Supply and Demand Shifts in the Shorting Market

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Abstract

Using proprietary data on stock loan fees and stock loan quantities from a large institutional investor, we examine the link between the shorting market and stock prices. Employing a unique identification strategy, we are able to classify shifts in the supply and demand for shorting. We find that shorting demand is an economically and statistically important predictor of future stock returns. The magnitude of this effect is large: an increase in shorting demand leads to negative abnormal returns of 2.54% in the following month. Second, we find that the shorting market is an important mechanism for private information revelation into prices. Specifically, we show that our results are stronger in environments with less public information flow, and that *net* of shorting costs, trading strategies based on our identification strategy yield over 3% per month on average.

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I. Introduction

Exploring the link between the market for short selling and stock prices is the subject of a large and growing literature. Despite the large body of work on this subject, the literature has not reached a consensus on two of the most fundamental questions in this area, namely: 1) what is driving the relation between shorting indicators and subsequent stock returns? and 2) what type of information is being revealed in this market? In this article, we address both issues.

Our primary goal is to determine not only the existence, size, and persistence of the relation between shorting indicators and stock prices, but also to explore specifically what is *driving* the relation. In essence, we ask a simple question, which turns out to be a crucial one: is shorting demand or shorting supply the key ingredient? We believe this distinction is important as the drivers of shorting supply and shorting demand can be vastly different, and so have differing implications for future returns. Shifts in the demand curves represent shifts in the marginal benefit of investors. Shorting demand can be viewed as a measure of investor sentiment (e.g., Lamont and Thaler (2003)) or informed trading. In contrast, shifts in supply are driven by changes in marginal costs. An increase in shorting supply can be viewed as a relaxation of short sale constraints. Since a host of papers (see, for example, Miller (1977), Pontiff (1996) and Shleifer and Vishny (1997)) incorporate investor sentiment, information revelation, or limited arbitrage in explaining stock price dynamics, understanding the precise roles of shorting demand and shorting supply is important.

Most existing studies either construct *proxies* for the supply or demand for shorting (e.g., institutional ownership, as in Nagel (2004) or breadth of ownership, as in Chen, Hong, and Stein (2002)) or employ equilibrium prices (e.g., rebate rates) or equilibrium quantities (e.g., short interest).[1] For example, several recent papers use the rebate rate as a direct measure of the cost of shorting.[2] The rebate rate is a fee that the lender of a stock must pay to the borrower of that stock,

[1] Asquith, Pathak, and Ritter (2005) combine both short interest *and* institutional ownership data to identify stocks with high shorting demand and low shorting supply.

[2] See, for example, Jones and Lamont (2002), Reed (2002), Geczy, Musto, and Reed (2002), D'Avolio (2002), Mitchell, Pulvino, and Stafford (2002), Ofek and Richardson (2003), and Ofek, Richardson, and Whitelaw (2003), among others.

and is an equilibrium price determined by the supply and demand for that stock in the equity lending market. Thus, one problem with interpreting evidence on rebate rates is that while low rebate rates likely indicate high shorting costs, it is not clear if this is because shorting demand is high or because loan supply is low.[3] We show that this distinction between supply and demand is crucial in identifying and understanding its effects on future returns.

Our empirical strategy allows us to classify supply and demand shifts in the equity lending market. Instead of taking an intersection of supply and demand and using it to proxy for demand or supply (thus assuming the opposite curve is inelastic, or does not shift), as is common in the literature, we attempt to disentangle these two effects. Using a novel 4-year panel dataset consisting of actual loan prices and quantities (not proxies) from a large institutional investor, we are able to infer if a stock has experienced an increase or decrease in shorting demand or shorting supply. We do this by exploiting price/quantity "pairs." For example, an increase in the loan fee (i.e., price) coupled with an increase in shares lent out (i.e., quantity) corresponds to at least an increase in shorting demand, as would be the case with any increase in price coupled with an increase in quantity. We do not maintain that this is the only shift that occurred. However, for a shift of price and quantity into this quadrant, a demand shift outwards *must* have occurred.[4] By classifying shifts in this way, we are able to identify clear shifts in shorting demand and supply, and then explore the effect of these shifts on future stock returns. This allows us to identify the precise nature of the relation between activity in the shorting market and future stock returns.

Our second set of tests focus on the issue of the actual information in this market. A market frictions story versus an informed trading story may each yield different implications on the mechanism, and effects of this market, on security prices. For example, from a market frictions perspective, if the cost of shorting is high enough, this can prevent negative information from being impounded into prices. This in turn may cause prices to deviate from fundamental value if some

[3]Short interest is an even more flawed metric. Like rebate rates, the quantity of shorting also represents the intersection of supply and demand; however, while a low rebate rate likely indicates a high cost of shorting (for whatever reason), a high level of short interest may not. Stocks that are impossible to short have an infinite shorting cost, yet the level of short interest is zero.

[4]We assume that demand curves are not upward sloping, and that supply curves are not downward sloping.

investors have downward sloping demand curves (see Miller (1977)). Alternatively, high shorting demand could indicate informed trading, which then leaks out to the market and reduces prices.

To explore private information, we first exploit instances where outside public information is unlikely to drive the observed price movements. We do this to test if the shorting market itself is a mechanism through which information is impounded into prices. The concern is that if increases in shorting demand, for example, coincide with public releases of bad news about a company, a subsequent price movement may have nothing to do with the information arrival through the shorting market. In this case, movements in the shorting market are correlated with public information, but are not the mechanism through which information flows into prices.[5] We test this by exploiting variation in the public information environment, and relating this variation to the strength of the shorting market's predictive ability of future returns.

We then examine implications of private information flow as an important mechanism in this market, relative to costs. Specifically, we examine the costs and benefits in terms of returns to a demand shift based trading strategy, net of the cost of shorting. If this market represented only a costly market friction, we would not expect to see substantial profits *net* of trading costs. If the lending market is an important channel for private information revelation, however, substantial profits net of trading costs would not be unreasonable.

Our results are easily summarized. We show that specialness (i.e., a high loan fee) or a high utilization rate (i.e., a high lending quantity), both of which have been shown in prior studies to affect asset prices, are less informative about future returns than demand and supply shifts. It is specifically shorting demand that plays a key role. For example, our pooled, cross-sectional regression estimates indicate that an increase in shorting demand leads to a significant negative average abnormal return of 2.54% in the following month. Decreases in shorting supply play a more minor role.

[5] Our companion paper Cohen, Diether, and Malloy (2005)) addresses the issue of causation by exploiting a change in the regulatory environment for securities lenders in Canada. Canadian mutual funds were strictly prohibited from lending out shares of the stocks they held until May 2, 2001, when an Amendment to National Instruments 81-102 (NI81-102) was passed allowing funds to lend out up to 50% of their shares. We use the passage of this Amendment as the setting for a natural experiment to identify exogenous shifts in loan supply in the Canadian equity lending market.

We also show that these results are unlikely to be driven by public information flow. For example, the effect of shorting demand on future stock returns is concentrated during times when no forecast revisions take place. Finally, we estimate the return to an investor from using our identification strategy to form trading rules. We find that *net* of shorting costs, the investor makes on average over 50% per year. Thus, indirect shorting costs and other transaction costs would have to be substantial to subsume this return.

The paper is organized as follows. Section II provides some background and a description of the data, while Sections III and IV present our empirical design and results. Section V provides further interpretation and results, and Section VI concludes.

II. Methodology

A. Background and Motivation

A voluminous literature explores the theoretical link between short sale constraints and asset prices.[6] In Miller (1977), short sale constraints can lead to overpricing. The mechanism is straightforward. Short sale constraints can prevent negative information from being impounded into prices. This in turn may cause prices to deviate from fundamental value if some investors have downward sloping demand curves.[7] As Diamond and Verrecchia (1987) point out, without this latter condition prices may remain unbiased. If rational uninformed agents take the presence of short sale constraints into account when forming their valuations, prices will remain unbiased because all participants recognize that negative opinions have not made their way into the order flow.

The effect of short sale constraints on prices is thus ultimately an empirical question. The key empirical issue is determining an appropriate measure of shorting demand or shorting costs. Due to the difficulty of obtaining data on direct shorting costs, a variety of studies exploit the fact that unwillingness to short may limit the revelation of negative opinions in the same way as

[6] See, for example, Miller (1977), Duffie, Garleanu, and Pedersen (2002), Diamond and Verrecchia (1987), Harrison and Kreps (1978), Scheinkman and Xiong (2003), Duffie (1996), and Krishnamurthy (2002), among others.

[7] See Diether, Malloy, and Scherbina (2002) for a discussion.

shorting costs. For example, institutional or cultural norms may limit shorting. Almazan, Brown, Carlson, and Chapman (2000) find that only about thirty percent of mutual funds are allowed by their charters to sell short and only two percent actually do sell short. Chen, Hong, and Stein (2002) use this fact to motivate their choice of breadth of mutual fund ownership as an indicator of the extent to which negative valuations are not expressed in prices. They find that reductions in breadth, signaling an increase in the amount of negative information held off the market, leads to negative subsequent abnormal returns on average. Similarly, Nagel (2004) uses residual institutional ownership as a proxy for shorting demand (again assuming that low residual institutional ownership signals that negative information is being withheld from stock prices); he finds that underperformance in growth stocks and high dispersion stocks is concentrated among stocks with low institutional ownership.

Note however, as Nagel (2004) points out, that residual institutional ownership may also proxy for shorting supply, since low institutional ownership restricts the supply of available shares lent out. As in Chen, Hong, and Stein (2002), it is not clear which channel (shorting demand or supply) drives the results. Mutual fund and institutional investment, aside from representing only a portion of the investing universe, are also endogenous quantities, and thus possibly driven by information flow or stock picking ability.

Another common proxy for shorting demand is short interest, which measures the number of shares sold short in a given period. Figlewski and Webb (1993), Figlewski (1981), Dechow, Hutton, Meulbroek, and Sloan (2001), and Asquith, Pathak, and Ritter (2005) show that stocks with high short interest have low subsequent returns. As noted above, however, the problem with using the level of short interest as a proxy for shorting demand is that short interest represents the intersection of supply and demand. For example, a low level of short interest may not indicate low shorting demand: Stocks that are impossible to short have an infinite shorting cost, yet the level of short interest is zero.

Asquith, Pathak, and Ritter (2005), one of the few papers that explicitly recognizes the competing effects of shorting supply and shorting demand, argue that stocks with high shorting demand

and low shorting supply are the most likely to face binding short-sale constraints. However, they proxy for shorting demand using short interest and shorting supply using institutional ownership, and thus face the same problems of interpretation mentioned above.

