

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 clarify the nature of the correlation between shorting indicators and stock prices. Employing a unique identification strategy, we are able to isolate shifts in the supply and demand for shorting. We find that shorting demand is an important predictor of future stock returns. The magnitude of this effect is large: an increase in shorting demand leads to a significant negative average abnormal return of 2.52% in the following month. We also provide evidence of a *causal* link between shorting demand and future stock returns by showing that these results are unlikely to be driven by public information flow.

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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 the precise nature of the correlation between shorting indicators and subsequent stock returns? and 2) is there a causal link between this market and subsequent stock returns? 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 and 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, 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

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

²See, 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.

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 identify 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. Our approach is simple. 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 causation. Is there a *causal* link between movements in the shorting market and stock prices? Arguments for a causal interpretation typically rely on either market frictions or informed trading. For example, 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 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 causation, we first exploit instances where outside 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

³Short 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.

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

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 Our approach is to determine if outside information flow drives the results in our first section. Specifically, we replicate these tests on subsamples of firms or times where information is scarce, such as firms with low residual analyst coverage (see Hong, Lim, and Stein (2000)), firm months with no analyst revisions, or earnings announcements.

We then examine an implication of private information flow being an important mechanism of this market. 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 it were only a costly market friction, we would not expect to see substantive profits *net* of trading costs. If the lending market is an important channel for private information revelation, substantial profits net of trading costs would not be unreasonable. However, this test is ultimately only suggestive since we only can measure direct shorting costs. Profitability net of direct costs may reflect large indirect/implicit costs.

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 2.52% in the following month. Decreases in shorting supply also play a role, albeit a noisier.

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 over 50% per year. Thus, indirect shorting costs and other transaction costs would have to be quite

⁵Our companion paper Cohen, Diether, and Malloy (2004) 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.

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 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

⁶See, 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.

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

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.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

⁸See, 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).

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

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 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 whether these measures *cause* 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 (2004), 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 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 spreads are almost always very similar. In most cases, the spreads 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 spread (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. 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 lending, and for 7.4% of observations the fund is responsible for all of the lending.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 COMPUSTAT, 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.

Table II presents summary statistics for our main sample, broken down into large stocks (Panel B, for stocks above the NYSE Median market cap), and small stocks (Panel C, for stocks below the NYSE Median market cap). Clearly small stocks have much higher loan fees on average (spread=3.94%, 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

¹⁰We 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.

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. 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 each 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 price (spread) and quantity on loan are in Table III Panel D. 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%.

B. Portfolio Strategies

Our baseline tests employ portfolio sorts using the four quadrant classifications defined earlier. We use these to draw conclusions about average returns for these classes of stocks. 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).¹¹ We place stocks into shift portfolios: demand in (*DIN*), demand out (*DOU*), supply in (*SIN*), and supply out (*SOU*). Shift portfolios are formed in month $t - 1$, and the stocks are held in the portfolios during month t .¹² We rebalance the portfolios monthly. To focus our attention on those stocks where short selling effects are likely to be most important (i.e., small stocks), we exclude all stocks above the NYSE median market cap (in month $t - 1$) from our tests.

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 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,

$$r_{jt}^{sbm} = r_{jt} - R_t^{SBM_{j,t-1}}, \quad (1)$$

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.¹³ 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.

¹¹In alternate specifications, we check if there has been a shift in lending supply or demand during the last trading *week* of the month.

¹²Following 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.

¹³See Daniel, Grinblatt, Titman, and Wermers (1997) and Grinblatt and Moskowitz (1999) for more details on characteristically adjusting returns.

i. Monthly Portfolio Results

Table III presents our results for monthly portfolio sorts. The mean characteristics in Panel D reveal that the stocks in our shift portfolios tend to be small, growth stocks with higher than average volume. Table III highlights several other interesting findings. First of all, 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. Panels B and C show that *DOUT* stocks earn average (equal-weight) abnormal returns in the subsequent month of -2.51% per month when benchmarked relative to size-BE/ME portfolios and -2.76% per month when benchmarked relative to size-BE/ME-Momentum portfolios.¹⁴ The value-weight results are also negative, but smaller in magnitude and insignificant. An equally weighted portfolio which goes long *DIN* and short *DOUT* earns a large and significant 3.60% per month in average abnormal returns. These results suggest a statistically significant, economically important link between increases in shorting demand and future abnormal returns.

Table III also indicates a possible role for shorting supply. Increases in shorting supply lead to an average abnormal return between -2.41% and -2.64% per month for the value-weight *SOUT* portfolio and these results are significant. Similarly, a value-weight portfolio that goes long *SIN* and short *SOUT* earns an average abnormal return between 2.40% and 2.90% per month, but is only marginally significant when benchmarked relative to size-BE/ME-Momentum portfolios. Since an increase in shorting supply can be interpreted as a relaxation of short sale constraints, these results provide modest evidence that short sale constraints affect stock prices in our sample.

The final result of note in Table III is the finding that a portfolio of “special” stocks does not earn significantly negative future abnormal returns. 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. These results are robust to using 1% and 3% lending fee cutoffs as well. However, when the lending fee cutoff is 5% the magnitude of the average abnormal return is almost -2% per month, but the result is still insignificant (untabulated results). In contrast to other papers (see, for example, Jones and Lamont (2002) and Geczy, Musto, and Reed (2002)) that use specialness as a measure of shorting costs and find it to be a strong

¹⁴Untabulated statistics reveal virtually identical results if we use factor loadings to compute abnormal returns instead.

predictor of negative future returns, we find *SPECIAL* to be less informative about future returns than *DOUT* shifts.

ii. Weekly Portfolio Results

We explore if our results are robust to shorter return horizons by analyzing weekly portfolio sorts and weekly shifts in shorting supply and demand. These results confirm our prior findings. Stocks that experience an increase in shorting demand (*DOUT*) are met with large negative abnormal returns on average in the following week. Panels B and C of Table IV show that *DOUT* stocks earn significant future average (equal-weight) abnormal returns of -1.00% per week (t-stat = -2.00) when benchmarked relative to size-BE/ME portfolios and -1.05% per week (t-stat = -2.52) when benchmarked relative to size-BE/ME-Momentum portfolios. The value-weight results are also significant and similar in magnitude.

