Supply and Demand Shifts in the Shorting Market

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Abstract

Using proprietary data on stock loan fees and quantities from a large institutional investor, we examine the link between the shorting market and stock prices. Employing a unique identification strategy, we isolate shifts in the supply and demand for shorting. We find that shorting demand is an important predictor of future stock returns: an increase in shorting demand leads to negative abnormal returns of 2.54% in the following month. Second, we show that our results are stronger in environments with less public information flow, suggesting that the shorting market is an important mechanism for private information revelation into prices.

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A common theme in the literature on short selling is that activity in the shorting market can be used to predict future stock returns. Theory suggests that this link originates for one of two reasons. One strand of the literature argues that short sale constraints can prevent negative information from being impounded into prices (Miller (1977)). Coupled with difference of opinion, due either to irrational optimism or rational speculative behavior, these constraints can allow stocks to be overpriced and thus earn low subsequent returns.[1] An interesting cross-sectional implication of this idea is that stocks with the most tightly binding short sale constraints will have the lowest subsequent returns, a prediction that has spawned a series of recent empirical tests. A second strand of the literature argues that stock prices will remain unbiased conditional on public information (Diamond and Verrecchia (1987). Given rational expectations, uninformed agents take the presence of short sale constraints into account when forming their valuations. Since all participants recognize that negative opinions have not made their way into the order flow, stock prices will be unbiased. However, since short sale constraints impede the flow of *private* information, the release of unexpected negative private information leads to negative returns. Thus both theories predict a relation between the shorting market and future stock returns, but through different channels.

The standard empirical approach to testing this relation relies on finding an appropriate measure of short sale constraints. Existing studies generally approach this problem in one of two ways: 1) by obtaining data on direct costs of shorting from the stock loan market,[2] or 2) by employing *proxies* for shorting demand or shorting supply. The idea behind looking at shorting demand is that some investors may want to short a stock but may be impeded by constraints; if one can measure the size of this group of investors, one can measure the extent of overpricing or the extent of private information left out of the market. The idea behind looking at shorting supply is that since shorting a stock requires one first to borrow the shares, a low supply of lendable shares may indicate that short sale constraints are binding tightly.

In this paper, we provide a new framework for testing how stock prices respond to activity in the shorting market. Our approach allows us to construct actual measures of shorting supply and shorting demand (not proxies), and enables us to explicitly test which theoretical channel drives the

[1]For other theoretical work on the implications of short sale constraints for stock prices, see Harrison and Kreps (1978), Jarrow (1980), Diamond and Verrecchia (1987), Allen, Morris, and Postlewaite (1993), Morris (1996), Duffie, Garleanu, and Pedersen (2002), Hong and Stein (2003), and Scheinkman and Xiong (2003).

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

relation between the shorting market and future returns. We argue that decomposing the competing effects of shorting supply and shorting demand is a crucial and overlooked aspect of the empirical literature on short selling. For example, several studies use the direct cost of shorting as a measure of short sale constraints. In these tests, the cost of shorting is determined by the "rebate rate," which is the amount that the lender of a stock must pay to the borrower of that stock; this amount represents the interest on the collateral posted by the borrower in order to borrow the shares. The rebate rate is a price that equilibrates supply and demand in the lending market. The extent to which the rebate rate is below the market rate (such as the federal funds rate in the United States) is called the "loan fee," and represents a direct cost of shorting for the borrower.[3] As we demonstrate below, one problem with interpreting evidence on rebate rates is that while low rebate rates (i.e., high loan fees) likely indicate high shorting costs, it is not clear if this is because shorting demand is high or because loan supply is low. Since shorting costs are endogenously determined in the equity lending market, the common practice of using shorting costs as an exogenous measure of short sale constraints may be problematic if high shorting costs are in fact driven by shorting demand that is correlated with private information.

Utilizing proxies for shorting demand or shorting supply is also problematic. For example, short interest (the quantity of shares shorted as a percentage of shares outstanding) is a commonly used proxy for shorting demand. But like rebate rates, short interest represents the intersection of supply and demand. However, while a high loan fee 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. Another common proxy for tightly binding short sale constraints is low institutional ownership (see, for example, Chen, Hong, and Stein (2002), Nagel (2004), and Asquith, Pathak, and Ritter (2005)). The identifying assumption in these studies is that most lendable shares are supplied by institutional owners, and/or that low institutional ownership signals latent shorting demand; since most institutions cannot or do not engage in shorting, they can only express their pessimism by choosing not to hold shares. Thus institutional ownership is again an intersection of supply and demand; it is also an endogenous quantity, and thus possibly driven by stock-picking ability.

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

Using a novel 4-year panel dataset consisting of actual loan prices and quantities from a large institutional investor, we employ an empirical strategy that allows us to isolate 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. We are able to infer if a stock has experienced an increase or decrease in shorting demand or shorting supply by exploiting price/quantity "pairs." For example, an increase in the loan fee (our measure of price) coupled with an increase in the percentage of outstanding shares lent out (our measure of 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.