Rather than defining proxies for shorting demand or shorting supply, a series of recent papers analyzes direct measures of shorting costs (price).[8] The most commonly used metric is the rebate rate, and specifically the spread between the rebate rate and the collateral account interest rate.[9] The rebate rate is the fee that the lender of the stock must pay back to the borrower of that stock. This fee arises because in order to sell a stock short, an investor must borrow shares from an investor who owns them and is willing to lend them. The short-seller must leave collateral with the lender in order to borrow the shares; in turn, the lender pays the short-seller interest-the "rebate" rate- on this collateral. The difference or spread between the interest rate on cash funds and the rebate rate is a direct cost to the short-seller and a benefit to the lender; this spread is often called the "loan fee." The rebate rate serves to equilibrate supply and demand in the stock lending market, much like the "repo" rate in the fixed income market.

Using an eight year time-series of shorting costs from 1926-1933, Jones and Lamont (2002) find that stocks with low rebate rates have low subsequent returns. However, the effect is modest; only when the authors explore low rebate stocks that are also introduced into the loan crowd (another proxy for high shorting demand) do they find large negative size-adjusted returns (-2.52% in the following month). Jones and Lamont (2002) argue that "we do not need to identify the reason for the low rebate rate in order to test whether it results in overpricing" and "it does not matter whether a stock is added to the list because of changes in supply or demand. In either case, the inclusion on the list indicates that there exists substantial demand for borrowing the stock to short it." Ideally, rather than assuming that the correlation between shorting costs and future returns is due to shorting demand, one would like to test this. Our paper is unique in that we are able to use

[8] See, for example, Jones and Lamont (2002), Geczy, Musto, and Reed (2002), Ofek and Richardson (2003), Reed (2002), Ofek, Richardson, and Whitelaw (2003), and Mitchell, Pulvino, and Stafford (2002).

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

actual data on loan fees and loan amounts (not proxies) to decompose the effect on stock prices that is due to shorting demand, and the part that is due to shorting supply.

Virtually all existing papers also fail to address the exact mechanism causing the observed movement in stock prices. Breadth of ownership, residual institutional ownership, rebate rates, and introductions to the loan crowd are all endogenous quantities. Movements in these and other measures of shorting demand or supply may coincide with news about the stock; rather than causing price movements, they may simply be correlated with price movements.

The problem of causation has been mitigated in a few papers. For example, Sorescu (2000) looks at options introductions, while Ofek and Richardson (2003) look at lockup expirations; lockup expirations, in particular, are exogenous events that might reduce short sale constraints. Both papers find significant negative abnormal returns following these events. However, both of these papers again use proxies for shorting demand or shorting supply, and both focus on selected samples of stocks. Sorescu (2000) only analyzes optionable stocks, which tend to be large, while Ofek and Richardson (2003) only explores Internet IPOs. In addition, Mayhew and Mihov (2004) find no evidence that investors disproportionately take bearish positions in newly listed options; this finding casts doubt on the causal link between a relaxation of short sale constraints and stock prices in the context of option introductions. In this paper, and in Cohen, Diether, and Malloy (2005), we focus on the entire universe of small stocks (where shorting costs should be most relevant) and try to address the endogeneity of shorting indicators explicitly.

B. Data

We exploit a proprietary database of lending activity from a large institutional investor. The firm is a market maker in many small stock lending markets. We have daily data on prices (e.g., rebate rates, market rates), quantities (e.g, loan amount, percent on loan), and other loan characteristics (e.g., collateral amounts and rates, estimated income from each loan, broker firm name, etc.) for the entire universe of lending activity for this firm from September, 1999 to August, 2003.

For each observation, we compute the "spread" or "loan fee," which is equal to the interest rate on cash funds (the market rate) minus the rebate rate. As noted above, the rebate rate is the portion of the collateral account interest rate that the short-seller receives. Variation in the rebate rate thus determines cross-sectional variation in the loan fee, and hence the direct cost to the short-seller of maintaining the short position. Each stock on a given day may have multiple lending contracts, but the loan fees are almost always very similar. In most cases, the loan fees are identical for a given stock-day observation. We use the spread of the largest contract in our tests, but our results are unaffected by using the average or share-weighted average spread instead.

Table I presents some stylized lending activity examples. A typical large stock like Intel has a very small loan fee (0.05% per year), and our lending institution lends out only a fraction of the total shares outstanding. By contrast, for a small stock, like Atlas Air, the loan fee can be very high (7.25% per year), and our institution may lend out a large share (almost 5 percent) of the total shares outstanding. The fund is a large presence in the small cap market. They own five percent or more in over 600 small cap stocks throughout the sample period. In addition, they own at least a small stake in the vast majority of stocks below the NYSE median market cap. They are more active in the small stock lending market, making an average of 11.79 loans per stock-day as opposed to 4.64 for large stocks. Untabulated statistics suggest that increases in loan supply by our fund results in an increase to the market, rather than just a substitution across lenders. For example, among Nasdaq stocks below the NYSE median market capitalization, the average ratio of our fund's percentage on loan to the total short interest is 26% (for stocks above the median the ratio is 1%); in 13.5% of observations the fund is responsible for at least 67% of the short interest, and for 7.4% of observations the fund is responsible for all of the short interest.[10] Thus our lender appears to account for a significant portion of the lending supply in many small cap stocks. On the other hand, they seem to be a relatively unimportant lender in the large cap lending market.

We merge our lending data with information from a variety of other sources. We draw data on stock returns, shares outstanding, volume, and other items from CRSP, book equity from COM-

[10]We only have short interest data for Nasdaq stocks. Thus we can only compute these statistics for the Nasdaq stocks in our sample. However, Nasdaq stocks account for roughly 70% of our lending sample.

PUSTAT, monthly short interest data from Nasdaq, quarterly earnings forecasts and announcement dates from I/B/E/S, and quarterly institutional holding data from CDA/Spectrum.

Panel B of Table I presents summary statistics for our main sample, broken down into large stocks (stocks above the NYSE Median market cap), and small stocks (stocks below the NYSE Median market cap). Clearly small stocks have much higher loan fees on average (*Loan Fee* = 3.94% per annum, versus 0.39% for large stocks), and our institution lends out much larger shares of these small stocks (0.85% of shares outstanding on average, versus 0.14% for large stocks). To limit the substitution problem noted above, and to focus our analysis on the area where short sale constraints are presumably most important, our tests examine only stocks below the NYSE median market capitalization.

III. Isolating Supply and Demand Shifts Using Data on Loan Prices and Quantities

A. Empirical Design: Price and Quantity "Pairs"

Our primary goal is to isolate clear shifts in the supply and demand for shorting, and evaluate the effect of these shifts on future stock returns. To do this, our identification strategy consists of constructing price/quantity "pairs" using our data from the equity lending market. For example, an increase in the stock loan fee (i.e., price) coupled with an increase in shares lent out (i.e., quantity) corresponds to an increase in shorting demand, as would be the case with any increase in price coupled with an increase in quantity. As noted earlier, we do not insist that this is the only shift that occurred. However, for a shift of price and quantity into this quadrant, a demand shift outwards *must* have occurred. A key point to understand is that these price/quantity shifts refer to movements in a stock's *loan* price and *loan* quantity, not its actual share price or number of shares outstanding.

We classify movements in loan prices and quantities (i.e., loan fees and shares lent out as a percentage of shares outstanding) by placing stocks into one of four quadrants at each point in time: those that have experienced at least a demand shift out ($DOUT$), at least a demand shift in

(DIN), at least a supply shift out ($SOUT$), or at least a supply shift in (SIN). More precisely, stocks in $DOUT$ have seen their loan fee rise and their loan amount rise (over the designated horizon), stocks in DIN have seen their loan fee fall and loan quantity decrease, stocks in $SOUT$ have seen their loan fee fall but their loan quantity increase, and stocks in SIN have seen their loan fee rise but their loan quantity fall.[11] Thus our classification scheme allows us to infer whether the stock has experienced an increase or decrease in the supply or demand for shorting over the chosen horizon.

This simple approach raises a number of obvious questions. For example, the horizon over which these shifts is measured is potentially crucial. One could observe an increase in the loan fee followed by a fall in the loan fee, but over some horizon the net change might be zero. As a result, we experiment over a variety of possible horizons. Further, by placing a stock into only one of the four quadrants at any point in time, we are restricting our attention to cases where there is "at least" a shift of the type described. Clearly a stock placed in $DOUT$ may also have experienced an $SOUT$ over the designated period. While both shifts imply an increase quantity lent out, only $DOUT$ implies an increase in the loan fee. Thus our approach would, in this case, take an observed increase in the loan fee and quantity loaned out to infer that the stock experienced "at least" an increase in shorting demand, when in reality the stock may have experienced both an increase in shorting demand and supply (with the demand shock being larger). It is in this sense that we refer to each of our quadrants as signifying "at least" a shift of a given type. Summary statistics of the effect of each shift on loan fee (price) and quantity on loan are in Table II. The average change in spread from each of the shifts is roughly 40 basis points, except for $SOUT$, which results in a 56 bp decrease on average. The average change in percentage shares outstanding on loan by our institution following each shift is approximately 0.30%.

[11] Shifts where only one variable changes (e.g., the quantity rises but the loan fee does not) are excluded from the tests, since they are ambiguous. Assigning these infrequent cases to one shift classification versus the other yields virtually identical results. Observations where no change occurs in either price or quantity *are* kept in the baseline regressions, however; the dummy variable for all four shifts is set to zero in this case.

B. Cross-Sectional Regressions

Our baseline tests employ pooled, cross-sectional regressions on the universe of securities below the NYSE median market capitalization breakpoint to determine the effect of the shift portfolios in *predicting* future returns. To control for the well-known effects of size (Banz (1981)), book-to-market (Rosenberg, Reid, and Lanstein (1985), Fama and French (1992)), and momentum (Jegadeesh and Titman (1993), Carhart (1997)), we characteristically adjust the left-hand side returns (as in Grinblatt and Moskowitz (1999)) for size and book-to-market using 25 equal-weight size/book-to-market benchmark portfolios, and control for past returns on the right-hand side. Specifically, we regress the cross-section of characteristically-adjusted individual stock returns at time t on a constant, DIN, $DOUT$, SIN, $SOUT$, *Loan Fee*, $Utilization$, $\Delta(\text{Loan Fee})$, $\Delta(\text{Quantity})$, r_{-1} (last month's/week's return), $r_{-12,-2}$ (the return from month $t-12$ to $t-2$), $r_{-52,-2}$ (the return from week $t-52$ to $t-2$), IO (institutional ownership, measured as a fraction of shares outstanding lagged one quarter), and volume (the average daily exchange adjusted share turnover during the previous 6 months). We compute our four variables of interest (DIN, $DOUT$, SIN, and $SOUT$) as follows. The last trading day of month $t-1$ we check if there was some kind of shift in supply or demand during the month (based on changes in loan fees and shares lent out).[12] We define DIN as a dummy variable equal to 1 if the stock experienced an inward demand shift last month (or week, depending on the horizon of the left-hand side returns); $DOUT$, SIN, and $SOUT$ are defined analogously for outward demand shifts, inward supply shifts, and outward supply shifts, respectively. *Loan Fee* is a continuous variable measuring the spread between the market rate and rebate rate, and $Utilization$ ("utilization rate") equals the end-of-month/week ratio of shares lent out by our institution to shares owned by our institution. Stocks with high utilization rates have relatively high quantities of shares lent out (in the same way that specialness captures high relative loan fees, or prices).[13] $\Delta(\text{Loan Fee})$ is the change in loan fee over the past month,

[12] In alternate specifications, we check if there has been a shift in lending supply or demand during the last trading *week* of the month.

