006	0.007	-0.003	0.005	0.011	0.007	-0.008
4	-0.004	-0.003	-0.009	-0.002	-0.019	-0.004	-0.001
High	-0.015	-0.015	-0.013	-0.014	-0.019	-0.015	-0.022
Low-High	0.043	0.046	0.025	0.043	0.050	0.043	0.041
T-stat	3.470	3.475	1.064	3.476	1.568	3.466	0.785

Panel B: Nasdaq Stocks (Average Abnormal Returns)

relss quintiles	All Stocks	Excluding Top 20%	Top 20%	Excluding Top 10%	Top 10%	Excluding Top 5%	Top 5%
low	0.038	0.047	0.000	0.042	0.006	0.042	-0.043
2	0.012	0.020	-0.023	0.015	-0.017	0.016	-0.058
3	-0.007	0.000	-0.041	-0.003	-0.053	-0.002	-0.090
4	-0.017	-0.010	-0.043	-0.012	-0.066	-0.013	-0.129
High	-0.011	-0.011	-0.012	-0.008	-0.046	-0.008	-0.123
Low-High	0.049	0.058	0.012	0.050	0.052	0.050	0.080
T-stat	2.366	2.702	0.321	2.314	1.032	2.318	0.984

Table A1
Summary Statistics: New Threshold Listings

This table presents summary statistics as of the first day a stock is published on the threshold list. *Days listed* refers to the total number of days a stock stays on the list. $relss$ is the number of shorted shares divided by traded shares (in percent) on the day of listing. fee is the loan fee on the day of listing. $fee_{max,-125,-43}$ is the maximum loan fee during day t-125 to t-43. $price$ is the share price of a stock on day $t-1$. ME is the market-cap (in millions) on the day $t-1$. B/M is lagged book to market equity as defined in Fama and French (1993). $instown$ is quarterly institutional ownership as a fraction of shares outstanding from the end of the quarter before listing. $r_{-5,-1}$ is the return from $t-5$ to $t-1$ before listing. $r_{-125,-6}$ is the return from day $t-125$ to $t-6$. The sample only includes NYSE and Nasdaq stocks with CRSP share code 10 or 11 and with a price greater than or equal to $1 at the end of year 2004. The stocks also must be available from the lender. The time period is January 6, 2005 to August 31, 2005.

	NYSE Stocks			Nasdaq Stocks		
	Stocks	Mean	Median	Stocks	Mean	Median
Days Listed	43	40.19	15.00	289	21.79	12.00
$relss$	43	0.27	0.26	289	0.24	0.22
fee	43	3.63	2.90	289	4.16	3.47
$fee_{max,-125,-43}$	43	3.92	3.00	289	4.94	4.71
$price$	43	17.51	9.69	289	8.72	4.14
ME	43	1622.05	469.62	289	232.40	110.16
B/M	34	0.97	0.69	258	0.50	0.27
$instown$	43	0.70	0.75	289	0.34	0.25
$r_{-5,-1}$	43	-0.01	-0.00	289	0.01	-0.01
$r_{-125,-6}$	43	-0.04	-0.12	289	0.08	-0.06

Table A2
Short Selling Activity, Past Returns, and The Threshold List

We regress stock level shorting activity ($relss_t$) on past returns, threshold list based dummy variables, other stock level control variables, and day fixed effects. $relss_t$ is the number of shorted shares divided by traded shares on day t. $r_{-5,-1}$ is the return from $t-5$ to $t-1$. $r^+_{-5,-1}$ ($r^-_{-5,-1}$) equals $|r_{-5,-1}|$ if the return is positive (negative) and zero otherwise. $thresh$ equals one if a stock is on the threshold list. We form dummy variables based days listed for $thresh$. The dummies are interacted with $r^+_{-5,-1}$ and $r^-_{-5,-1}$). The control variables are $relss_{-10,-6}$, ME, B/M, $r_{-125,-6}$, $spread_{-10,-6}$, $oimb_{-10,-6}$, $\sigma_{-10,-6}$, and $tv_{-10,-6}$ $relss_{-10,-6}$ is average daily relss from $t-10$ to $t-6$. ME is market-cap from day $t-6$. B/M is book to market ratio defined as in Fama and French (1993). $r_{-125,-6}$ is the return from $t-125$ to $t-6$. $spread_{-10,-6}$ is average daily effective spread from $t-10$ to $t-6$. $oimb_{-10,-6}$ is daily order imbalance from $t-10$ to $t-6$. Order imbalance is computed as daily buys minus sells scaled by daily volume (as in Lee and Ready (1991)). $\sigma_{-10,-6}$ is the average daily volatility from $t-10$ to $t-6$ where volatility is $(P_{high}-P_{low})/P_{high}$. $tv_{-10,-6}$ is average daily share turnover from day $t-10$ to day -6. The sample only includes NYSE (Nasdaq) stocks with CRSP share code 10 or 11, stocks with lagged price greater than \$5, and stocks available to be borrowed from the lender. The regressions include calendar day dummies, and the standard errors take into account clustering by calendar date and stock (Thompson (2009)). The time period is January 17, 2005 to October 31, 2005. T-statistics are in parenthesis.

	Threshold list / past positive return interaction Nasdaq Stocks				
	β^+_{not}	β^+_{thresh}	$\beta^+_{thresh}-\beta^+_{not}$		
Estimate	0.221	0.161	-0.060		
	(15.40)	(2.73)	(-0.98)		
	β^+_{not}	$\beta^+_{thresh\leq 13}$	$\beta^+_{thresh>13}$	$\beta^+_{thresh\leq 13}-\beta^+_{not}$	$\beta^+_{thresh>13}-\beta^+_{not}$
Estimate	0.221	0.197	0.126	-0.024	-0.095
T-stat	(15.40)	(2.24)	(2.14)	(-0.27)	(-1.58)