Differentiating these two effects is crucial for determining the channel through which and thus the reason *why* stock prices respond to activity in the shorting market. Consider the case of high loan fees, which can result from increased shorting demand or decreased shorting supply. Jones and Lamont (2002) employ high loan fees as a measure of short sale constraints in order to test Miller's (1977) hypothesis that short sale constrained stocks may be overpriced, and thus earn low subsequent returns. In this application, the loan fee is a sufficient statistic for overpricing, and the manner in which the loan fee is bid up should be irrelevant for its effect on future returns. However, high shorting costs may arise endogenously due to increased shorting demand. Mechanically, if shorting demand is the important channel, then both increased price (i.e., loan fee) and increased quantity (i.e., short interest, or percentage of shares on loan) are important. Increased quantity could be informative for future stock returns if it proxies for additional market frictions or risks of shorting, or if it signals a higher probability of informed trading. For example, if short-selling capital is limited, then taking a large short position in a stock potentially subjects a short-seller to idiosyncratic risk that she cannot diversify away. Non-price marginal costs of shorting such as recall risk may also be increasing in quantity.[5] Either way, large short positions may require a

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

[5]Recall risk is the risk that a lender recalls their shares early, forcing a borrower to close out her short position immediately.

risk premium. Alternatively, as in Diamond and Verrecchia (1987), high unexpected short interest may signal a large quantity of negative private information, since fewer liquidity traders (or those shorting for hedging purposes) are likely to short in the face of high short selling costs. Diamond and Verrecchia (1987) stress that stocks should not be overpriced conditional on publicly available information, but that the release of negative private information should lead to subsequent price declines. Since our data is not publicly available, private information release is one possible interpretation of why quantity could be important in our setting. Overall, changes in shorting demand represent changes in the marginal benefits of investors. If shorting demand is important empirically, then private information or other indirect costs/risks of shorting are key factors in the link between the shorting market and stock prices.

The factors driving changes in shorting supply are different. Since most lending institutions (including ours) also operate mutual funds, they have other incentives for holding stocks. For instance, following a sale of the shares of a certain stock, a lending institution experiences an inward shift of its 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.[6] Supply curve shifts thus represent shifts in the marginal costs of lending institutions. Consider again the case of high loan fees, but driven now by contractions in shorting supply (as opposed to increases in shorting demand); in a Miller (1977) world this scenario suggests that short sale constraints have tightened, which predicts positive returns (i.e., increased overpricing) in the short-run and low subsequent returns in the long-run as overpricing gets corrected. Clearly the interpretation and implications of high loan fees driven by contractions of shorting supply are different from a situation where high loan fees are driven by increases in shorting demand. Supply shifts inward (outward) indicate tightening (loosening) of short sale constraints, while demand shifts capture either informed trading or additional market frictions and risks of shorting. Isolating the relative effects of supply and demand empirically is crucial for developing a better understanding of the impact of the shorting market on stock prices.

Our tests reveal that shorting demand is an economically and statistically significant predictor of future stock returns. 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

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

month. Decreases in shorting supply play a more minor role. Further, the loan fee is *not* a sufficient statistic for overpricing: "specialness" (i.e., a high loan fee) is only important for future returns when driven by increases in shorting demand.

Turning to the issue of interpretation, we then investigate if increased shorting demand signals informed trading (which then leaks out to the market and reduces prices), or if it proxies for additional market frictions (which lead to higher expected returns for shorting, net of loan fees). 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. We test this by exploiting variation in the public information environment, and relating this variation to the strength of the shorting market's ability to predict 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 explicit cost of shorting. We would not expect to see substantial profits *net* of trading costs, unless the indirect costs or risks of shorting are extremely large. If the lending market is an important channel for private information revelation, however, substantial profits net of trading costs would not be unreasonable. Lastly, we explore the extent to which additional indirect costs and risks of shorting (e.g., recall risk or arbitrage risk) can explain the predictive ability of shorting demand.

We show that our key results are unlikely to be driven by public information flow. The effect of shorting demand on future stock returns is concentrated among stocks with low analyst coverage (a proxy for public information flow), and is *not* driven by predictable shifts in shorting demand such as stock splits or dividends. We also estimate the return to an investor from using our identification strategy to form trading rules, and find that *net* of shorting costs, the investor makes on average over 47% per year. Even after incorporating conservative estimates of additional trading costs such as commissions, bid-ask spreads, and price impact, the strategy still yields 4.5% per year. The Sharpe Ratio of the strategy is about 2.5-3.5 times that of the market and *HML*. Thus indirect costs of shorting would have to be extremely large, or arbitrage capital would have to be very limited for this strategy to represent a risk premium earned by short-sellers. However, we find little evidence that the profits to the shorting demand strategy vary with proxies for recall risk or stock-level arbitrage risk. Overall, our results indicate that the shorting market is an important mechanism for private information revelation into prices.

The paper is organized as follows. Section I reviews the related literature. Section II describes our research design and the data used in the study. Sections III and IV present empirical results, and Section V concludes.

I. Related Literature

A voluminous literature explores the theoretical link between short sale constraints and asset prices.[7] In Miller (1977), the combination of differences of opinion and short sale constraints can lead to overpricing. Differences of opinion can arise from overconfidence (Scheinkman and Xiong (2003)) or from differences in prior beliefs which are updated rationally as information arrives (Morris (1996)). In this setting, stock prices reflect the views of optimists, and this pattern of overpricing leads to low subsequent returns.[8] In Diamond and Verrecchia (1987), however, rational uninformed agents take the presence of short sale constraints into account when forming their valuations, and there is no overpricing conditional on public information, because all participants recognize that negative opinions have not made their way into the order flow. Diamond and Verrecchia's (1987) common-priors rational expectations model *does* predict that short sale constraints impede the flow of private information, and that the release of negative private information (e.g., via an unexpected increase in short interest) leads to negative returns.

The effect of short sale constraints on stock prices is thus ultimately an empirical question. One key empirical issue is determining an appropriate measure of short sale constraints. Due to the difficulty of obtaining data on direct shorting costs, a variety of studies exploit the fact that unwillingness or inability 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

[7] See Rubinstein (2004) for a summary.