[13] These utilization rate results should be interpreted with some caution, since holdings for our institution are measured rather coarsely using quarterly holdings data. For example, occasionally we observe utilization rates greater

while $\Delta(\text{Quantity})$ is the change in fraction of shares on loan by the lender over the past month. We restrict our sample to stocks with lagged ($t-1$) price greater than or equal to five dollars. The regressions include calendar month dummies, and the standard errors take into account clustering by employing a robust cluster variance estimator. We have run these regressions using a Fama and MacBeth (1973) approach as well, and the results are very similar. We prefer the pooled approach because some of the time periods used in the Fama and MacBeth (1973) regressions contain few observations that experienced a particular shift.

i. Monthly Return Regressions

The estimates in Table III indicate that increases in the demand for shorting ($DOUT$) lead to large negative abnormal returns in the future. Column two of Table III indicates that even after characteristically adjusting for size, book-to-market, and controlling for past returns, institutional ownership, and volume on the right-hand side of these regressions, average abnormal returns for stocks experiencing an outward shift in shorting demand are -2.54% in the following month (t=-3.32). This large negative abnormal return is robust across the specifications in Table III. The shifts have an economically and statistically large predictive ability on future abnormal returns. By contrast, the other shifts have less predictive ability, despite the fact that the average effect of each of the shifts on loan fee and quantity (as shown in Table II) are roughly equivalent; $DOUT$ shifts are actually the least common in frequency. For example, column 2 shows that average abnormal returns for stocks experiencing an outward shift in shorting supply are -0.66% in the following month (t=-0.96). The effect of utilization rates ($Utilization$) and loan fees (*Loan Fee*) are considered in regressions 3-7 in Table III. Consistent with a number of recent papers (Jones and Lamont (2002), Reed (2002), Geczy, Musto, and Reed (2002), D'Avolio (2002)), we do find that high shorting costs, specifically $Loan\ Fee > 500bp$, predict future negative returns. However, when we

than 100% using this calculation method; in these cases, we set the utilization rate equal to 100%. Dropping these observations changes no conclusions. Stocks that the lending institution does not own are excluded from these tests and tests involving the variable *Loan Fee*.

include the shift portfolios, the conditional effect of these high costs is no longer significant, while $DOUT$ remains large and significant (-2.36%, t=-3.27). These results suggest an economically and statistically important link between increases in shorting demand and future abnormal returns.

As a comparison highlighting the importance of our classification into each of the shift portfolios, we examine the predictability of the more coarse classification of quantity changes and loan fee changes. The quantity can increase because of an $SOUT$ or $DOUT$, and decrease because of an SIN or DIN. In contrast, the loan fee can increase because of an SIN or $DOUT$, and decrease because of an $SOUT$ or DIN. We form portfolios of quantity and loan fee changes at month $t-1$, and test their predictive ability of the future month's returns. The results are in the final two columns of Table III. In column 8, returns are negative following loan fee increases and quantity increases, and significant for $\Delta(\text{Quantity})$, although the magnitudes are more modest than the shift portfolios. Again, however, when the shift portfolios are included, the conditional effect of $\Delta(\text{Quantity})$ decreases. Also, $DOUT$ remains negative and significant (-2.01%, t=-2.52). In fact, the results suggest that the quantity increases and loan fee increases may be noisy proxies for a portion of $DOUT$. These results coupled with those of the shift portfolios highlight the importance of understanding not only cost and quantity changes, but in fact what is "driving" these changes. They also highlight the ability to make richer empirical predictions of future prices by using the shift portfolio classification.

ii. Weekly Return Regressions

We find a similar relation between abnormal returns and outward demand shifts using weekly return data (Table IV). Demand shifts out ($DOUT$) in week $t-1$ lead to large negative abnormal returns on average in week t. The coefficient on $DOUT$ ranges from -0.41% to -0.52% per week. Compounding these to monthly returns yields similar magnitudes to those in Table III. The $DOUT$ slope coefficient is significant in the first regression, but only marginally significant after characteristically adjusting for size, book-to-market, and controlling for past returns, institutional ownership, and volume. The coefficients on the other shifts are again insignificant and fairly small in magnitude. In the weekly specification neither shorting cost (*Loan Fee*) nor *Utilization* significantly predict future abnormal returns.

iii. Euclidean Distance Regressions

Table V reports estimates from an alternate regression specification, one that uses information on the magnitude of the shifts rather than simply employing dummy variables. The magnitudes of these shifts are determined by computing the Euclidean distance ($\sqrt{\Delta x^2 + \Delta y^2}$) of each shift, where the inputs to this distance calculation are the change in loan quantity (x-axis) and the change in loan fee (y-axis) for the stock over the given horizon. The idea behind this test is that larger shifts in shorting supply and demand may be more informative/predictive than smaller shifts. The average (median) shift distance for each of the shift portfolios are roughly equivalent.[14] Indeed, the coefficient estimates presented in Table V support this conjecture. In fact, both demand shifts in and out have a significant link with future monthly returns, when controlling for other sources of variation. Larger *DOUT* shifts predict significantly more negative abnormal returns, while larger *DIN* shifts predict significantly more positive returns. Again, shifts in supply are not significantly related to future returns. As an alternative specification, we also classified shifts into portfolios based on the size of the shift. An example is given in column 3, where we split shifts into above median size (*DOUT_BIG*) and below median size (*DOUT_SMALL*). Large increases in shorting demand (*DOUT_BIG*) are associated with larger negative abnormal returns in the future (-3.14% per month, t=-3.14) than small increases in shorting demand (-1.901% per month, t=-1.60). Further, this difference between *DOUT_SMALL* and *DOUT_BIG* is statistically significant. At the weekly level, although the results have the same sign, the magnitudes are smaller and not significant.

[14]The mean (median) shift distances are: *SIN*-0.608(0.289), *SOUT*-0.722(0.402), *DIN*-0.571(0.275), and *DOUT*-0.612(0.313).

iv. Lag Lengths In Figures

Finally, we examine the effect of using different lag lengths. In figure 1 we regress weekly abnormal returns on DIN, $DOUT$, SIN, $SOUT$, and a constant for each lag length from one week to eight weeks. Figure 1 confirms the monthly results. Increases in demand lead to low average abnormal returns during the first four weeks (with the exception of the 2nd week after a shift). The total effect for the first four weeks is about -1.56% and is significant (result computed but not shown in figure).[15] Five to eight weeks after an outward demand shift, abnormal returns are consistently negative, much smaller in magnitude, and no longer significant. $SOUT$ is negative for virtually every lag length, but is never significant.

Figure 2 extends the lag results out to 6 months using monthly abnormal returns. Confirming the weekly lag results we find that the $DOUT$ coefficient is negative during the first two months after a shift, but only significant in the first month after a shift. $SOUT$ is negative for virtually ever lag length, but is never significant. A similar regression of monthly abnormal returns on a dummy variable that equals one if there was a supply shift out in any of the last three months also yields an insignificant coefficient on the supply shift variable.

C. Portfolio Strategies

We also examine average returns on portfolios formed using the four quadrant classifications defined above. We place stocks into four shift portfolios: demand in (DIN), demand out ($DOUT$), supply in (SIN), and supply out ($SOUT$). Shift portfolios are formed in month $t-1$, and the stocks are held in the portfolios during month t.[16] We rebalance the portfolios monthly. As before, we

[15] The total effect over four weeks is smaller in magnitude than the monthly results (-1.56 compared to -2.84). The smaller magnitude may be related to the fact that computing shifts over a one week period delivers a much smaller shift on average in terms of Euclidean distance.

[16] Following Jegadeesh and Titman (2001), stocks with share price lower than $5 are omitted from the portfolios (and the benchmark portfolios) in order to ensure that the results are not driven by small, illiquid stocks or by bid-ask bounce. In addition, collateral requirements have a nonlinearity below prices of $5 for our lender, which may distort lending preferences and rebate rates. Finally, low-priced stocks are more likely to go bankrupt, and in the case of bankruptcy a short-seller may have to wait months to recover the collateral funds.

exclude all stocks above the NYSE median market cap (in month $t-1$) from our tests.

As before, we proxy for expected returns characteristically using 25 size/book-to-market benchmark portfolios, as well as 75 (3x5x5) size/book-to-market/momentum benchmark portfolios. For example, when using the 75 size/book-to-market/momentum benchmark portfolios, we compute each stock's abnormal return as,

$$r_{jt}^{sbm} = r_{jt} - R_t^{SBM_j,t-1}, \tag{1}$$

where r_{jt} is the return on security j, and $R_t^{SBM_j,t-1}$ is the return on the size/book-to-market/momentum matched portfolio. This approach allows us to avoid estimating factor loadings over our (relatively) short time period, and alleviates the concern that the changing composition of our portfolio may yield unstable factor loadings.[17] However, all the portfolio tests in the paper are robust to using a multifactor time-series approach to estimate factor loadings and compute abnormal returns.

i. Monthly Portfolio Results

Table VI presents our results for monthly portfolio sorts. Forming portfolios based on the shifts allows us to evaluate a trading strategy based on the shift portfolio. Consistent with the regression findings, stocks that experience an increase in shorting demand ($DOUT$) over the prior month earn negative returns on average in the following month. This holds for raw returns, excess returns, and abnormal returns. This effect is not significant in Panel A (excess returns), but Panels B and C show that $DOUT$ stocks earn average (equal-weight) abnormal returns in the subsequent month of -2.34% per month when benchmarked relative to size-BE/ME portfolios and -2.10% per month when benchmarked relative to size-BE/ME-Momentum portfolios.[18] In addition, the trading strategy of going long in stocks that have demand shifts inward and short stocks that demand shifts

[17]See Daniel, Grinblatt, Titman, and Wermers (1997) and Grinblatt and Moskowitz (1999) for more details on characteristically adjusting returns.