The supply channel estimates again suggest a negative relation between increases in supply and subsequent returns. According to Panel C, increases in shorting supply (*SOUT*) are met with significant negative (equal-weight) abnormal returns in the following week. (-0.57%, $t=-2.04$). However, the value-weight *SOUT* results, as well as the equal- and value-weight hedge portfolio (*SIN* minus *SOUT*) estimates are smaller and insignificant. Finally, future abnormal returns associated with *SPECIAL* portfolios are again insignificant.

In sum, the portfolio return results presented in Tables III and IV suggest the importance of isolating the precise roles of supply and demand shifts. These tables indicate an economically and statistically important link between shorting demand and future stock returns. Increases in shorting demand over the prior month (or week) lead to large negative abnormal returns on average over the subsequent month (or week). Also, although it is more noisy and the effect is smaller in magnitude, it seems that increases in supply also lead to future negative abnormal returns. In any case, unconditional shorting costs (e.g. "specialness") seem to be less informative about future returns than *DOUT* shifts.

C. Cross-Sectional Regressions

We run pooled, cross-sectional regressions on the universe of securities below the NYSE median market capitalization breakpoint. This allows us to control for other potential return dynamics and characteristics we think are important in the lending market. As in Grinblatt and Moskowitz (1999) and Tables III, we characteristically adjust the left-hand side returns for size and book-to-market 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 , $SOUT$, $SPECIAL$, $UTIL$, 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). As before, DIN is 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, an outward supply shifts, respectively. $SPECIAL$ is a dummy variable equal to one if a stock's end-of-month/week spread is greater than 0.50%, and $UTIL$ ("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).¹⁵ 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.

The coefficient estimates in Table V, for the monthly abnormal return regressions, confirm the evidence presented earlier in the portfolio sorts. In all specifications, increases in the demand for shorting ($DOUT$) lead to large negative abnormal returns in the future. Column three of Table V

¹⁵These 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 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 $SPECIAL$.

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 -2.52% in the following month ($t=-3.25$). By contrast, utilization rates (*UTIL*) and specialness (*SPECIAL*) are not informative about future returns on these stocks. The supply channel, which appeared to play a large and significant role in the portfolio sorts, shows much less predictive power in these regressions. The coefficient estimates for *SOUT* are now insignificant and not as large in magnitude relative to the portfolio results. For example in the third regression 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 supply are -0.65% in the following month ($t=-0.94$).

As a comparison highlighting the importance of our classification into each of the shift portfolios, we examine the predictability of only the more coarse classification of quantity changes and loan fee (spread) changes. The quantity can increase because of an *SOUT* or *DOUT*, and decrease because of and *SIN* or *DIN*. In contrast, the spread 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 V. Although returns are negative following loan fee increases and quantity increases, the effects are more modest than the shift portfolios. In fact, the quantity increases and loan fee increases seem to be noisy proxies for *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.

We find a similar relation between abnormal returns and outward demand shifts using weekly return data (Table VI). 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 -0.44% to -0.54% per week. The *DOUT* slope coefficient is significant in the first two regressions, but only marginally significant after characteristically adjusting for size, book-to-market, and controlling for past returns, institutional ownership, and volume. The supply out coefficient is quite small in these specifications, and once again not significant. In addition the specialness and utilization rate estimates are small and insignificant.

Table VII reports estimates from an alternate regression specification, one that uses information on the magnitude of the shifts rather than simply employing dummy variables. For example, in place of *DIN* we now use *DIN_SMALL* and *DIN_BIG*. *DIN_SMALL* is a dummy variable for a “small” shift in demand, where small indicates a shift below the median shift. 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. Indeed, the coefficient estimates presented in Table VII support this conjecture. Large increases in shorting demand (*DOUT_BIG*) are associated with larger negative abnormal returns in the future (-3.17 to -3.44% per month) than small increases in shorting demand (-1.86 to -2.22% per month). The difference between *DIN_SMALL* and *DIN_BIG* is significant in all the monthly abnormal return regressions, but not in the weekly abnormal return regressions. Meanwhile, neither increases nor decreases in the supply of shorting are reliable predictors of future returns, even when small and large shifts are examined separately.

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).¹⁶ 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 every 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

¹⁶The 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.

an insignificant coefficient on the supply shift variable.

D. Robustness: Dividend-dates, Collateral Issues, and Alternate Specifications

Our baseline results are robust to a variety of permutations. For brevity, we only explain a few such checks.¹⁷ For example, one concern when analyzing lending data is that many stocks experience a huge spike in borrowing and lending right around dividend dates, and that these spikes may be driving any empirical regularities.¹⁸ However, we can report that excluding dividend payers in months in which they pay a dividend has virtually no effect on our results; since most of our tests constrain our sample to exclude stocks above the NYSE median market capitalization (and hence, the majority of dividend payers), this is not surprising.

We have also 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. In fact, the coefficient on DOUT is actually a little bigger and more significant in each regression specification. SOUT's coefficient is also bigger in magnitude but still insignificant. Adding industry dummy variables to our regressions helps alleviate the concern that our results are driven by a few industries (e.g., tech stocks).

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

¹⁷These and other untabulated statistics are available from the authors on request.

¹⁸See Christoffersen, Geczy, Musto, and Reed (2004) for a discussion of related issues.

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, 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. Causation

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 on their own (signaling the potential importance of market frictions), or if they are simply correlated with underlying movements in outside 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).¹⁹ 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 as a control variable and interact it with *DOUT*. As shown in column 2 of Table VIII, the evidence for increases in shorting demand leading to large declines in future stock returns is not concentrated in low or 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.