[8] In Harrison and Kreps (1978) and Duffie, Garleanu, and Pedersen (2002), stock prices can be higher than even the most optimistic investor's assessment of their value.

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, lead to negative subsequent abnormal returns on average over the sample period 1979-1998. 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. However, Nagel also finds that when he combines his sample period with Chen *et al*'s period, there is no longer a reliable pattern during 1980-2003 between breadth of mutual fund ownership and future returns. As noted earlier, residual institutional ownership may also proxy for shorting supply, since low institutional ownership restricts the supply of available shares lent out. As in Chen *et al*, it is not clear which channel (shorting demand or shorting 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.

The oldest strand of the empirical literature on short selling focuses on short interest ratios (shares sold short divided by shares outstanding) as a proxy for shorting demand. Many of the early empirical studies (see Desai, Ramesh, Thiagarajan, and Balachandran (2002) for a summary) fail to find a consistent relation between short interest and abnormal returns. This could be due to the problematic nature of short interest. As noted earlier, 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. The weak results could also be due to the typical focus on levels of short interest, rather than changes.[9] On the other hand, as argued by Desai, Ramesh, Thiagarajan, and Balachandran (2002), the weak results could be due to the use of small and/or biased samples in these early studies. Indeed, much of the modern empirical literature linking the level of short sales with future returns finds consistent evidence that high short interest is followed

[9]Strictly speaking, as noted in Desai, Ramesh, Thiagarajan, and Balachandran (2002), testing the Diamond and Verrecchia (1987) proposition requires a measure of unexpected short interest, since only private information affects prices in this setting. By contrast, in a Miller (1977) setting, overpricing conditional on public information is possible; even so, Duffie, Garleanu, and Pedersen's (2002) model of overpricing suggests that price declines can be more directly related to expected *changes* in the short interest over time.

by low future returns. For example, Asquith and Meulbroek (1995) and Desai, Ramesh, Thiagarajan, and Balachandran (2002) find significant abnormal returns for stocks with high short interest on, respectively, the NYSE and AMEX exchanges for 1976-1993 and 1988-1994.[10] Meanwhile, Boehme, Danielsen, and Sorescu (2004) and Mohanaraman (2003) combine high short interest with measures of differences of opinion (the standard deviation of residuals and dispersion in analysts' forecasts, respectively) to test the Miller (1977) story; Boehme, Danielsen, and Sorescu (2004) find that the underperformance of stocks with high short interest ratios is concentrated among small stocks with high residual standard deviation, and Mohanaraman (2003) finds that high short interest stocks have lower returns the greater is the dispersion in analysts' forecasts. And finally, two recent papers (Aitken, Frino, McCorry, and Swan (1998) and Angel, Christophe, and Ferri (2003) look at daily short sales and subsequent returns on the Australian and Nasdaq markets, respectively, and show that high daily short sales are followed quickly by negative abnormal returns.

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. Asquith, Pathak, and Ritter (2005) show that stocks in the highest percentile of short interest (their proxy for shorting demand) and the lowest third of institutional ownership (their proxy for shorting supply) underperform by 215 basis point per month during 1988-2002 on an equal-weight basis. However, they do not attempt to disentangle the individual effects of shorting supply and shorting demand, and their focus is on levels (rather than changes); since they proxy for shorting supply and demand using institutional ownership and short interest, they also face the same problems of interpretation mentioned above. 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.

A series of recent papers analyzes direct measures of shorting costs (price).[11] The most commonly used metric is the rebate rate, and specifically the spread between the rebate rate and the

[10] See also Figlewski and Webb (1993), Figlewski (1981), and Dechow, Hutton, Meulbroek, and Sloan (2001) for evidence that stocks with high short interest experience low subsequent returns.

[11] See, for example, D'Avolio (2002), 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).

market interest rate. As noted earlier, 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. Retail borrowers typically receive no interest on their proceeds, so the situation described above applies mainly to institutional short-sellers. 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, and is often referred to as 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.[12] Obviously, if every investor were willing and able to lend shares in a competitive market, the lending fee would be zero. But, as Duffie (1996) and Krishnamurthy (2002) show, if some investors willing to hold overpriced assets do not lend, a strictly positive fee can arise.

The existing evidence on rebate rates has generally been limited to proprietary databases over short time periods. D'Avolio (2002), using a database from a single lender from April 2000 through September 2001, reports that only nine percent of the stocks in his sample are "on special" (defined here as a loan fee greater than 1% per annum) on a typical day. The other 91 percent have a rebate rate approximately equal to the Fed funds overnight rate. He does find that stocks on special have higher short interest. Geczy, Musto, and Reed (2002), using a sample of rebate rates from a single lender from November 1998 through October 1999, conclude that short sale constraints are unable to explain anomalous patterns in stock returns. Meanwhile Ofek, Richardson, and Whitelaw (2003), using proprietary data from July 1999 to December 2001, document that stocks on special are more likely to violate put-call parity.[13] Finally, using a small database of rebate rates hand-collected from the *Wall Street Journal* 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

[12]The one caveat to this statement is that the shorting market is not completely centralized. Thus, different lenders sometimes charge different loan fees. Conversations with our lender, however, suggest that the market is fairly competitive.

[13]Battalio and Schultz (2005) have recently questioned these put-call parity violations, claiming that the use of intraday options data, rather than closing quotes, resolves most of them.

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." These preceding statements are correct, but potentially incomplete. Low rebate rates (i.e., high loan fees) should be related to overpricing, but as noted earlier, the quantity lent out may also be informative. In this paper we explicitly examine the premise that the loan fee is a sufficient statistic for overpricing.