[18]Untabulated statistics reveal virtually identical results if we use factor loadings to compute abnormal returns instead. In particular, monthly alphas in 4 factor regressions for the four shift portfolios are: DIN (1.32%, $= 1.30$), $DOUT$ (-2.41%, $t = -2.48$), SIN (0.44, $t = 0.50$), and $SOUT$(-1.65, $t = -1.27$).

outward (*DIN-DOUT*), yields a large and statistically significant return of over 3% per month in each panel of abnormal returns. The value-weight results for these outward demand shifts, however, are smaller and insignificant. Also, unlike in the regression results, the outward supply shifts are correlated with future negative returns (and significant in the value-weight tests). These supply results should be interpreted with caution, though; simply adding time fixed effects in a regression framework (regression 1 of Table III) drives out the effect. In the portfolio context, the high cost portfolio (*SPECIAL*), also do not have a significant link with future returns.[19] The equal-weight portfolio results reinforce a statistically significant and economically important link between increases in shorting demand and future abnormal returns, and suggest a potentially large return from exploiting a trading strategy based upon the shifts.

D. Robustness: Industry Effects, Market Power, Short Interest, and Alternative Specifications

Our baseline results are robust to a variety of permutations. For brevity, we only provide a few such checks here.[20] For example, we have augmented our cross-sectional regressions in Table V by using industry dummy variables in addition to calendar time dummies. We use Fama and French's (1997) 48 industry classification scheme. The results are unaffected, as shown in Table VII. In fact, the coefficient on *DOUT* is slightly larger and more significant in each regression specification. *SOUT*'s coefficient is also larger in magnitude but still insignificant. Adding industry dummy variables to our regressions helps alleviate the concern that are results are driven by a few industries (e.g., tech stocks).

Since we only have loan quantities from a single lending institution, another important check on our results is to examine how our results vary with the size of our institution's share of the total lending activity for a given stock. For example, we would expect that for those stocks for which our institution lends out most of the available shares that our results would be even stronger.

[19] The *SPECIAL* portfolio is formed by assigning all stocks with lending fees greater than 0.5% (per year) at the end of each month to the portfolio, and then computing future average abnormal returns.

[20] Other untabulated statistics are available from the authors on request.

To test this idea we collect short interest data on all the Nasdaq stocks in our dataset. We then compute the "Market Power" of our lender in a given stock as the number of shares lent out by the lender in month $t-1$ divided by total short interest in month $t-1$. Column 3 of Table VIII shows that interacting Market Power with $DOUT$ produces a large (-5.492 percent per month) decline in future abnormal returns, although this result is insignificant. When we interact $DOUT$ (in column 4 of Table VIII) with a dummy variable indicating that our institution's Market Power is greater than 2/3, the coefficient on this interaction term is large (-10.01 percent per month) and significant (t=2.70). Thus, the effect of $DOUT$ shifts are even larger in stocks for which our institution is a major lender.

As another check to overcome the shortcoming of having one lender we use monthly short interest from Nasdaq as a quantity measure, and match it with the loan fees from our lender. Short interest is reported on 15th of every month or the last trading day before the 15th. Since it usually take 3 trading days to settle short-sell trades, short interest include short-sale trades up to 3 trading days before the 15th. We match Nasdaq short interest with loan fees from the the day after the last trade date included in the report. We compute DIN, DOUT, SIN, SOUT shifts in month $t-1$ based on changes in loan fees since month $t-2$. We also compute monthly returns on the 16th of each month by compounding daily returns to the monthly level. We then run a cross-section regression using monthly returns. The first column of Table VIII reports the results. Even after characteristically adjusting for size, book-to-market, and controlling for past returns, institutional ownership, and volume on the right-hand side of these regressions, average abnormal returns for stocks experiencing an outward shift in shorting demand are -1.33% in the following month (t=-2.07).

The number of stocks that experience a particular shift in a given month can be small in some months. For example, on average the number of stocks per month that experience at least an outward demand shift (DOUT) is 22 (see Table II). To alleviate concerns related to sample size, we rerun our cross-sectional monthly abnormal return regressions using a lagged price cutoff of one dollar instead of five dollars. This increases the average number of DOUT shifts per month to over

48. The previous results persist in that we still find a significant relation between DOUT and future abnormal returns, but not the other shift portfolios. For example, even after characteristically adjusting for size, book-to-market, and controlling for past returns, institutional ownership, and volume on the right-hand side of these regressions, average abnormal returns for stocks experiencing an outward shift in shorting demand are -1.79% in the following month (t=-2.27).

Another potential problem is that collateral amounts are sometimes adjusted in certain ways to offset a particular loan fee. For example, a borrower might pay a lower loan fee if she posts more collateral. Therefore, one might find cross-sectional variation in rebate rates/loan fees that is simply related to the amount/type of collateral being posted. Again, this concern is alleviated in our sample, since our institution charges 102 percent as collateral based on price, and then marks to market as the stock price changes. The only exception is for stocks with a price below five dollars, for which they use a basis stock price of five dollars to calculate collateral; since all of our tests (exclude stocks priced below five dollars, we can report that collateral-related issues do not appear to drive our results.

We have also explored alternate identification strategies aimed at isolating shifts in shorting supply and demand. For example, another way to identify a demand shift out is to exploit situations where lending activity increases from zero to a large amount, conditioning on our lender already owning a large amount (here 5 percent of shares outstanding) so as to ensure that this lending activity is demand driven. Specifically, we look at the returns in month t of stocks in month $t-1$ that are on special, but that in month $t-2$ had zero lending activity. Although we can identify only 205 such shifts, untabulated results reveal that this type of demand shift is associated with a large -1.95% subsequent monthly average abnormal return, which is very similar in magnitude to our prior results.

IV. Short-Selling and Private Information

Having identified a large and significant link between the shorting market and stock prices, we now turn to the issue of causation. As noted earlier, a major weakness of the literature on the effect of short sale constraints on stock prices is that very few papers address the fact that commonly used shorting indicators are endogenous. Ideally one would like to know if shorting indicators have explanatory power abstracting from public information (signaling the potential importance of market frictions), or if they are simply correlated with underlying movements in public information flow. To addressing this problem we isolate firms and times where public information is likely to be scarce.

A. Firms with Low (Residual) Analyst Coverage

Analyst coverage is a commonly used measure of information flow (see, for example Hong, Lim, and Stein (2000)), but suffers from the obvious problem that coverage is highly correlated with size. As a result, we explore the effect of residual coverage (i.e., coverage orthogonalized by size).[21] Our goal in these tests is to isolate firms in our sample that have relatively low coverage, which suggests an environment in which public information is more limited. To do this, we replicate our prior monthly regression results, but add residual analyst coverage ($RCOV_{t-1}$) as a control variable and interact it with $DOUT$. As shown in column 2 of Table IX, the evidence for increases in shorting demand leading to large declines in future stock returns is not concentrated in stocks with high residual coverage. The interaction term between $DOUT$ and residual coverage is very close to zero. This suggests that the effect of shorting on prices is important in sparse information environments, and not just in dense information environments.

B. Times of No Information: No Revisions, No Earnings Announcements

In addition to the level of public information available about a stock, *changes* in the amount of information about a stock may have an important effect on the link between shorting indicators and stock prices. To address this possibility we isolate times where stocks have not experienced any recent quarterly earnings forecast revisions or any recent earnings announcements. Table IX

[21] Our results using regular coverage, rather than residual coverage, are very similar. These results are available on request.

shows our monthly abnormal return regression results when we add forecast revisions as a control variable and as an interaction variable with $DOUT$. Column 4 shows that interacting demand shifts with a dummy for if the firm had no revisions last month ($REVZERO_{t-1} * DOUT$), we find that increases in shorting demand during times of no new public information lead to large negative future abnormal returns (-3.37% per month). While this interaction effect is only marginally significant (t=1.56), an F-test (unreported) reveals that the total effect ($DOUT + REVZERO_{t-1}\_DOUT$) is strongly significant at the .01 level. In addition, for stocks that experience an unambiguously negative revision the $DOUT$ effect is very small and insignificant. Thus, we find that stocks with no recent revisions are associated with even larger shorting demand effects, but that stocks that receive unambiguously negative revisions are not. This is consistent with a private information link between $DOUT$ and future returns, since times with no revisions are likely to be times of sparse public information.

$DOUT$ is not simply capturing $future$ earnings revisions either. As shown in column 5 of Table IX, including contemporaneous revisions ($REVNEG_t$ and $REVZERO_t$) in the return regressions does not diminish the explanatory power of a demand shift out last month, even though these revision variables have predictive power for contemporaneous returns. Similarly, the interactions of $DOUT$ with these contemporaneous revision variables are insignificant.

Table X explores the effect of earnings announcements in our context. We compute the variables $EAPOS_{t-1}$ and $EANEG_{t-1}$ to capture these effects; $EAPOS_{t-1}$ equals the SUE of an earnings announcement if it was a positive surprise and zero otherwise, and $EANEG_{t-1}$ equals the SUE of an earnings announcement if it was a negative surprise and zero otherwise. The estimates in column 3 show that the effect of $DOUT$ is negative and significant, even after controlling for the marginal effect of $EAPOS_{t-1}$ and $EANEG_{t-1}$ (interaction terms capturing the effect of demand shifts that occur during months with positive or negative earnings surprises).

As before, $DOUT$ is not merely capturing the effect of $future$ earnings announcements. Column 4 indicates that even after controlling for the effects of contemporaneous earnings surprises ($EAPOS_t$ and $EANEG_t$), the effect of a demand shift last month on stock returns in month t is large (-2.534 percent per month) and significant (t=3.33).[22]

In summary, scarce information environments (proxied by no revisions, low coverage, or no earnings announcements) generate the largest and most reliable links between $DOUT$ and future stock returns. In addition, $DOUT$ is not just a proxy for future public information releases, such as future analyst revisions or future earnings surprises. Together these findings support the notion that the shorting market is an economically important mechanism for information revelation in prices.

C. Times of Predictable Demand: Splits and Dividends

One concern when analyzing lending data is that many stocks experience a huge spike in borrowing and lending right around dividend dates and split dates, and that these spikes may be driving any empirical regularities.[23] Stock splits and dividends also provide an ideal test of the private information channel hypothesis, in that these are both events which yield *predictable* shifts in shorting demand ($DOUT$), which are unrelated to private information.

The regression results for both splits and dividends are in the first three columns of Table VII. The table shows that the effect of $DOUT$ is still negative and strongly significant after controlling for those $DOUT$ shifts that occur during dividend or split months. However, both interaction terms $SPLIT * DOUT$ and $DIV * DOUT$ are positive, although not significant. Consistent with $DOUT$ being linked to returns through private information, when there are predictable demand shifts outward not related to private information, these break the link between $DOUT$ and future returns.

D. Costs and Benefits of Shorting

If the lending market is an important source of private information revelation, then when it is costly to bet against a stock, we should see larger returns to better private information from this "betting,"

[22]This result seems consistent with Mercado-Mendez, Best, and Best's (2004) finding that short interest does not increase on average the month before a large negative earnings surprise.