¹⁹Our results using regular coverage, rather than residual coverage, are very similar. These results are available on request.

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 VIII shows our monthly abnormal return regression results when we add forecast revisions as a control variable and as an interaction variable with *DOUT*. Interacting demand shifts with a dummy for if the firm had no revisions last month ($REVZERO * DOUT$), we find that increases in shorting demand during times of no new public information lead to large negative future abnormal returns (-3.79% per month).²⁰ 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 large shorting demand effects, but that stocks that receive unambiguously negative revisions do not.

We also run cross-sectional regressions of the type reported in Table V to explore the effect of earnings announcements. Our results in column 4 show that *DOUT* is negative and significant, even after controlling for the marginal effect of $EA * DOUT$ (an interaction term capturing the effect of demand shifts that occur during months with earnings announcements).

In summary, scarce information environments (proxied by no revisions, low coverage, or no earnings announcements) generate a large and reliable link with future returns. Together these findings support the notion that the shorting market is an economically important mechanism for information revelation in prices.

C. Costs and Benefits of Shorting

Another piece of evidence consistent with the lending market being important for private information revelation and not solely as a market friction is the relative cost and benefit in returns from a demand shift based trading strategy. From Table III, the average spread, or cost, following *DOUT* is 3.72% per year. From Table III, the strategy *DIN-DOUT* yields 3.96% per month.²¹ Reforming

²⁰While this interaction effect is only marginally significant ($t = -1.62$), an F-test (unreported) reveals that the total effect ($DOUT + REVZERO_DOUT$) is strongly significant.

²¹Here 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 IX.

the portfolio at the end of every month $t - 1$ and holding it during month t gives roughly a 59% 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 55% average annual return.²² Thus, as long as the monthly rebalancing of the portfolio does not on average cost 55% per year, the strategy appears on average highly profitable. The magnitude of this result net of shorting costs provides evidence that the market may be important for private information revelation, and not simply represent 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 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.²³ 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 (spread) is correlated with future returns.²⁴ Table III and Table IX have 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

²²There is a confidence interval about this return, but even assuming that the lowest 5% bound of return is realized every month (a return of 1.06% per month), the strategy still makes almost 10% per year net of shorting costs.

²³As there are most probably some rents that are paid to the lender.

²⁴Although many of these cases are coupled with potential demand shifts such as additions to the loan crowd (Jones and Lamont (2002)) and mergers.

not matter how cost was bid up. We argue differently. We argue that the information content of *DOUT* and *SIN* differ. Specifically, 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 IX. This regression looks at abnormal returns in month t , and conditions on the level of spread greater than 300 basis points at the end of month $t - 1$. It then interacts this spread with each of the shifts during that month $t - 1$. From the 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*²⁵ for a given level of cost, when *DOUT* causes the higher cost, it has significant predictive power for subsequent abnormal returns which is almost 3 times the magnitude of *SIN*. However, *SIN* does not have significant predictive power over subsequent abnormal returns. In addition the difference between the effects is statistically significant (F-stat = 8.61 and p-value = 0.003). This is consistent with it being important to understand "how" the cost of shorting was driven up, and not simply the cost of shorting itself being 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 the precise nature of the relation between the shorting market and stock prices?, and 2) is there a causal link between the shorting market and stock prices? 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. Increases in shorting supply also lead to negative abnormal returns in the future, but these results are

²⁵From Table III the average effect of *DOUT* and *SIN* shift on spread is similar, 42 bp and 40 bp, respectively.

noisier and not of the same magnitude; thus our evidence that relaxations in short sale constraints are driving prices is modest.

We find that the effect of shorting demand on future prices is still large (economically and statistically) 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 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 that this market solely represents a costly market friction, and both of these are evidence in favor of this market being an important mechanism for private information revelation into prices.

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.

References

- Almazan, A., K. Brown, M. Carlson, and D. Chapman, 2000, Why constrain your fund manager?, Working paper, University of Texas at Austin.
- Asquith, Paul, Parag Pathak, and Jay Ritter, 2005, Short interest, institutional ownership, and stock returns, *Journal of Financial Economics*, forthcoming.
- Banz, Rolf W., 1981, The relationship between return and market value of common stocks, *Journal of Financial Economics* 9, 3–18.
- Carhart, Mark M., 1997, On persistence in mutual fund performance, *Journal of Finance* 52, 57–82.
- Chen, Joseph, Harrison Hong, and Jeremy C. Stein, 2002, Breadth of ownership and stock returns, *Journal of Financial Economics* 66, 171–205.
- Christoffersen, Susan E. K., Christopher C. Geczy, David K. Musto, and Adam V. Reed, 2004, The limits to dividend arbitrage: Implications for cross-border investment, Working paper, University of Pennsylvania.
- Cohen, Lauren, Karl B. Diether, and Christopher J. Malloy, 2004, Relaxing short sale constraints: Evidence from a natural experiment, Working paper, London Business School.
- Daniel, Kent D., Mark Grinblatt, Sheridan Titman, and Russ Wermers, 1997, Measuring mutual fund performance with characteristic-based benchmarks, *Journal of Finance* 52, 1035–1058.
- D’Avolio, Gene, 2002, The market for borrowing stock, *Journal of Financial Economics* 66, 271–306.
- Dechow, P., A. Hutton, L. Meulbroek, and R. Sloan, 2001, Short-sellers, fundamental analysis and stock returns, *Journal of Financial Economics* 61, 77–106.
- Diamond, Douglas W., and Robert E. Verrecchia, 1987, Constraints on short-selling and asset price adjustment to private information, *Journal of Financial Economics* 18, 277–311.