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 may serve to weaken the causal link between a relaxation of short sale constraints and stock prices in the context of option introductions. In this paper, 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.

II. Research Design

A. Data

We exploit a proprietary database of stock lending activity from a large institutional investor. This institution–unnamed for confidentiality purposes–is a market maker in many small stock lending markets. We have daily data on rebate rates, shares on loan, collateral amounts, collateral/market rates, estimated income from each loan, and broker firm names for the entire universe of lending activity for this firm from September, 1999 to August, 2003.

As noted above, the rebate rate is the portion of the collateral account interest rate that the short-seller receives. For each observation, we compute the loan fee, which is equal to the interest rate on cash funds (known as the "market rate" or "collateral rate") minus the rebate rate. 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. The loan fee is our measure of price throughout the paper. 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 loan fee of the largest contract in our tests, but our results are unaffected by using the average or share-weighted average loan fee instead. Throughout the paper we use shares on loan divided by shares outstanding as our measure of quantity in order to use a consistent measure across stocks; however, untabulated results indicate that our key findings are slightly stronger if we use raw, unscaled shares lent out as our measure of quantity instead.

Panel A of Table I presents lending activity examples from our sample. 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.

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.

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). The market (or collateral) interest rate in Panel B for stocks above the NYSE median is more than 260 basis points less than the market rate for stocks below the NYSE median, but this result is simply due to the calendar timing of these two samples. Our institution dramatically increased its large-cap (above NYSE median) lending program in 2002 and 2003, while maintaining its small-cap (below NYSE median) lending program at a relatively constant level throughout our sample period. For example, the average number of stocks on loan per day for a given calendar year is 366, 438, 320, and 317 for the years 2000-2003 for small-cap stocks, compared to 20, 68, 249, and 350 for these years for large-cap stocks. Therefore, the large-cap sample is tilted towards the end of the sample, when market interest rates were lower. To avoid this calendar clustering in our sample, to focus our analysis on the area where short sale constraints are presumably most important, and to mitigate the substitution problem noted below, our tests examine only stocks below the NYSE median market capitalization.

B. 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 the percentage of 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 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.[14] 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.

C. Testable Hypotheses

Our shifts allow us to test a variety of hypotheses about the relation between the shorting market and future stock returns. The first important factor in forming testable hypotheses is a careful consideration of the timing involved. In a rational expectations framework like Diamond and Verrecchia (1987), it is reasonable to expect that prices will incorporate negative private information fairly quickly. By contrast, the empirical literature on overpricing has largely abstracted from the issue of timing, although several papers seem to argue that overpricing is a long-run phenomenon that is corrected slowly over a series of months and quarters (rather than days or weeks). For

[14] 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 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.

example, Chen, Hong, and Stein (2002) use changes in breadth of mutual fund ownership to forecast returns up to four quarters in the future, and Lamont (2004) looks at returns 1-3 years after firms' battles with short-sellers. Of course there is no clear theoretical reason why this should be the case and since we have no clear priors over what exactly is the "short-run" versus the "long-run," our preferred approach is to let the data speak for itself. However, in the interests of formulating clear hypotheses, keeping our results comparable to the literature, and given that our dataset spans only four years, our tests are best viewed as tests of the short-run effects of activity in the shorting market.

Hypothesis 1: $DOUT$ predicts negative returns in the future.

$DOUT$ captures the case where the cost of shorting (loan fee) increases, but the amount that investors are willing to short at this higher cost also increases. More capital is betting that the price will decrease, despite the higher explicit cost of betting. $DOUT$ may signal a large quantity of negative private information, since fewer liquidity traders (or those shorting for hedging purposes) are likely to short in the face of high short selling costs (Diamond and Verrecchia (1987)).[15] In Diamond and Verrecchia (1987), the release of unexpected negative private information should lead to subsequent price declines; for a given quantity of private information, the higher the cost, the worse the news. Since our data is not publicly available, private information release is one possible reason why $DOUT$ could predict returns. Alternatively, $DOUT$ may capture additional costs or risks of shorting. For example, if short-selling capital is limited, then taking a large short position in a stock potentially subjects a short-seller to idiosyncratic risk that she cannot diversify away. Non-price marginal costs of shorting such as recall risk may also be increasing in quantity. In this view, large short positions may require a risk premium, and $DOUT$ should predict negative returns above and beyond the effect of direct costs of shorting (i.e., the loan fee).

Hypothesis 2: DIN predicts positive returns in the future.

DIN captures the case where shorting costs decrease, but the amount that investors are willing to borrow at this lower price also decreases. DIN predicts future positive returns: even though

[15] Although high shorting costs will generally reduce the number of liquidity short sellers and hedgers, the cost could be endogenously related to the demand for shorting for any reason; if this were true, we would not expect a large price reaction following $DOUT$ shifts.

shorting costs have decreased, investors are willing to put less capital into shorting. We expect this to be a weak predictor of positive future returns, however. If investors have positive opinions or information about the company, they could express this (often in a much less costly way) by actually purchasing the stock. Contrast this with the expected effect of $DOUT$. Because options do not exist for most of the stocks in our sample, shorting is the only way to bet on a downturn in the security price. We therefore expect $DOUT$ to be a stronger predictor of future returns than DIN.

Hypothesis 3: SIN predicts positive returns in the future, as tightening the constraint allows additional overpricing.