[23]See Christoffersen, Geczy, Musto, and Reed (2004) for a discussion of related issues.

in order to cover these costs. We test this in column 4 of Table XI. High cost stocks at the end of month $t-2$ are followed to month $t-1$. We then measure the returns in month t to betting on these stocks in month $t-1$. From column 4 in Table XI, we see that when costs of shorting are high (loan fee > 300 bp), that the returns from betting against the stock are large. Specifically, the combined effect of borrowing more at an even higher cost in month $t-1$, or a $DOUT$ at $t-1$, results in a -6.44% (=-1.46%+-4.98%) average abnormal return next month, which is significant at the .01 level. This return is over twice as large as the return following an unconditional $DOUT$ from Table III (-2.54%).

Another piece of evidence consistent with the lending market being important for private information revelation and not solely a market friction is the relative cost and benefit in returns from a demand shift based trading strategy. From Table II, the average loan fee, or cost, following $DOUT$ is 3.72% per year. From Table VI, the strategy DIN-$DOUT$ yields 3.76% per month.[24] Reforming the portfolio at the end of every month $t-1$ and holding it during month t gives roughly a 55.7% average annual return. As the average cost of shorting the $DOUT$ portion of the portfolio is 3.72% per year, subtracting this yields about a 52% average annual return.[25] Thus, as long as the monthly rebalancing of the portfolio and other transaction costs do not on average cost 52% per year, the strategy appears on average highly profitable. The magnitude of this result net of shorting costs provides evidence that the market is likely important for private information revelation, and not simply a costly market friction preventing arbitrage.

V. Interpretation

One of the most important reasons we decompose this data into shifts in the lending market is that we believe these shifts have vastly different implications on future price dynamics. Shifts in the demand curve represent shifts in the marginal benefit of investors. These can occur for a number

[24] Here we use unconditional returns, because they are the raw returns from the strategy. The results are similar using risk adjusted returns from Table III and Table V, and are actually a fair amount larger using strategies as in Table XI.

[25] There is a confidence interval about this return, but even assuming that the lowest 5% bound of return is realized in every month (a return of 0.88% per month), the strategy still makes 7.38% per year net of shorting costs.

of reasons, including private information. Supply curve shifts represent shifts in the marginal cost to our institution. One shifter of this curve comes as the institution also operates mutual funds, and has other incentives for holding (and so having the ability to lend) stocks. For instance, following a sale of the shares of a certain stock, our institution has an inward shift of the supply curve for this stock. The new marginal cost of lending shares is the cost of borrowing them in the market, and relending them, and so it is almost surely higher.[26] The curve shifters of supply and demand can be thus quite different, and have different implications for future returns. In this section we look at one example that highlights the importance of this difference.

A. High Shorting Costs: SIN and $DOUT$

A number of papers have found that the cost of shorting (loan fee) is correlated with future returns.[27] In the regressions in Table III, we also find evidence consistent with this. There are two ways that a high cost of shorting can develop. A ceteris paribus demand shift outward for borrowing shares ($DOUT$) or a contraction in the supply of lendable shares (SIN). If cost is a sufficient statistic, then it should not matter how cost was bid up. We argue differently. We argue that the information content of $DOUT$ and SIN differ. Specifically, from the evidence in the paper, we expect the flow of information from $DOUT$, and so the information driving movements in the marginal benefit of investors, to have more predictive power over future returns, as discussed in Section IV. This is especially true considering our lender is a passive investor with well-defined trading rules that routinely screens so as not to trade at high information times. The lender's actions, however, still significantly affect the lending supply in many securities.

A test of this is in the third column of Table XI. This regression looks at abnormal returns in month t, and conditions on the level of the loan fee greater than 300 basis points at the end of month $t-1$. It then interacts this loan fee with each of the shifts during that month $t-1$. From the

[26] As there are likely some rents that are paid to the lender.

[27] Although many of these cases are coupled with potential demand shifts such as additions to the loan crowd (Jones and Lamont (2002)) and mergers.

table, the strongest and most reliable negative abnormal returns following these high cost months occur after shifts *DOUT* (-4.468%, *t*=2.88). Comparing the effect of *DOUT* and *SIN*[28] for a given level of loan fee, when *DOUT* causes the higher loan fee, it has significant predictive power for subsequent abnormal returns which is almost 3 times the magnitude of *SIN*. In addition the difference between the marginal effects of *DOUT* causing the high loan fee and *SIN* causing the high loan fee is statistically significant (F-stat = 8.61 and p-value = 0.003). This result suggests that the cross-sectional relation between high shorting costs and future negative returns is driven largely by demand shifts. It also highlights the importance of understanding "how" the cost of shorting was driven up (and not simply that the cost of shorting is high) to understand effects on future returns.

VI. Conclusion

The main contribution of this paper is to explore two fundamental and unanswered questions in the literature on short selling, namely: 1) what is driving the relation between shorting indicators and subsequent stock returns? and 2) what type of information is being revealed in this market? We make progress in both directions.

Employing an identification strategy that allows us to isolate shifts in the supply and demand for shorting, we show that increases in shorting demand have large and significant negative effects on future stock returns. The magnitude of these results is striking: virtually all our estimates range between 2-3% negative abnormal returns *per month* following increases in shorting demand. Alternatively, we do not find strong evidence that shifts in shorting supply are strongly linked to future returns.

We find that the effect of shorting demand on future prices is still large (economically and statistically), and in some cases even larger, in those environments where other information is scarce. This indicates that the shorting market is an important mechanism for information revelation in stock prices, and suggests a causal link between private information flow through shorting markets

[28] From Table III the average effect of *DOUT* and *SIN* shift on loan fee is similar, 42 bp and 40 bp, respectively.

and future price movements. Along these same lines of causation, we find that the returns to a trading strategy based on our shift identification yields on average over 50% per year *net* of shorting costs. This latter result casts doubt on the view that the main link between the shorting market and stock prices is due to costly market frictions such as short sale constraints.

We further find that the cross-sectional relation between high shorting costs and future negative returns is driven to a much larger extent by demand shifts than by supply shifts. This reinforces the importance of separating the shorting market into demand and supply effects in order to understand the driving mechanism linking the shorting market and stock returns.

There are a number of avenues of future research in this area. For example, further work is needed to understand the cross-sectional variation in the relation between shorting indicators and stock prices. In addition, identifying precise shifts in shorting demand and shorting supply using exogenous variation in these markets is an important task. This would provide a cleaner laboratory for establishing and enriching the causal link between the shorting market and stock prices.

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Table I
Lending Activity

Reb. Rate refers to the rebate rate. For a given stock-day observation we use the rebate rate of the largest short-sale contract (largest = most shares on loan). Col Rate refers to the collateral account interest rate. The loan fee is the difference between the collateral rate and the rebate rate, and is the interest rate the lender receives from the short-sale. %Shr Out is the total number of shares on loan by our lender expressed as a percentage of shares outstanding. Num Cont is the number of short-sale lending contracts that the lender is engaged in for a given stock-day observation. Ptile ME is the NYSE market cap percentile.

Panel A: Lending Activity Examples (July 29, 2003)						
Stock	Reb Rate	Col Rate	Loan Fee	%Shr Out	Num Cont	Ptile ME
Intel	0.95	1.00	0.05	0.01	1	99.8
Johnson & Johnson	0.95	1.00	0.05	0.03	2	99.7
PeopleSoft	0.00	1.00	1.00	0.00	1	88.0
Bally Total Fitness	0.25	1.00	0.75	1.78	14	33.0
American Superconductor	-1.50	1.00	2.50	5.51	40	28.4
Atlas Air	-6.25	1.00	7.25	4.75	26	4.5
Questcor Pharmaceutical	-13.75	1.00	14.75	0.34	10	3.9

Panel B: Lending Summary Statistics				
All Stocks				
	Mean	Median	25 Ptile	75 Ptile
Reb Rate	0.55	0.25	-0.00	1.10
Loan Fee	2.60	1.82	0.14	4.20
%Shr Out	0.58	0.16	0.03	0.50
Num Cont	9.09	4.00	2.00	8.00
Ptile ME	38	28	7	62
Above NYSE Median ME				
	Mean	Median	25 Ptile	75 Ptile
Reb Rate	1.75	1.53	1.09	1.64
Loan Fee	0.39	0.13	0.10	0.16
%Shr Out	0.14	0.03	0.001	0.08
Num Cont	4.64	3	1	4
Ptile ME	78	81	65	89
Below NYSE Median ME				
	Mean	Median	25 Ptile	75 Ptile
Reb Rate	-0.17	0.00	-0.01	0.12
Loan Fee	3.94	3.93	1.99	5.30
%Shr Out	0.85	0.38	0.10	0.86
Num Cont	11.79	6	2	11
Ptile ME	15	10	4	20

Table II
Supply and Demand Shifts: Summary Characteristics

The last trading day of month t we check if there was some kind of shift in supply or demand during the month (based on changes in loan fees and shares lent out). We place stocks into shift categories: demand in (DIN), demand out ($DOUT$), supply in (SIN), and supply out ($SOUT$). Only stocks with market cap below the NYSE median and with price at least equal to 5 dollars are included in the sample. *Before Shift Loan Fee* is the lending fee before the shift. *New Loan Fee* is the lending fee when the shift occurs. *Before Shift %Shr Out* is the number of shares on loan by our lender before the shift occurs as a percentage of shares outstanding. *New %Shr Out* is the percentage of shares on loan by our lender when the shift occurs. ME is market cap, and BE/ME is the book to market ratio. *Vol* is the average daily exchange adjusted turnover of a stock during the past six-months. The time period is September 1999 to August 2003.