- Diether, Karl B., Christopher J. Malloy, and Anna Scherbina, 2002, Differences of opinion and the cross-section of stock returns, *Journal of Finance* 57, 2113–2140.
- Duffie, Darrell, 1996, Special repo rates, *Journal of Finance* 51, 493–526.
- Duffie, Darrell, Nicolae Garleanu, and Lasse Heje Pedersen, 2002, Securities lending, shorting, and pricing, *Journal of Financial Economics* 66, 307–339.
- Fama, Eugene F., and Kenneth R. French, 1992, The cross-section of expected stock returns, *Journal of Finance* 46, 427–466.
- Fama, Eugene F., and Kenneth R. French, 1997, Industry costs of equity, *Journal of Financial Economics* 43, 153–193.
- Fama, Eugene F., and James MacBeth, 1973, Risk, return and equilibrium: empirical tests, *Journal of Political Economy* 51, 55–84.
- Figlewski, S., 1981, The informational effects of restrictions on short sales: Some empirical evidence, *Journal of Financial and Quantitative Studies* 16, 463–476.
- Figlewski, S., and G. Webb, 1993, Options, short sales, and market completeness, *Journal of Finance* 48, 761–777.
- Geczy, Chris, David Musto, and Adam Reed, 2002, Stocks are special too: An analysis of the equity lending market, *Journal of Financial Economics* 66, 241–269.
- Grinblatt, Mark, and Tobias Moskowitz, 1999, Do industries explain momentum?, *Journal of Finance* 54, 1249–1290.
- Harrison, J., and D. Kreps, 1978, Speculative investor behavior in a stock market with heterogeneous expectations, *Quarterly Journal of Economics* 92, 323–336.
- Hong, Harrison, Terence Lim, and Jeremy C. Stein, 2000, Bad news travels slowly: Size, analyst coverage, and the profitability of momentum strategies, *Journal of Finance* 55, 265–295.
- Jegadeesh, Narasimham, and Sheridan Titman, 1993, Returns to buying winners and selling losers: Implications for stock market efficiency, *Journal of Finance* 48, 65–91.

- Jegadeesh, Narasimham, and Sheridan Titman, 2001, Profitability of momentum strategies: An evaluation of alternative explanations, *Journal of Finance* 56, 699–720.
- Jones, Charles M., and Owen A. Lamont, 2002, Short sale constraints and stock returns, *Journal of Financial Economics* 66, 207–239.
- Krishnamurthy, Arvind, 2002, The bond/old-bond spread, *Journal of Financial Economics* 66, 463–506.
- Lamont, Owen A., and Richard H. Thaler, 2003, Can the market add and subtract? Mispricing in tech stock carve-outs, *Journal of Political Economy* 111, 227–268.
- Mayhew, S., and V. Mihov, 2004, How do exchanges select stocks for option listing?, *Journal of Finance* 59, 447–472.
- Miller, Edward M., 1977, Risk, uncertainty, and divergence of opinion, *Journal of Finance* 32, 1151–1168.
- Mitchell, Mark, Todd Pulvino, and Eric Stafford, 2002, Limited arbitrage in equity markets, *Journal of Finance* 57, 551–584.
- Nagel, Stefan, 2004, Short sales, institutional investors, and the cross-section of stock returns, *Journal of Financial Economics*, forthcoming.
- Ofek, Eli, and Matthew Richardson, 2003, Dot com mania: The rise and fall of Internet stock prices, *Journal of Finance* 58, 1113–1137.
- Ofek, Eli, Matthew Richardson, and Robert Whitelaw, 2003, Limited arbitrage and short sales restrictions: Evidence from the options markets, *Journal of Financial Economics*, forthcoming.
- Pontiff, Jeffrey, 1996, Costly arbitrage: evidence from closed-end funds, *Quarterly Journal of Economics* 111, 1135–1151.
- Reed, Adam, 2002, Costly short-selling and stock price adjustment to earnings announcements, Working paper, University of North Carolina.

Rosenberg, Barr, Kenneth Reid, and Ronald Lanstein, 1985, Persuasive evidence of market inefficiency, *Journal of Portfolio Management* 11, 9–17.

Scheinkman, Jose, and Wei Xiong, 2003, Overconfidence and speculative bubbles, *Journal of Political Economy* 111, 1183–1219.

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

Sorescu, S., 2000, The effect of options on stock prices, *Journal of Finance* 55, 487–514.

Table I
Lending Activity Examples

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 Spread 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 express as a percentage of shares outstanding. Num Cont is the number of short-sale lending contracts that the lender is engaged for a given stock-day observation. Ptile ME is the NYSE market cap percentile.

| Date: July 29, 2003 | | | | | | |
|-------------------------|-------------|-------------|--------|-------------|-------------|-------------|
| Stock | Reb Rate | Col Rate | Spread | %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 |

Table II
Summary: 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 Spread is the difference between the collateral rate and the rebate rate, and is the interest rate the lender receives from the short-sale loan. %Shr Out is the total number of shares on loan by our lender express as a percentage of shares outstanding. Num Cont is the number of short-sale lending contracts that the lender is engaged for a given stock-day observation. Ptile ME is the NYSE market cap percentile. The time period is September 1999 to August 2003.

| Panel A: All Stocks | | | | |
|-------------------------------|-------|--------|----------|----------|
| | Mean | Median | 25 Ptile | 75 Ptile |
| Reb. Rate | 0.55 | 0.25 | -0.00 | 1.10 |
| Spread | 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 |
| Panel B: Above NYSE Median ME | | | | |
| | Mean | Median | 25 Ptile | 75 Ptile |
| Reb. Rate | 1.75 | 1.53 | 1.09 | 1.64 |
| Spread | 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 |
| Panel C: Below NYSE Median ME | | | | |
| | Mean | Median | 25 Ptile | 75 Ptile |
| Reb. Rate | -0.17 | 0.00 | -0.01 | 0.12 |
| Spread | 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 III
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. *Before Shift Spread* is the lending fee before the shift. *New Spread* 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 lagged 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.