We postulate that decreases in shorting supply (SIN) indicate tightening of short sale constraints, and increases in shorting supply ($SOUT$) indicate relaxing of short sale constraints. SIN indicates an increase in the cost of shorting, but a decrease in the amount that investors are willing to short at this higher price. With less shares being shorted at a higher cost, this constriction of the supply of lendable shares represents a tightening of the constraint on shorting. Investor capital leaves the shorting market facing this higher cost, which allows stocks to become more overpriced. Contrast this prediction with Chen, Hong, and Stein's (2002) view that decreases in breadth of ownership (i.e., the tightening of short sale constraints) should predict low returns. Their focus is on the eventual correction of long-run overpricing, while our focus is on the short-run effects of increased overpricing.

Hypothesis 4: SOUT predicts negative returns in the future: the constraint on previously overpriced securities relaxes, and their prices converge back to fundamental value.

By contrast, $SOUT$ indicates a decline in the cost of shorting, but an increase in the amount investors are willing to borrow at this lower rate. The lowering of the cost makes it possible for more investors to enter the market; as we see increased shorting at this lower price, this signals that there may have been a constraint relaxation. Note that if this relaxation leads to an immediate downward price adjustment, then $SOUT$ will be a weaker signal then $DOUT$ for predicting subsequent returns since some of the mispricing may be mitigated immediately.[16]

[16]In a rational expectations framework like Diamond and Verrecchia (1987), relaxing short sale constraints has no direct effect on average stock returns (since stocks are correctly priced conditional on public information), but does affect the distribution of price changes on announcement days (see Reed (2002)); since our focus in this paper is on

D. Shift Characteristics

Summary statistics of the effect of each type of shift on loan fee (price) and quantity on loan are in Table II. The average change in loan fee 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 shares lent out as a percentage of shares outstanding by our institution following each shift is approximately 0.30%. 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 (median=14). For this reason, we perform a variety of robustness checks below designed to analyze the extent to which our results are sample-specific.

One potential caveat with our shift measures is that because we only have one lender, we might capture substitution across lenders within a security instead of actual increases in supply or demand. For example, if an investor moves her lending activity from Institution A to our institution, we may measure this as a $DOUT$ (perhaps), when there has in fact been no increase in the demand for shorting this stock. We employ a number of tests to address this issue, all of which indicate that this caveat is unlikely to affect our results.

First, we tabulate statistics that suggest that our lender accounts for a substantial fraction of overall market lending. For example, among stocks below the NYSE median market capitalization that are also being lent out by or lender, the average ratio of our fund's percentage on loan to the total short interest is 27% (for stocks above the median the ratio is 2%); in 15.2% of observations the fund is responsible for at least 67% of the short interest, and for 9.4% of observations the fund is responsible for all of the short interest. 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 less important lender in the large cap lending market.

Second, as described below, we run additional tests that attempt to exploit the variation in market share of our lender. For example, we run regressions that interact the shift portfolios with the percentage of aggregate short interest that our institution is lending out. We find that the shift results are significantly stronger for stocks in which our institution lends out a substantial fraction. We also use aggregate short interest as a measure of quantity (in place of the amount lent out by our lender), since substitution is obviously not an issue using aggregate short interest. Again,

average stock returns, we do not test this prediction.

our results are robust to this alternate specification. However, in light of practitioners' claims that monthly short interest is subject to window dressing (see D'Avolio (2002)) and is only a single snapshot in time, we prefer to use the daily lending quantities from our institution in our baseline tests.

E. 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, $SOUT$, 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), volume (the average daily exchange adjusted share turnover during the previous 6 months), *Loan Fee*, *Quantity*, Δ(Loan Fee), and Δ(Quantity). 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).[17] 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 *Quantity* equals the end-of-month/week ratio of shares lent out by our institution to total shares outstanding. Δ(Loan Fee) is the change in loan fee over the past month, and Δ(Quantity) is the change in the fraction of shares on loan by the lender over the past

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

month.

Therefore, the baseline model takes the form:

$$\begin{aligned} r_{j,t} - R_t^{SB_{j,t-1}} = {} & \alpha_{j,t} + \beta_1 DIN_{j,t-1} + \beta_2 DOUT_{j,t-1} + \beta_3 SIN_{j,t-1} + \beta_4 SOUT_{j,t-1} \\ & + \beta_5 r_{j,t-1} + \beta_6 r_{j,t-12,-2} + \beta_7 IO_{j,t-3} + \beta_8 Volume_{j,t-7,-1} + \varepsilon_{j,t}, \end{aligned} \tag{1}$$

where $r_{j,t}$ is the return on security j, and $R_t^{SB_{j,t-1}}$ is the return on the size/book-to-market matched portfolio.

We restrict our sample to stocks with lagged ($t-1$) price greater than or equal to five dollars to ensure that our results are not driven by small, illiquid stocks. In addition, collateral requirements have a nonlinearity below prices of $5 for our lender, which may distort lending preferences and rebate rates. Low-priced stocks are also more likely to go bankrupt, and in the case of bankruptcy a short-seller may have to wait months to recover the collateral funds. 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.

III. Empirical Results

A. Monthly Return Regressions

The cross-sectional regression 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). In column three, we restrict the sample to only those stocks that our institution owns. We do this because many of our subsequent tests rely on a valid measure of the *Loan Fee* for each stock, and this measure is unavailable in our data unless our institution owns the stock. All of our key results are robust to dropping this restriction. Table III indicates that

DOUT shifts consistently exhibit large predictive ability for future stock 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) is 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 (*SOUT*) are -0.63% in the following month (t=0.91). Decreases in shorting demand (*DIN*) and decreases in shorting supply (*SIN*) lead to positive, but insignificant abnormal returns in the future (0.50% and 0.35% per month, respectively). Overall, our results suggest an economically and statistically important link between increases in shorting demand (*DOUT*) and future abnormal returns, but almost no link between *SOUT*, *SIN*, *DIN* and future abnormal returns.