	Panel A: Mean			
	DIN	DOUT	SIN	SOUT
Number of Stocks Per Month	34	22	38	31
Percentile ME	25	22	22	23
Percentile BE/ME	37	32	38	34
Percentile Vol	72	74	71	74
Before Shift Loan Fee	2.57	3.30	2.88	3.11
New Loan Fee	2.16	3.72	3.28	2.55
Before Shift %Shr Out	1.09	0.78	0.98	0.79
New %Shr Out	0.80	1.10	0.65	1.09
	Panel B: Median			
Number of Stocks Per Month	34	14	21	34
Percentile ME	22	19	19	22
Percentile BE/ME	29	23	29	24
Percentile Vol	79	81	79	82
Before Shift Loan Fee	2.07	3.52	2.47	2.69
New Loan Fee	1.74	4.22	3.05	2.07
Before Shift %Shr Out	0.58	0.40	0.58	0.34
New %Shr Out	0.35	0.63	0.30	0.62

Table III
Cross Sectional Regressions: Monthly Abnormal Returns

The dependent variable is monthly abnormal returns in percent. We proxy for expected returns characteristically using 25 equal weight size-BE/ME portfolios. All stocks below the NYSE median market cap and with lagged price at least equal to 5 dollars are included in sample. DIN is a dummy variable for a inward demand shift last month. DOUT is a dummy variable for an outward demand shift last month. SIN is a dummy variable for an inward supply shift last month. SOUT is a dummy variable for an outward supply shift last month. r_{-1} is last months return. $r_{-12,-2}$ is the return from month $t-12$ to $t-2$. IO is institutional ownership measured as a fraction of shares outstanding lagged one quarter. Volume is the average daily exchange adjusted share turnover during the previous 6 months. Loan Fee > x equals 1 if the loan fee is greater than x and zero otherwise. Utilization equals the ratio of shares lent out by our institution to shares owned by our institution. Quantity is the fraction of shares outstanding on loan by the lender at the end of month $t-1$. The regressions include calendar month dummies, and the standard errors take into account clustering by calendar date. The time period is October 1999 to September 2003. T-statistics are in brackets. The intercept is estimated but not reported.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]
DIN	0.308	0.482			0.481		0.346		0.005
	[0.47]	[0.93]			[0.92]		[0.69]		[0.01]
DOUT	-2.857	-2.537			-2.362		-2.923		-2.010
	[2.85]	[3.32]			[3.27]		[3.67]		[2.52]
SIN	0.303	0.405			0.499		0.041		0.653
	[0.27]	[0.50]			[0.79]		[0.05]		[0.77]
SOUT	-0.858	-0.660			-0.603		-0.792		-1.081
	[1.08]	[0.96]			[0.90]		[1.16]		[1.57]
r_{-1}		-0.009	-0.012	-0.012	-0.012	-0.010	-0.010	-0.010	-0.009
		[0.35]	[0.50]	[0.48]	[0.48]	[0.42]	[0.40]	[0.36]	[0.35]
$r_{-12,-2}$		0.004	0.005	0.005	0.005	0.005	0.005	0.004	0.004
		[0.69]	[0.85]	[0.84]	[0.83]	[0.84]	[0.83]	[0.70]	[0.69]
IO		0.708	0.266	0.241	0.219	0.328	0.285	0.745	0.714
		[1.12]	[0.38]	[0.35]	[0.32]	[0.46]	[0.40]	[1.17]	[1.13]
Volume		-0.118	0.006	0.006	0.021	0.006	0.024	-0.138	-0.118
		[0.40]	[0.02]	[0.02]	[0.06]	[0.02]	[0.07]	[0.46]	[0.40]
Loan Fee > 0.5%			-0.589						
			[1.30]						
Loan Fee > 5.0%				-2.031	-1.608				
				[2.09]	[1.64]				
Utilization						-0.421	0.063		
						[1.05]	[0.20]		
Δ(Loan Fee)								-0.916	-0.962
								[1.90]	[1.83]
ΔQuantity								-0.958	-0.375
								[2.57]	[0.83]

Table IV
Cross Sectional Regressions: Weekly Abnormal Returns

The dependent variable is weekly abnormal returns in percent. We proxy for expected returns characteristically using 25 equal weight size-BE/ME portfolios. All stocks below the NYSE median market cap and with lagged price at least equal to 5 dollars are included in sample. DIN is a dummy variable for a inward demand shift last week. DOUT is a dummy variable for an outward demand shift last week. SIN is a dummy variable for an inward supply shift last week. SOUT is a dummy variable for an outward supply shift last week. r_{-1} is last weeks return. $r_{-52,-2}$ is the return from week $t-52$ to $t-2$. IO is institutional ownership measured as a fraction of shares outstanding lagged one quarter. Volume is the average daily exchange adjusted share turnover during the previous 6 months. Loan Fee > x equals 1 if the loan fee is greater than x and zero otherwise. Utilization equals the ratio of shares lent out by our institution to shares owned by our institution. The regression include calendar month dummies, and the standard errors take into account clustering by calendar date. The time period is the 3rd week of September 1999 to the first week of September 2003. T-statistics are in brackets. The intercept is estimated but not reported.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]
DIN	0.016	0.055			0.052		0.015
	[0.08]	[0.31]			[0.32]		[0.08]
DOUT	-0.518	-0.414			-0.422		-0.460
	[2.05]	[1.70]			[1.69]		[1.72]
SIN	-0.143	-0.101			-0.112		-0.168
	[0.49]	[0.36]			[0.42]		[0.61]
SOUT	-0.124	-0.033			-0.028		-0.136
	[0.52]	[0.15]			[0.13]		[0.58]
r_{-1}		-0.041	-0.039	-0.039	-0.039	-0.038	-0.038
		[4.65]	[4.67]	[4.67]	[4.67]	[4.55]	[4.54]
$r_{-52,-2}$		0.001	0.002	0.002	0.002	0.002	0.002
		[1.27]	[1.38]	[1.38]	[1.37]	[1.41]	[1.41]
IO		0.179	0.091	0.096	0.092	0.112	0.108
		[1.46]	[0.70]	[0.76]	[0.73]	[0.83]	[0.81]
Volume		-0.041	-0.011	-0.013	-0.011	-0.015	-0.013
		[0.67]	[0.16]	[0.19]	[0.16]	[0.22]	[0.19]
Loan Fee > 0.5%			-0.146				
			[1.49]				
Loan Fee > 5.0%				-0.318	-0.285		
				[1.55]	[1.41]		
Utilization						-0.032	0.035
						[0.20]	[0.20]

Table V
Cross Sectional Regressions: Euclidean Distance Shifts

The dependent variable in the first three columns is monthly abnormal returns in percent, and the dependent variable in the last three columns is weekly abnormal returns in percent. We proxy for expected returns characteristically using 25 equal weight size-BE/ME portfolios. All stocks below the NYSE median market cap and with lagged at least equal to 5 dollars are included in sample. DIN, DOUT, SIN, SOUT equal the magnitude of the shift. We measure the magnitude of a shift using Euclidean distance. DOUT_SMALL (DOUT_BIG) is a dummy variable for a small (big) outward demand shift last month (week). A shift is small if is less than the median r_{-1} is last month's (week's) return, $r_{-12,-2}$ is the return from month $t-12$ to $t-2$, and $r_{-52,-2}$ is the return from week $t-52$ to $t-2$. IO is institutional ownership lagged one quarter. Volume is the average daily exchange adjusted share turnover during the previous 6 months. The regressions include calendar month dummies, and the standard errors take into account clustering by calendar date. The time period in the first three columns is October 1999 to September 2003, and the time period in the last three columns is the 3rd week of September 1999 to the first week of September 2003. T-statistics are in brackets. The intercept is estimated but not reported.

	Monthly Abnormal Returns			Weekly Abnormal Returns		
	[1]	[2]	[3]	[4]	[5]	[6]
DIN	0.965	1.046		0.185	0.221	
	[1.58]	[1.99]		[0.62]	[0.76]	
DOUT	-1.944	-1.803		-0.232	-0.103	
	[2.37]	[2.40]		[0.74]	[0.38]	
SIN	0.037	0.105		-0.281	-0.263	
	[0.04]	[0.13]		[1.23]	[1.23]	
SOUT	0.049	0.155		0.020	0.068	
	[0.08]	[0.29]		[0.07]	[0.26]	
DOUT_SMALL			-1.901			-0.330
			[1.60]			[1.01]
DOUT_BIG			-3.137			-0.482
			[3.14]			[1.50]
r_{-1}		-0.009	-0.009		-0.041	-0.041
		[0.35]	[0.35]		[4.65]	[4.65]
$r_{-12,-2}$		0.004	0.004			
		[0.70]	[0.69]			
$r_{-52,-2}$					0.001	0.001
					[1.27]	[1.27]
IO		0.734	0.709		0.181	0.179
		[1.16]	[1.11]		[1.48]	[1.46]
Volume		-0.133	-0.117		-0.043	-0.041
		[0.45]	[0.39]		[0.69]	[0.67]

Table VI
Supply and Demand Shifts: Monthly Portfolio Returns (in Percent)

The last trading day of month $t-1$ we check if there was some kind of shift in supply or demand during the month (based on changes in loan fees and shares lent out). We place stocks into shift portfolios: demand in (DIN), demand out ($DOUT$), supply in (SIN), and supply out ($SOUT$). Shift portfolios are formed in month $t-1$ and the stocks are held in the portfolios during month t. Only stocks with lagged market cap below the NYSE median and with lagged price at least equal to 5 dollars are included in the portfolios. The *SPECIAL* portfolio is formed by assigning all stocks with lending fees greater than 0.5% per year at the end of month $t-1$ to this portfolio. We proxy for expected returns characteristically using 25 equal weight size-BE/ME portfolios and 75 (3x5x5) equal weight size-BE/ME-Momentum portfolios. The benchmark portfolios also contain the restriction that lagged price must be at least 5 dollars. The time period is October 1999 to September 2003.

Panel A: Excess Returns							
	SPECIAL	DIN	DOUT	SIN	SOUT	DIN-DOUT	SIN-SOUT
Equal-Weight							
Mean	0.47	1.94	-1.82	0.86	-1.12	3.76	1.99
T-stat	0.30	0.95	-1.01	0.51	-0.57	2.56	1.57
Value-Weight							
Mean	-0.21	0.84	-0.51	0.43	-2.19	1.35	2.62
T-stat	-0.12	0.44	-0.26	0.23	-1.11	0.83	1.96
Panel B: Abnormal Returns (Benchmark Portfolios: 25 Size-BE/ME Portfolios)							
	SPECIAL	DIN	DOUT	SIN	SOUT	DIN-DOUT	SIN-SOUT
Equal-Weight							
Mean	-0.31	1.19	-2.34	0.50	-1.80	3.53	2.30
T-stat	-0.53	1.00	-2.51	0.59	-1.43	2.48	1.83
Value-Weight							
Mean	-0.83	0.24	-1.03	0.02	-2.65	1.27	2.67
T-stat	-1.22	0.26	-0.86	0.02	-2.27	0.79	1.96
Panel C: Abnormal Returns (Benchmark Portfolios: 75 Size-BE/ME-Mom Portfolios)							
	SPECIAL	DIN	DOUT	SIN	SOUT	DIN-DOUT	SIN-SOUT
Equal-Weight							
Mean	-0.24	0.93	-2.10	0.11	-1.62	3.03	1.73
T-stat	-0.47	0.90	-2.13	0.14	-1.34	2.36	1.34
Value-Weight							
Mean	-0.72	-0.12	-0.83	-0.20	-2.39	0.71	2.19
T-stat	-1.16	-0.13	-0.70	-0.21	-2.14	0.48	1.61

Table VII
Cross Sectional Regressions: Robustness Tests

The dependent variable is monthly abnormal returns in percent. We proxy for expected returns characteristically using 25 equal weight size-BE/ME portfolios. All stocks below the NYSE median market cap and with lagged price at least equal to 5 dollars are included in sample. DIN is a dummy variable for a inward demand shift last month. DOUT is a dummy variable for an outward demand shift last month. SIN is a dummy variable for an inward supply shift last month. SOUT is a dummy variable for an outward supply shift last month. r_{-1} is last months return. $r_{-12,-2}$ is the return from month $t-12$ to $t-2$. IO is institutional ownership measured as a fraction of shares outstanding lagged one quarter. Volume is the average daily exchange adjusted share turnover during the previous 6 months. DIV is a dummy variable that equals 1 if there was a dividend in month $t-1$, and SPLIT is a dummy variable that equals 1 if there was a stock split or stock dividend in month $t-1$. The standard errors take into account clustering by calendar date. The time period is October 1999 to September 2003. T-statistics are in brackets. The intercept is estimated but not reported.