| Panel A: Excess Returns | | | | | | | | |
|--|---------|-------|-------|------|--------|----------|----------|------|
| | SPECIAL | DIN | DOUT | SIN | SOUT | DIN-DOUT | SIN-SOUT | |
| Equal-Weight | | | | | | | | |
| Mean | 0.46 | 1.85 | -2.11 | 0.84 | -1.08 | 3.96 | 1.92 | |
| T-stat | 0.30 | 0.90 | -1.19 | 0.52 | -0.55 | 2.67 | 1.54 | |
| Value-Weight | | | | | | | | |
| Mean | -0.20 | 0.82 | -0.90 | 0.63 | -2.18 | 1.72 | 2.81 | |
| T-stat | -0.12 | 0.43 | -0.47 | 0.35 | -1.11 | 1.05 | 2.21 | |
| Panel B: Abnormal Returns (Benchmark Portfolios: 25 Size-BE/ME Portfolios) | | | | | | | | |
| | SPECIAL | DIN | DOUT | SIN | SOUT | DIN-DOUT | SIN-SOUT | |
| Equal-Weight | | | | | | | | |
| Mean | -0.32 | 1.09 | -2.51 | 0.47 | -1.74 | 3.60 | 2.22 | |
| T-stat | -0.56 | 0.91 | -2.74 | 0.62 | -1.38 | 2.52 | 1.79 | |
| Value-Weight | | | | | | | | |
| Mean | -0.83 | 0.22 | -1.28 | 0.26 | -2.64 | 1.49 | 2.90 | |
| T-stat | -1.22 | 0.24 | -1.11 | 0.27 | -2.26 | 0.93 | 2.25 | |
| Panel C: Abnormal Returns (Benchmark Portfolios: 75 Size-BE/ME-Mom Portfolios) | | | | | | | | |
| | SPECIAL | DIN | DOUT | SIN | SOUT | DIN-DOUT | SIN-SOUT | |
| Equal-Weight | | | | | | | | |
| Mean | -0.25 | 0.83 | -2.76 | 0.12 | -1.56 | 3.60 | 1.68 | |
| T-stat | -0.48 | 0.80 | -2.91 | 0.16 | -1.29 | 2.67 | 1.32 | |
| Value-Weight | | | | | | | | |
| Mean | -0.73 | -0.16 | -1.62 | 0.00 | -2.41 | 1.46 | 2.41 | |
| T-stat | -1.18 | -0.18 | -1.41 | 0.00 | -2.17 | 0.92 | 1.88 | |
| Panel D: | | | | | | | | |
| | Mean | | | | Median | | | |
| | DIN | DOUT | SIN | SOUT | DIN | DOUT | SIN | SOUT |
| Number of Stocks | 34 | 22 | 38 | 31 | 34 | 14 | 21 | 34 |
| Percentile ME | 25 | 22 | 22 | 23 | 22 | 19 | 19 | 22 |
| Percentile BE/ME | 37 | 32 | 38 | 34 | 29 | 23 | 29 | 24 |
| Percentile Vol | 72 | 74 | 71 | 74 | 79 | 81 | 79 | 82 |
| Before Shift Spread | 2.57 | 3.30 | 2.88 | 3.11 | 2.07 | 3.52 | 2.47 | 2.69 |
| New Spread | 2.16 | 3.72 | 3.28 | 2.55 | 1.74 | 4.22 | 3.05 | 2.07 |
| Before Shift %Shr Out | 1.09 | 0.78 | 0.98 | 0.79 | 0.58 | 0.40 | 0.58 | 0.34 |
| New %Shr Out | 0.80 | 1.10 | 0.65 | 1.09 | 0.35 | 0.63 | 0.30 | 0.62 |

Table IV
Supply and Demand Shifts: Weekly Portfolio Returns (in Percent)

The last trading day of week $t - 1$ we check if there has been some kind of shift in supply or demand during week (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 week $t - 1$ and the stocks are held in the portfolios during week t . The portfolios are rebalanced every week. 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. 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 the 3rd week of September 1999 to the first week of September 2003. Returns are in weekly percentages.

| Panel A: Excess Returns | | | | | | | |
|--|---------|------|-------|------|-------|----------|----------|
| | SPECIAL | DIN | DOUT | SIN | SOUT | DIN-DOUT | SIN-SOUT |
| Equal-Weight | | | | | | | |
| Mean | 0.01 | 0.41 | -1.00 | 0.14 | -0.49 | 1.41 | 0.63 |
| T-stat | 0.03 | 0.86 | -2.00 | 0.31 | -1.20 | 2.66 | 1.40 |
| Value-Weight | | | | | | | |
| Mean | -0.12 | 0.47 | -1.14 | 0.30 | -0.26 | 1.61 | 0.56 |
| T-stat | -0.37 | 0.86 | -2.18 | 0.65 | -0.61 | 2.78 | 1.21 |
| Panel B: Abnormal Returns (Benchmark Portfolios: 25 Size-BE/ME Portfolios) | | | | | | | |
| | SPECIAL | DIN | DOUT | SIN | SOUT | DIN-DOUT | SIN-SOUT |
| Equal-Weight | | | | | | | |
| Mean | -0.12 | 0.25 | -1.05 | 0.09 | -0.57 | 1.30 | 0.66 |
| T-stat | -1.06 | 0.75 | -2.52 | 0.24 | -2.04 | 2.50 | 1.50 |
| Value-Weight | | | | | | | |
| Mean | -0.23 | 0.35 | -1.18 | 0.19 | -0.32 | 1.53 | 0.51 |
| T-stat | -1.78 | 0.85 | -2.69 | 0.57 | -1.04 | 2.60 | 1.13 |
| Panel C: Abnormal Returns (Benchmark Portfolios: 75 Size-BE/ME-Mom Portfolios) | | | | | | | |
| | SPECIAL | DIN | DOUT | SIN | SOUT | DIN-DOUT | SIN-SOUT |
| Equal-Weight | | | | | | | |
| Mean | -0.10 | 0.19 | -1.13 | 0.20 | -0.53 | 1.32 | 0.73 |
| T-stat | -0.99 | 0.60 | -2.88 | 0.60 | -2.01 | 2.70 | 1.74 |
| Value-Weight | | | | | | | |
| Mean | -0.17 | 0.31 | -1.27 | 0.35 | -0.24 | 1.58 | 0.60 |
| T-stat | -1.52 | 0.78 | -3.16 | 1.05 | -0.82 | 2.90 | 1.32 |