To highlight the importance of our shift portfolio classification strategy, we examine the predictability of different specifications that include quantity levels, loan fee levels, quantity changes and loan fee changes. The effects of loan fees (*Loan Fee*) and quantities (*Quantity*) are displayed in regressions 4-8 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 find that high shorting costs, specifically *Loan Fee* $> 500bp$, predict future negative returns. However, when we include the shift portfolios in column 8, the conditional effect of these high costs is no longer significant, while *DOUT* remains large and significant (-2.36%, t=3.27).[18] The quantity level is uninformative; as shown in columns 5 and 7, the marginal effect of the interaction of quantity level with high loan fees (either *Loan Fee* > 300 or *Loan Fee* > 500) is insignificant. Lastly, we examine the effects of quantity changes and loan fee changes separately, since quantity can increase because of an *SOUT* or *DOUT* (and decrease because of an *SIN* or *DIN*), while 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 for next month's returns in columns 9 and 10 of Table III. Column 9 indicates that returns are negative following loan fee increases and quantity increases, and significant for Δ(Quantity), although the magnitudes are smaller than for the shift portfolios. Again, however, when the shift portfolios are included,

[18]Untabulated results indicate that the effect of *DOUT* is smaller but still significant (-1.53%, t=2.69) when we run this same regression on *all* stocks (rather than just stocks below the NYSE median market cap), while the effect of *Loan Fee* > 500 is still insignificant (-1.42%, t=1.44), indicating that our results are *not* driven by the decision to restrict our analysis to small stocks with relatively high loan fees.

the conditional effect of Δ(Quantity) decreases. Also, *DOUT* remains negative and significant (-2.49%, t=-3.19). In fact, our results suggest that quantity increases and loan fee increases may be noisy proxies for a portion of *DOUT*. Using the raw number of shares on loan as our measure of quantity (rather than dividing shares on loan by shares outstanding for each firm) changes none of our conclusions: the effect of *DOUT* is still large (-2.23%, t=2.52), and the conditional effect of Δ(Quantity) is still insignificant. These results highlight the ability to make richer empirical predictions of future returns by using the shift portfolio classification.

B. Speed of Price Adjustment

An important issue in analyzing the effect of shifts in shorting supply and shorting demand on future stock returns is measuring the *speed* with which prices change. Our previous results indicate that increases in shorting demand at the monthly frequency lead to significantly lower returns in the following month; by contrast, shifts in shorting supply and decreases in shorting demand have weaker effects on future returns at the monthly horizon. However, it is possible that these shifts may affect prices at even higher frequencies, or that changes in shorting supply may change prices more quickly than changes in shorting demand.

To explore the stock price dynamics in greater depth, we perform a variety of tests. First, we replicate all of our monthly regressions at the weekly level. These weekly estimates (unreported, but available on request) reveal a similarly strong relation between abnormal returns and increases in shorting demand, and similarly weak relations between abnormal returns and the other three shift variables (*SOUT*, *SIN*, and *DIN*). 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 -0.43% to -0.56% per week. Compounding these to monthly returns yields similar magnitudes to those in Table III. The weekly *DOUT* slope coefficient is again significant (t=2.00) after characteristically adjusting for size, book-to-market, and controlling for the other 3 shift dummy variables, past returns, institutional ownership, and volume. The coefficients on the other three shifts (*SOUT*, *SIN*, and *DIN*) are insignificant and fairly small in magnitude. In the weekly specification neither shorting cost (*Loan Fee*) nor *Quantity* significantly predict future abnormal returns.

Second, we examine the effect of supply and demand shifts at a variety of different lag lengths. These results, shown in Figures 1-3, allow us to evaluate the speed with which prices adjust after each of the four types of shifts individually. For example, in Figure 1 we regress characteristically-adjusted daily returns on *DIN*, *DOUT*, *SIN*, *SOUT*, and a constant for each lag length from the first day up to the fifth day; we also control for returns lagged one day. For *DOUT* shifts, Figure 1 shows that abnormal returns are negative contemporaneously as well as on the second, fourth, and fifth days after the shift; the second and fourth days, as well as the five-day average (not shown), are marginally significant. None of the other shifts, however, produce reliably significant effects at a daily frequency. For example, abnormal returns are negative contemporaneously, and in the first, second, third, and fifth days following an increase in shorting supply (*SOUT*), but these effects are small and insignificant.

Turning to a weekly horizon, Figure 2 indicates that increases in shorting demand lead to low average abnormal returns during the next four weeks. The total effect for the first four weeks is about -1.68% and is significant (result computed but not shown in figure).[19] Abnormal returns following *SOUT* shifts are negative for every lag length, but neither the individual lags nor the total effect are significant. Returns following weekly *SIN* and *DIN* shifts are also never significant.

Figure 3 extends the lag results out to 6 months using monthly abnormal returns. The *DOUT* coefficient is negative for each of the six months following a shift, and is economically and statistically significant for the first two months. *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 an insignificant coefficient on the supply shift variable. The results for *DIN* and *SIN* reveal no significant patterns. In summary, prices respond mainly to increases in shorting demand, and this price adjustment seems to take place at the weekly and monthly frequency; price adjustments at a daily frequency are fairly small. As a result, and to keep our results comparable with the related literature, we focus on monthly horizons for the remainder of the paper.