	[1]	[2]	[3]	[4]	[5]
DIN	0.402	0.387	0.387	0.014	0.270
	[0.79]	[0.77]	[0.77]	[0.03]	[0.56]
DOUT	-2.546	-2.632	-2.655	-3.040	-2.626
	[3.36]	[3.27]	[3.34]	[3.38]	[3.47]
SIN	0.386	0.372	0.373	0.039	0.236
	[0.48]	[0.46]	[0.46]	[0.04]	[0.30]
SOUT	-0.657	-0.674	-0.674	-1.044	-0.768
	[0.96]	[0.99]	[0.99]	[1.49]	[1.15]
r_{-1}	-0.009	-0.009	-0.009		-0.010
	[0.34]	[0.35]	[0.35]		[0.39]
$r_{-12,-2}$	0.004	0.004	0.004		0.003
	[0.69]	[0.69]	[0.69]		[0.62]
IO	0.706	0.685	0.685		1.096
	[1.11]	[1.08]	[1.08]		[1.59]
Volume	-0.118	-0.125	-0.125		-0.170
	[0.40]	[0.43]	[0.43]		[0.71]
SPLIT	-0.146		-0.121		
	[0.17]		[0.15]		
SPLIT*DOUT	3.682		3.496		
	[0.38]		[0.36]		
DIV		-0.295	-0.294		
		[0.90]	[0.91]		
DIV*DOUT		2.266	2.217		
		[0.92]	[0.88]		
Fixed Effects	Calendar Month			Calendar Month & Industry	

Table VIII
Cross Sectional Regressions: Nasdaq Stocks

The dependent variable is monthly abnormal returns in percent. The returns are risk-adjusted using 25 equal weight size-BE/ME portfolios. Nasdaq stocks below the NYSE median market cap and with lagged price at least equal to 5 dollars are included in sample. DIN (DOUT) is a dummy variable for a inward (outward) demand shift last month. SIN (SOUT) is a dummy variable for an inward (outward) supply shift last month. In the first column, the loan quantity used to define the shifts is monthly short interest from Nasdaq. The loan fees are from our lender, and monthly returns are measured using closing prices from the 16th of the month. In columns 2 – 4 the shifts are defined using our lender's loan quantity (as a a fraction of shares oustatnading) and returns are measured at the months end. r_{-1} is last months return. $r_{-12,-2}$ is the return from month $t-12$ to $t-2$. IO is institutional ownership measured as a fraction of shares outstanding lagged one quarter. Volume is the average daily exchange adjusted share turnover during the previous 6 months. Market Power is the number of shares lent out by the lender in month $t-1$ divided by short interest in month $t-1$, while Market Power > 2/3 is a dummy variable equal to one if the lender's Market Power exceeds 2/3. The regressions include calendar month dummies, and the standard errors take into account clustering by calendar date. The time period is October 1999 to September 2003. T-statistics are in brackets. The intercept is estimated but not reported.

	Loan Quantity = Short Interest			Loan Quantity = Shares Lent By Our Lender
	[1]	[2]	[3]	4
DIN	0.666	0.656	0.474	0.594
	[1.06]	[0.92]	[0.55]	[0.83]
DOUT	-1.329	-2.905	-2.245	-2.517
	[2.07]	[3.31]	[2.55]	[2.63]
SIN	-0.414	0.251	0.825	0.555
	[0.46]	[0.25]	[0.74]	[0.54]
SOUT	-0.647	-0.435	-0.482	-0.325
	[1.22]	[0.49]	[0.61]	[0.39]
(Market Power)*DIN			1.267	
			[0.45]	
(Market Power)*DOUT			-5.492	
			[1.14]	
(Market Power)*SIN			-3.956	
			[1.45]	
(Market Power)*SOUT			0.437	
			[0.12]	
(Market Power>2/3)*DIN				1.252
				[0.46]
(Market Power>2/3)*DOUT				-10.01
				[2.70]
(Market Power>2/3)*SIN				-5.658
				[1.74]
(Market Power>2/3)*SOUT				-3.760
				[0.74]
Control Variables	r_{-1}, $r_{-12,-2}$, IO, Volume, and calendar month dummies			

Table IX
Cross Sectional Regressions: Analysts and Forecast Revisions

The dependent variable is monthly abnormal returns in percent. The returns are risk-adjusted using 25 equal weight size-BE/ME portfolios. All stocks below the NYSE median market cap and with lagged price $\geq$ \$5 are included in sample. DIN (DOUT) is a dummy variable for a inward (outward) demand shift last month. SIN (SOUT) is a dummy variable for an inward (outward) supply shift last month. r_{-1} is last months return. $r_{-12,-2}$ is the return from month $t-12$ to $t-2$. IO is institutional ownership lagged one quarter. Volume is the average daily exchange adjusted share turnover during the previous 6 months. $RCOV_{t-1}$ is last month's residual analyst coverage, and is computed by running a cross-sectional regression of analyst coverage on size, and then calculating the residual for each stock. $REVNEG_{t-1}$ is a dummy variable equal to one if the firm had at least one downward revision last month by an analyst (and no positive revisions) of a quarterly earnings forecast. $REVZERO_{t-1}$ is a dummy variable equal to one if the firm had zero revisions last month by any analysts in their quarterly earnings forecasts. Standard errors take into account clustering by calendar date. The time period is October 1999 to September 2003. T-statistics are in brackets. The intercept is estimated but not reported.

	[1]	[2]	[3]	[4]	[5]	[6]
DIN	0.482	0.484	0.458	0.462	0.380	0.381
	[0.93]	[0.94]	[0.88]	[0.89]	[0.73]	[0.74]
DOUT	-2.537	-2.508	-2.534	-0.478	-2.499	-1.203
	[3.32]	[3.50]	[3.32]	[0.42]	[3.31]	[1.01]
SIN	0.405	0.407	0.396	0.398	0.434	0.434
	[0.50]	[0.51]	[0.49]	[0.50]	[0.54]	[0.54]
SOUT	-0.660	-0.657	-0.667	-0.663	-0.704	-0.703
	[0.96]	[0.95]	[0.97]	[0.96]	[1.01]	[1.01]
$RCOV_{t-1}$		0.011				
		[0.18]				
$RCOV_{t-1}$*DOUT		0.054				
		[0.25]				
$REVNEG_{t-1}$			-0.464	-0.467		
			[1.64]	[1.69]		
$REVZERO_{t-1}$			-0.409	-0.375		
			[1.78]	[1.71]		
$REVNEG_{t-1}$*DOUT				0.312		
				[0.16]		
$REVZERO_{t-1}$*DOUT				-3.372		
				[1.56]		
$REVNEG_t$					-4.384	-4.359
					[9.79]	[9.78]
$REVZERO_t$					-2.008	-1.993
					[8.22]	[8.16]
$REVNEG_t$*DOUT						-2.249
						[0.84]
$REVZERO_t$*DOUT						-1.540
						[1.01]
Control Variables	r_{-1}, $r_{-12,-2}$, IO, Volume, and calendar month dummies					

Table X
Cross Sectional Regressions: Earnings Announcements

The dependent variable is monthly abnormal returns in percent. The returns are risk-adjusted using 25 equal weight size-BE/ME portfolios. All stocks below the NYSE median market cap and with lagged price $\geq$ \$5 are included in sample. DIN (DOUT) is a dummy variable for a inward (outward) demand shift last month. SIN (SOUT) is a dummy variable for an inward (outward) supply shift last month. r_{-1} is last months return. $r_{-12,-2}$ is the return from month $t-12$ to $t-2$. IO is institutional ownership lagged one quarter. Volume is the average daily exchange adjusted share turnover during the previous 6 months. $EAPOS_{t-1}$ equals the SUE of an earnings announcement if it was a positive surprise and zero otherwise. $EANEG_{t-1}$ equals the SUE of an earnings announcement if it was a negative surprise and zero otherwise. Standard errors take into account clustering by calendar date. The time period is October 1999 to September 2003. T-statistics are in brackets. The intercept is estimated but not reported.

	[1]	[2]	[3]	[4]	[5]
DIN	0.482	0.482	0.482	0.486	0.486
	[0.93]	[0.93]	[0.93]	[0.93]	[0.93]
DOUT	-2.537	-2.537	-2.476	-2.534	-2.525
	[3.32]	[3.32]	[3.27]	[3.33]	[3.35]
SIN	0.405	0.404	0.404	0.404	0.404
	[0.50]	[0.50]	[0.50]	[0.50]	[0.50]
SOUT	-0.660	-0.660	-0.661	-0.669	-0.668
	[0.96]	[0.96]	[0.96]	[0.97]	[0.97]
$EAPOS_{t-1}$		0.158	0.130		
		[0.30]	[0.25]		
$EANEG_{t-1}$		-0.020	0.011		
		[0.11]	[0.06]		
$EAPOS_{t-1}$*DOUT			2.313		
			[0.30]		
$EANEG_{t-1}$*DOUT			-5.918		
			[0.84]		
$EAPOS_t$				1.599	1.576
				[2.40]	[2.30]
$EANEG_t$				-0.764	-0.740
				[3.87]	[3.83]
$EAPOS_t$*DOUT					3.108
					[0.47]
$EANEG_t$*DOUT					-2.051
					[1.28]
Control Variables	r_{-1}, $r_{-12,-2}$, IO, Volume, and calendar month dummies				

Table XI
Cross Sectional Regressions: Interaction Between Loan Fees and Shifts

The dependent variable in the first three columns is monthly abnormal returns in percent, and the dependent variable in the last three columns is weekly abnormal returns in percent. We proxy for expected returns characteristically using 25 equal weight size-BE/ME portfolios. All stocks owned by our lending institution that are below the NYSE median market cap with lagged price greater than 5 dollars are included in sample. DIN is a dummy variable for a inward demand shift last month. DOUT is a dummy variable for an outward demand shift last month. SIN is a dummy variable for an inward supply shift last month. SOUT is a dummy variable for an outward supply shift last month. $LoanFee_{t-lag}$ is the loan fee from the end of the $t-lag$ month. $LoanFee_{t-lag}$ >x is a dummy variable that equals one of the loan fee is greater than x. The regressions include calendar month dummies, and the standard errors take into account clustering by calendar date. The time period is October 1999 to September 2003. T-statistics are in brackets. The intercept is estimated but not reported.