Table V
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 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. *SPECIAL* is a dummy variable equal to one if a stock's end-of-month spread is greater than 0.50%. *UTIL* equals the ratio of shares lent out by our institution to shares owned by our institution. Loan Fee Decrease (Increase) is a dummy variable that equals one if loan fees decreased (increased) last month. Quantity Decrease (Increase) is a dummy variable that equals one if lending decreased (increased) 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. The regression 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] |
|-------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|------------------|
| DIN | 0.232 [0.36] | 0.267 [0.44] | 0.403 [0.78] | | | | | |
| DOUT | -2.837 [2.79] | -2.691 [2.83] | -2.521 [3.25] | | | | | |
| SIN | 0.213 [0.19] | 0.172 [0.17] | 0.313 [0.39] | | | | | |
| SOUT | -0.842 [1.05] | -0.798 [1.00] | -0.646 [0.94] | | | | | |
| r_{-1} | | -0.010 [0.36] | -0.009 [0.34] | | | -0.011 [0.41] | -0.009 [0.34] | -0.009 [0.34] |
| $r_{-12,-2}$ | | 0.003 [0.52] | 0.004 [0.68] | | | 0.005 [0.86] | 0.004 [0.69] | 0.004 [0.68] |
| IO | | | 0.700 [1.09] | | | 0.072 [0.10] | 0.696 [1.09] | 0.690 [1.08] |
| Volume | | | -0.114 [0.39] | | | 0.072 [0.21] | -0.111 [0.38] | -0.109 [0.37] |
| SPECIAL | | | | | -1.089 [1.21] | -0.934 [0.78] | | |
| UTIL | | | | -0.645 [0.85] | | -0.328 [0.44] | | |
| Loan Fee Decrease | | | | | | | -0.101 [0.20] | |
| Loan Fee Increase | | | | | | | -1.098 [1.73] | |
| Quantity Decrease | | | | | | | | 0.348 [0.85] |
| Quantity Increase | | | | | | | | -1.481 [3.00] |

VI
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 greater than 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. *SPECIAL* is a dummy variable equal to one if a stock's end-of-week spread is greater than 0.50%. *UTIL* equals the ratio of shares lent out by our institution to shares owned by our institution. 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. 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] |
|--------------|------------------|------------------|------------------|------------------|------------------|------------------|
| DIN | 0.013 [0.06] | 0.000 [0.00] | 0.052 [0.29] | | | |
| DOUT | -0.536 [2.12] | -0.487 [1.99] | -0.435 [1.78] | | | |
| SIN | -0.145 [0.49] | -0.152 [0.52] | -0.105 [0.38] | | | |
| SOUT | -0.126 [0.53] | -0.085 [0.36] | -0.035 [0.16] | | | |
| r_{-1} | | -0.041 [4.66] | -0.041 [4.63] | | | -0.040 [4.72] |
| $r_{-52,-2}$ | | 0.001 [1.00] | 0.001 [1.26] | | | 0.002 [1.36] |
| IO | | | 0.177 [1.44] | | | 0.041 [0.30] |
| Volume | | | -0.040 [0.66] | | | 0.005 [0.07] |
| SPECIAL | | | | -0.180 [1.30] | | -0.034 [0.24] |
| UTIL | | | | | -0.317 [1.85] | -0.288 [1.26] |

Table VII
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 price greater than 5 dollars are included in sample. We classify all shifts as big or small. A shift is considered big if is greater than or equal to the median (where the magnitude of shift is determined by its Euclidean distance), and a shift is small if less than the median. DIN_SMALL (DIN_BIG) is a dummy variable for a small (big) inward demand shift last month (week). DOUT_SMALL (DOUT_BIG) is a dummy variable for a small (big) outward demand shift last month (week). SIN_SMALL (SIN_BIG) is a dummy variable for a small (big) inward supply shift last month (week). SOUT_SMALL (SOUT_BIG) is a dummy variable for a small (big) outward supply shift last month (week). 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_SMALL | -0.655 [1.04] | -0.543 [0.91] | -0.419 [0.75] | 0.097 [0.36] | 0.080 [0.30] | 0.131 [0.54] |
| DIN_BIG | 1.268 [1.39] | 1.208 [1.38] | 1.363 [1.81] | -0.078 [0.31] | -0.087 [0.36] | -0.035 [0.16] |
| DOUT_SMALL | -2.222 [1.58] | -2.028 [1.53] | -1.858 [1.54] | -0.420 [1.28] | -0.397 [1.22] | -0.355 [1.10] |
| DOUT_BIG | -3.444 [2.93] | -3.345 [2.83] | -3.171 [3.06] | -0.633 [1.91] | -0.562 [1.74] | -0.502 [1.56] |
| SIN_SMALL | -0.696 [0.68] | -0.753 [0.82] | -0.612 [0.76] | 0.006 [0.02] | 0.041 [0.12] | 0.085 [0.25] |
| SIN_BIG | 1.098 [0.78] | 1.072 [0.84] | 1.216 [1.15] | -0.306 [0.91] | -0.356 [1.09] | -0.306 [0.97] |
| SOUT_SMALL | -0.714 [0.56] | -0.647 [0.51] | -0.461 [0.38] | -0.141 [0.47] | -0.101 [0.33] | -0.036 [0.13] |
| SOUT_BIG | -0.950 [1.18] | -0.927 [1.19] | -0.801 [1.18] | -0.113 [0.38] | -0.071 [0.24] | -0.034 [0.12] |
| r_{-1} | | -0.010 [0.36] | -0.009 [0.34] | | -0.041 [4.66] | -0.040 [4.63] |
| $r_{-12,-2}$ | | 0.003 [0.52] | 0.004 [0.68] | | | |
| $r_{-52,-2}$ | | | | | 0.001 [1.00] | 0.001 [1.26] |
| IO | | | 0.700 [1.09] | | | 0.177 [1.44] |
| Volume | | | -0.115 [0.39] | | | -0.040 [0.66] |