C. Large Shifts

Motivated by recent evidence that extreme short positions are particularly important in understanding the link between the shorting market and stock prices, we also explore the extent to which large

[19] The total effect over four weeks is smaller in magnitude than the monthly results (-1.68 compared to -2.98). The smaller magnitude may be related to the fact that computing shifts over a one week period delivers a much smaller shift on average.

shifts in shorting supply and demand may be more informative/predictive than small shifts. For example, Desai, Ramesh, Thiagarajan, and Balachandran (2002) find that heavily shorted firms experience significant negative abnormal returns in the future, and that the magnitude of these negative abnormal returns increases with the level of short interest.

To investigate the importance of large shifts, we supplement our baseline regression specification by interacting our four shifts with three additional variables: 1) ΔFee^{+}_{big}, a dummy variable equal to one if the change in the loan fee for month $t-1$ is greater than the 90th percentile, 2) ΔFee^{-}_{big}, a dummy variable equal to one if the change in the loan fee for month $t-1$ is less than or equal to the 10th percentile, and 3) $\Delta Quantity^{+}_{big}$, a dummy variable equal to one if the change in quantity on loan for month $t-1$ is greater than the 90th percentile. These interactions allow us to examine the marginal effects of large shifts in shorting demand and supply. Columns 2 and 3 of Table IV indicate that the marginal effects of increases in shorting demand involving *either* large increases in loan fees *or* large increases in quantity are insignificant, while column 4 shows that the marginal effect of large increases in fees *coupled with* large increases in quantity (=ΔFee^{+}_{big}*$\Delta Quantity^{+}_{big}$) is huge in magnitude (-4.48%) and statistically significant (t=2.32). These findings are consistent with the evidence presented in Table III that the strong predictive power of *DOUT* relies on the joint roles of fee and quantity increases. Meanwhile, the marginal effect of large increases in shorting supply (i.e., large fee decreases coupled with large quantity increases=ΔFee^{-}_{big}*$\Delta Quantity^{+}_{big}$) is large but insignificant. The marginal effects for large *DIN* and *SIN* shifts (not shown) are small and insignificant. Overall, Table IV illustrates that *DOUT* shifts that involve large increases in loan fees and loan quantities are particularly informative for future stock returns.

D. High Shorting Costs: SIN and DOUT

To put our results into the context of the prior literature, we also evaluate the relation between our shifts and the cost of shorting. Specifically, we evaluate the hypothesis that the loan fee is a sufficient statistic for overpricing. As noted earlier, a number of papers have found that the cost of shorting (loan fee) is correlated with future returns.[20] In the regressions in Table III, we also find

[20]Note, however, that some of these cases are coupled with potential demand shifts (such as additions to the loan crowd, as in Jones and Lamont (2002)).

evidence of such a link. However, 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 for overpricing, then it should not matter how cost was bid up. However, we argue that the information content of *DOUT* and *SIN* differ. Specifically, from the evidence in the paper, we expect the flow of private information and/or non-price risks of shorting captured by *DOUT* to have more predictive power for future returns. 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.

We test this idea in our regression context by interacting each of the shifts during month $t-1$ with a dummy variable equal to one if the level of the loan fee is greater than 300 basis points at the end of month $t-1$. Column 6 of Table IV indicates that the strongest and most reliable negative abnormal returns following these high cost months occur after *DOUT* shifts (-4.14%, *t*=2.69). Comparing the effect of *DOUT* and *SIN*[21] 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 over 2 times the magnitude of *SIN*. 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.

E. Portfolio Strategies

We also examine average returns on portfolios formed using the four quadrant classifications defined above, in order to evaluate possible trading strategies based on our shifts. We place all NYSE, AMEX, and Nasdaq stocks with market capitalization below the NYSE median with lagged share prices above \$5 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. We rebalance the portfolios monthly.

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 exam-

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

ple, when using the 75 size/book-to-market/momentum benchmark portfolios, we compute each stock's abnormal return as,

$$r_{jt}^{sbm} = r_{jt} - R_t^{SBM_j,t-1}, \tag{2}$$

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.[22] However, all the portfolio tests in the paper are robust to using a multifactor time-series approach to estimate factor loadings in order to compute abnormal returns.

Table V reports average stock returns for monthly portfolio sorts. Panel A presents raw returns net of the risk-free rate (i.e., excess returns), Panel B presents abnormal returns net of 25 size/book-to-market benchmark portfolios, and Panel C presents abnormal returns net of 75 size/book-to-market/momentum benchmark portfolios. Forming portfolios based on the shifts allows us to evaluate a trading strategy based on each 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 (not shown), excess returns, and both types of abnormal returns. 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 -2.11% per month when benchmarked relative to size-BE/ME-Momentum portfolios.[23] The value-weight results for these outward demand shifts are smaller and insignificant. However, in unreported tests we find that if extend the holding period to 2 months, the value-weight results for $DOUT$ are again strongly negative (and significant).

Unlike in the regression results, outward supply shifts ($SOUT$) lead to large future negative returns in the value-weight portfolio tests in Panels B and C. These $SOUT$ results should be interpreted with some caution, however; simply adding time fixed effects in a regression framework (column 1 of Table III) drives out the $SOUT$ effect. Both DIN and SIN shifts lead to positive (but insignificant) returns in the future. The trading strategy of going long in stocks that have demand

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

[23] 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%, $t = 1.30$), $DOUT$ (−2.41%, $t = -2.48$), SIN (0.44, $t = 0.50$), and $SOUT$(−1.65, $t = -1.27$).

shifts inward and short stocks that demand shifts outward (*DIN-DOUT*), yields a large and statistically significant return of around 3% per month in each panel of equal-weight returns, although the value-weight results are weaker and insignificant. A trading strategy based on supply shifts (*SIN-SOUT*) yields a large return of around 2% per month, but is only marginally significant for the value-weight results in Panels A and B. Lastly, the high cost portfolio (*SPECIAL*) does not display a significant link with future returns.[24] Overall, the portfolio results suggest a possible link between increases in shorting supply and future returns (which was not found in our regression tests, however), and reinforce our earlier findings on the strong link between increases in shorting demand and future negative abnormal returns.