	[1]	[2]	[3]	[4]
DIN	0.288	0.312	-0.717	0.258
	[0.59]	[0.60]	[1.73]	[0.45]
DOUT	-2.937	-3.079	-0.672	-1.464
	[3.41]	[3.38]	[0.83]	[1.65]
SIN	0.135	0.123	0.729	0.770
	[0.15]	[0.12]	[0.99]	[0.79]
SOUT	-0.766	-0.800	-0.627	-1.135
	[1.26]	[1.17]	[1.00]	[2.07]
$LoanFee_{t-1} > 3\%$	-0.332		0.107	
	[0.34]		[0.12]	
$LoanFee_{t-2} > 3\%$		-0.376		0.523
		[0.39]		[0.47]
($LoanFee_{t-1} > 3\%$)*DIN			2.835	
			[2.14]	
($LoanFee_{t-1} > 3\%$)*DOUT			-4.468	
			[2.88]	
($LoanFee_{t-1} > 3\%$)*SIN			-1.684	
			[1.00]	
($LoanFee_{t-1} > 3\%$)*SOUT			-0.802	
			[0.48]	
($LoanFee_{t-2} > 3\%$)*DIN				-0.673
				[0.59]
($LoanFee_{t-2} > 3\%$)*DOUT				-4.979
				[2.71]
($LoanFee_{t-2} > 3\%$)*SIN				-3.048
				[1.56]
($LoanFee_{t-2} > 3\%$)*SOUT				0.121
				[0.07]

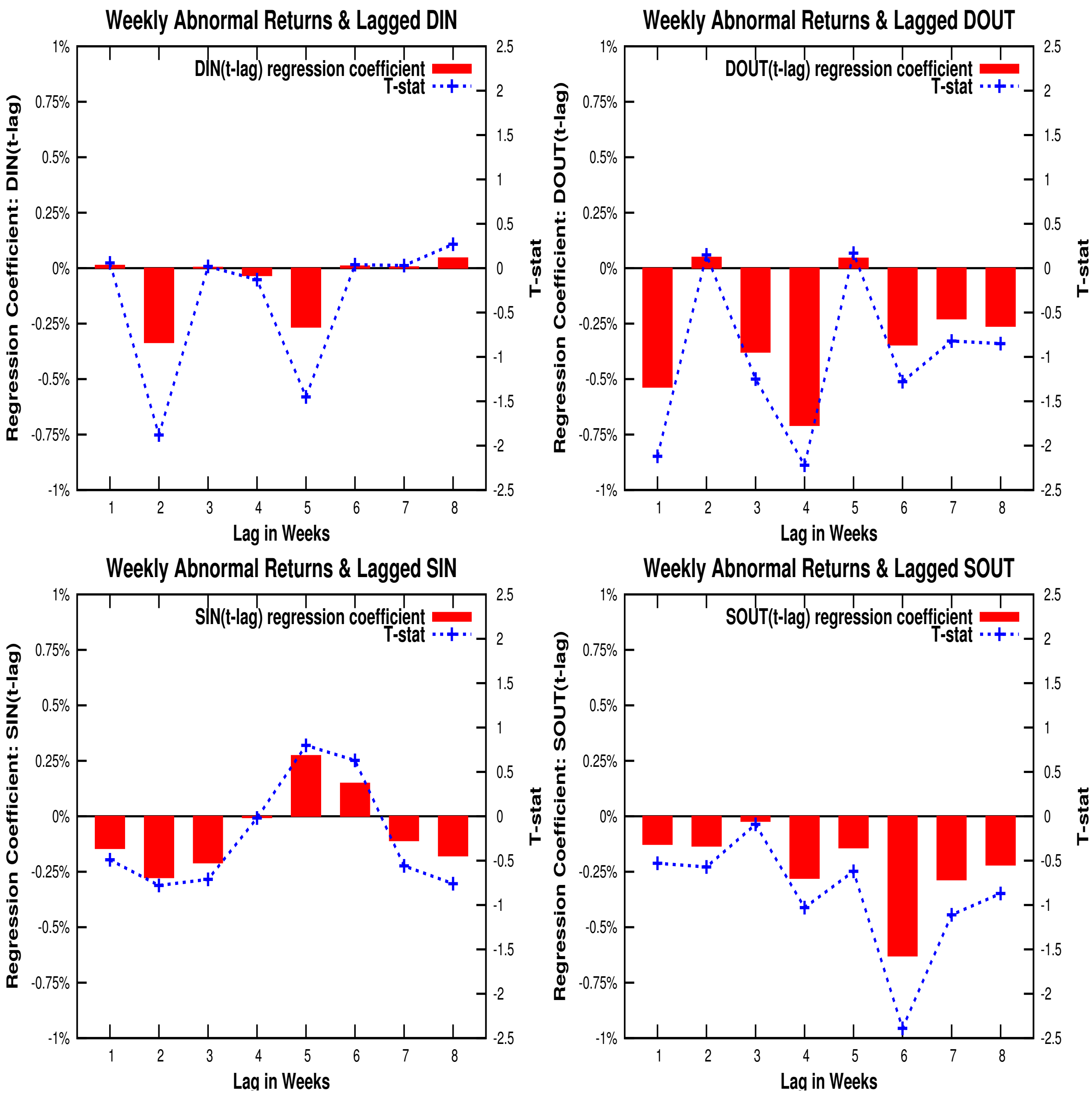

Figure 1: Weekly Abnormal Returns And Lagged Shifts

We regress weekly abnormal returns in percent on supply and demand shifts. We proxy for expected returns characteristically using 25 equal weight size-BE/ME portfolios. All stocks below the NYSE median market cap and with lagged price greater than 5 dollars are included in sample. DIN(t-lag) is a dummy variable for an inward demand shift lag weeks ago. DOUT(t-lag) is a dummy variable for an outward demand shift lag weeks ago. SIN(t-lag) is a dummy variable for an inward supply shift lag weeks ago. SOUT(t-lag) is a dummy variable for an outward supply shift lag weeks ago. We run separate regressions for each lag length. The regression include calendar month dummies, and the standard errors take into account clustering by calendar date.

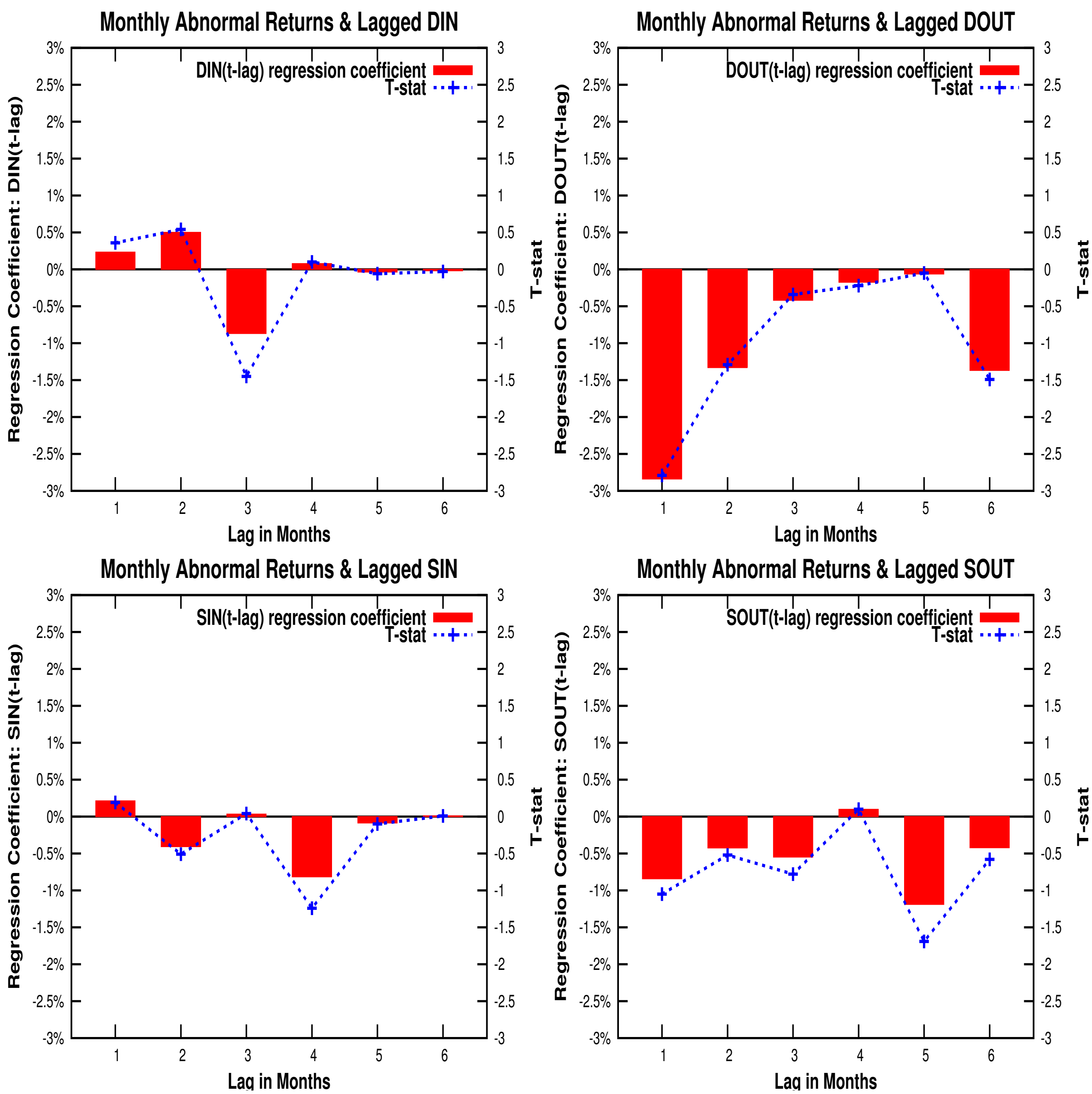

Figure 2: Monthly Abnormal Returns And Lagged Shifts
We regress monthly abnormal returns in percent on supply and demand shifts. We proxy for expected returns characteristically using 25 equal weight size-BE/ME portfolios. All stocks below the NYSE median market cap and with lagged price greater than 5 dollars are included in sample.

DIN(t-lag) is a dummy variable for an inward demand shift lag months ago. DOUT(t-lag) is a dummy variable for an outward demand shift lag months ago. SIN(t-lag) is a dummy variable for an inward supply shift lag months ago. SOUT(t-lag) is a dummy variable for an outward supply shift lag months ago. We run separate regressions for each lag length. The regression include calendar month dummies, and the standard errors take into account clustering by calendar date.