Table VIII**Cross Sectional Regressions: Analysts, Forecast Revisions and Earnings Announcements**

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 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. 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. RCOV is last months 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 is a dummy variable equal to one if the firm had a downward revision in the quarterly earnings forecast of an analyst last month. REVZERO is a dummy variable equal to one if the firm had zero revisions of quarterly earnings forecasts by analysts last month. EA is a dummy variable if the firm had an earnings announcement last month. 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 | 0.403 [0.78] | 0.405 [0.79] | 0.383 [0.74] | 0.404 [0.79] |
| DOUT | -2.521 [3.25] | -2.492 [3.43] | -0.355 [0.31] | -2.222 [2.43] |
| SIN | 0.313 [0.39] | 0.315 [0.39] | 0.306 [0.38] | 0.310 [0.38] |
| SOUT | -0.646 [0.94] | -0.643 [0.93] | -0.650 [0.94] | -0.657 [0.95] |
| $r_{-12,-2}$ | -0.009 [0.34] | -0.009 [0.34] | -0.009 [0.34] | -0.009 [0.34] |
| r_{-1} | 0.004 [0.68] | 0.004 [0.72] | 0.004 [0.69] | 0.004 [0.69] |
| IO | 0.700 [1.09] | 0.692 [1.12] | 0.572 [0.96] | 0.652 [1.02] |
| Volume | -0.114 [0.39] | -0.120 [0.40] | -0.126 [0.43] | -0.115 [0.39] |
| RCOV | | 0.012 [0.20] | | |
| RCOV*DOUT | | 0.052 [0.24] | | |
| REVNEG | | | -0.462 [1.66] | |
| REVZERO | | | -0.379 [1.73] | |
| REVNEG*DOUT | | | 0.149 [0.08] | |
| REVZERO*DOUT | | | -3.509 [1.62] | |
| EA | | | | 0.361 [2.38] |
| EA*DOUT | | | | -0.918 [0.51] |

Table IX
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. Spread(t-lag) is the loan fee from the end of the t-lag month. Spread(t-lag) > x is a dummy variable that equals one if 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 [0.59] | 0.411 [0.70] | -0.717 [1.73] | 0.177 [0.32] |
| DOUT | -2.937 [3.41] | -2.433 [2.93] | -0.672 [0.83] | -1.175 [1.36] |
| SIN | 0.135 [0.15] | 0.536 [0.61] | 0.729 [0.99] | 0.968 [1.19] |
| SOUT | -0.766 [1.26] | -0.602 [0.83] | -0.627 [1.00] | -0.871 [1.20] |
| Spread(t-1) > 3% | -0.332 [0.34] | | 0.107 [0.12] | |
| Spread(t-1) > 5% | | -1.738 [1.71] | | -0.752 [0.70] |
| (Spread(t-1) > 3%)*DIN | | | 2.835 [2.14] | |
| (Spread(t-1) > 3%)*DOUT | | | -4.468 [2.88] | |
| (Spread(t-1) > 3%)*SIN | | | -1.684 [1.00] | |
| (Spread(t-1) > 3%)*SOUT | | | -0.802 [0.48] | |
| (Spread(t-1) > 5%)*DIN | | | | 0.895 [0.49] |
| (Spread(t-1) > 5%)*DOUT | | | | -4.084 [1.76] |
| (Spread(t-1) > 5%)*SIN | | | | -2.303 [1.21] |
| (Spread(t-1) > 5%)*SOUT | | | | 0.700 [0.32] |

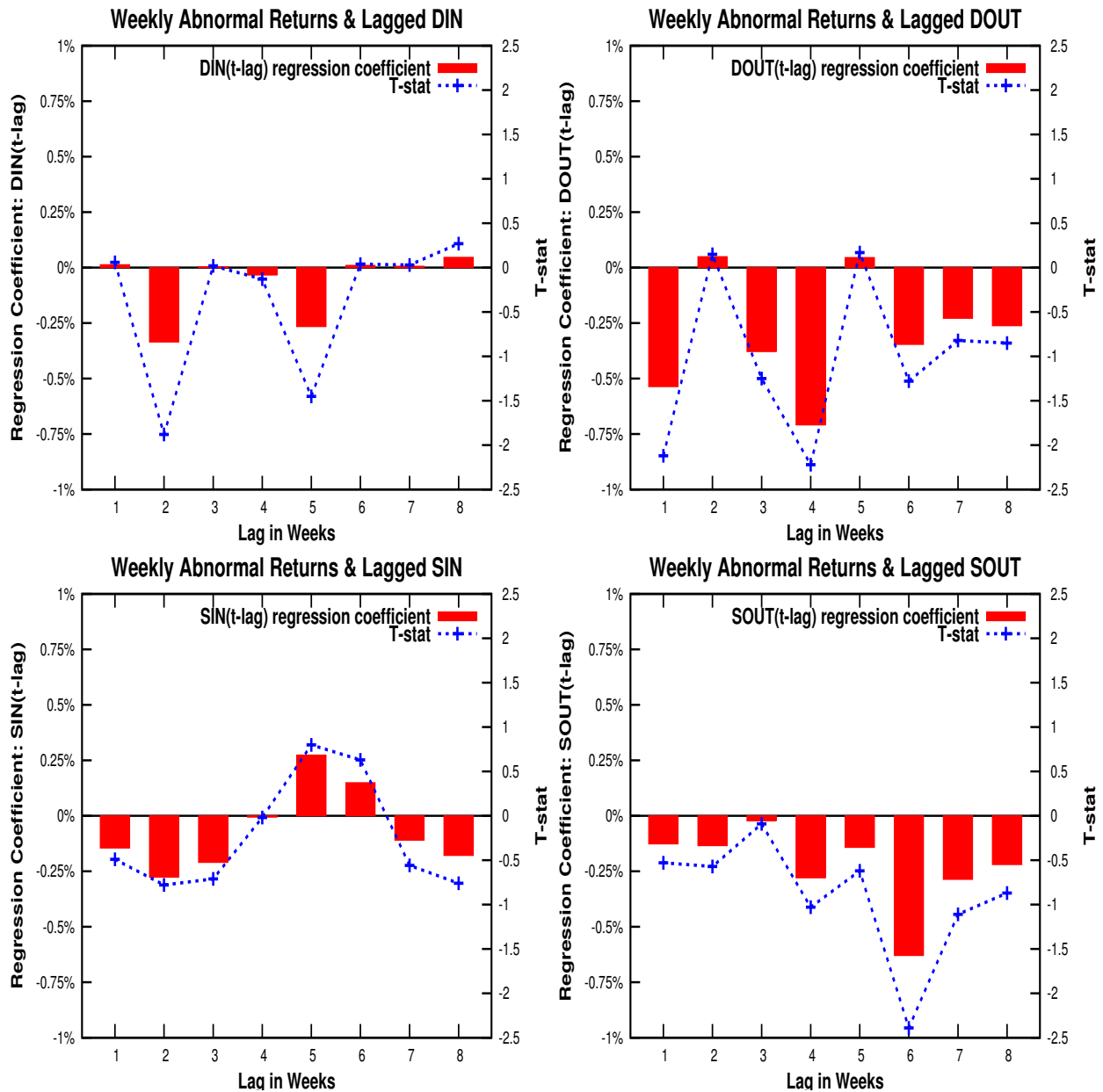


Figure 1: Weekly Abnormal Returns And Lagged Shifts

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 a 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.

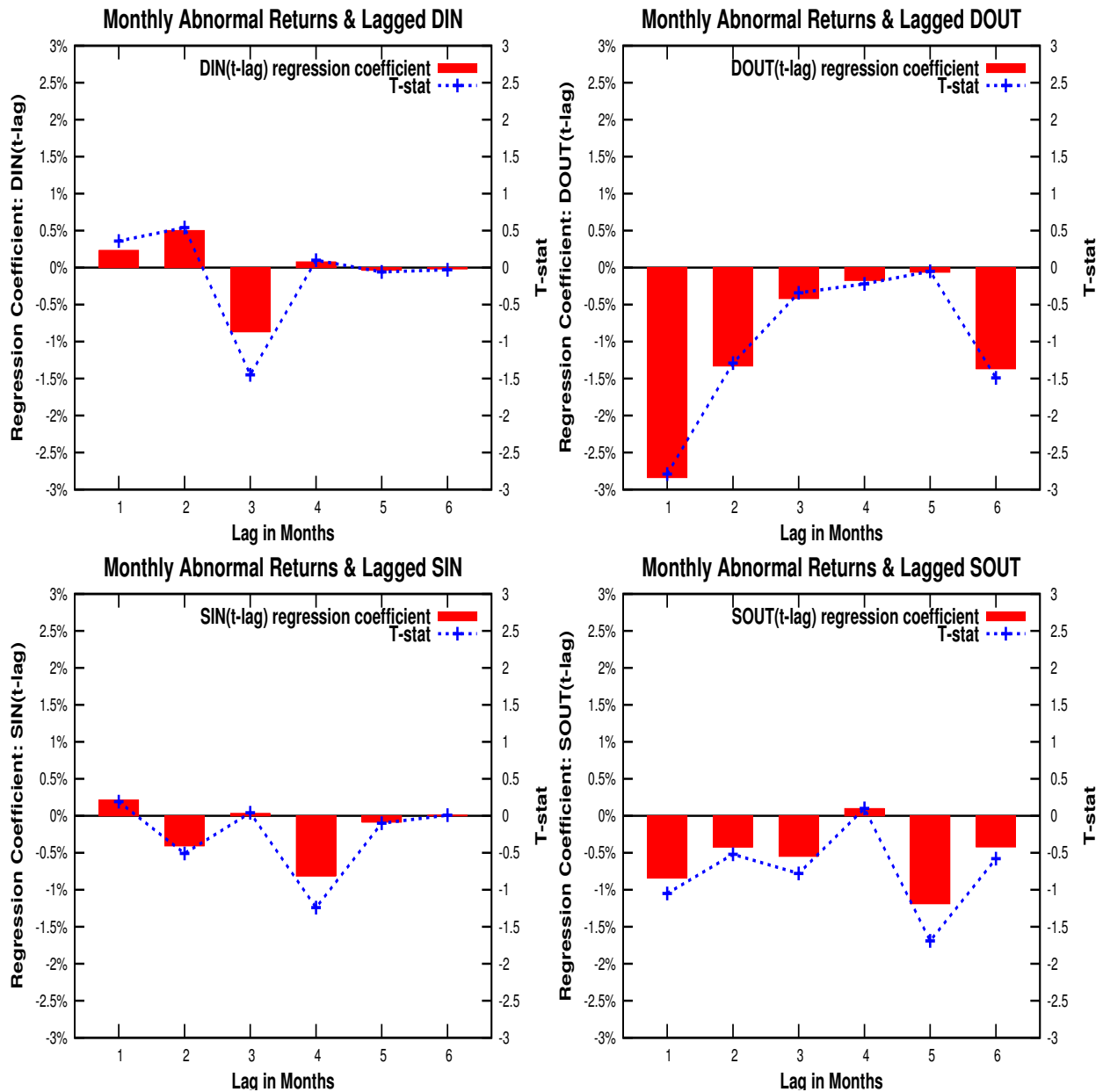


Figure 2: Monthly Abnormal Returns And Lagged Shifts

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.