F. Robustness: Industry Effects, Substitution, Sample Size, and Alternative Specifications

Our baseline results are robust to a variety of permutations. For brevity, we only discuss a few such checks here. For example, we augment our cross-sectional regressions in Table III by using industry dummy variables in addition to calendar time dummies, using the Fama and French's (1997) 48 industry classification scheme. Column 1 of Table VI shows that the coefficient on *DOUT* is slightly larger and even more significant using this 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 our results are driven by a few industries (e.g., tech stocks). In unreported tests we also run the regressions including firm fixed effects and clustering standard errors by firm or by industry (instead of time), and find very similar results.

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. To test this idea we collect monthly short interest data on all the NYSE, AMEX, and Nasdaq stocks in our dataset, for whom short interest data is publicly available. 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 VI shows that interacting Market

[24]The *SPECIAL* portfolio is formed by assigning all stocks with lending fees greater than 3.0% (per year) at the end of each month to the portfolio, and then computing future average abnormal returns.

Power with *DOUT* produces a large (-5.64 percent per month) decline in future abnormal returns, although this result is insignificant. When we interact *DOUT* (in column 4 of Table VI) with a dummy variable indicating that our institution's Market Power is greater than 2/3, the coefficient on this interaction term is large (-8.36 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 employ monthly short interest from NYSE, AMEX, and Nasdaq scaled by total shares outstanding as our quantity measure. We then match this variable with the loan fee from our lender in order to compute our shift variables for each stock. Short interest is reported on the 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 includes short-sale trades up to 3 trading days before the 15th. We match NYSE, AMEX, and Nasdaq short interest with loan fees from 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-sectional regression using monthly returns. Column 5 of Table VI shows 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 -1.26% in the following month (t=2.06).

As noted earlier, the number of stocks that experience a particular shift in a given month can be small in some months. Our baseline pooled regressions contain an average of 2098 stocks per month, of which 172 (8.2%) are eligible for a shift (since they are on loan); of these 172 stocks, 125 (6.0%) experience a shift. On average, the number of stocks per month that experience at least an outward demand shift (*DOUT*) is 22. 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 stocks per month with *DOUT* shifts to over 48 (out of 3760 stocks per month in the regressions). Unreported results using this larger sample again indicate a significant relation between *DOUT* and future abnormal returns, but insignificant relations between the other shift portfolios and future abnormal returns. 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 -2.23% in the following month (t=2.85). This result, coupled with our earlier finding that $DOUT$ is significant even when we run our baseline regression on *all* stocks (rather than just stocks below the NYSE median market cap), indicates that sample size issues are unlikely to be driving our key results.

Another potential problem with our tests 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 (e.g., 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 (but not significant) -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 focus on interpreting this finding. As noted earlier, one 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 are simply correlated with underlying movements in public information flow. To explore this issue, we first examine firms for which public information is likely to be scarce. We then investigate the extent to which $DOUT$ captures private information (which then leaks out to the market and reduces prices), as opposed to proxying for additional market frictions (which lead to higher expected returns for shorting, net of loan fees).

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 analyst coverage orthogonalized by size, a measure we call "residual analyst coverage".[25] We compute residual analyst coverage for each stock as the residual from month-by-month cross-sectional regressions of $ln(1+ number\_analysts)$ on $ln(size)$. 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 VII, 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 result suggests that the effect of shorting on prices is important in sparse information environments, and not just in dense information environments.[26]

B. Times of Predictable Demand: Splits and Dividends

One concern expressed by practitioners is that stocks may experience a spike in borrowing and lending right around dividend dates and split dates, and that these spikes may be driving any empirical regularities. Indeed, Christoffersen, Geczy, Musto, and Reed (2004) document a significant relation between the magnitude of the dividend and the amount loaned out. Stock splits and dividends also provide a nice test of the private information channel hypothesis, in that both of these

[25] The results using regular coverage, rather than residual coverage, are very similar.

[26] In unreported tests, we find similar results when we exploit *changes* in the amount of public information available about a stock. For example, shorting demand is still a strong negative predictor of future stock returns among stocks that have *not* experienced any recent quarterly earnings forecast revisions or any recent earnings announcements. These results are available on request.

events may result in *predictable* shifts in shorting demand (*DOUT*), which are unrelated to private information.

In our sample, untabulated results reveal that stock splits in a given month increase the probability of a *DOUT* shift in that month, while dividends do not. Panel A of Table VII shows that the effect of *DOUT* is still negative and strongly significant after controlling for those *DOUT* shifts that occur during split or dividend months. However, both interaction terms $SPLIT * DOUT$ and $DIV * DOUT$ are positive, although not significant. To explore a private information story, we want to test if predictable *DOUT* shifts (due to dividends and splits) forecast returns in future months. We therefore compute the combined effect: interaction + main effect. When adding these interaction terms to the main effect, both $DOUT + SPLIT * DOUT (= -0.164\%)$ and $DOUT + DIV * DOUT (= -0.845\%)$ are not significantly different from zero. Consistent with *DOUT* being linked to returns through private information, when there are predictable increases in shorting demand that are likely *not* related to private information, these break the link between *DOUT* and future returns.

C. Costs, Benefits, and Indirect Risks of Shorting

Our final set of tests examines the costs, benefits, and indirect risks 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," in order to cover these costs. In unreported tests we follow high cost stocks at the end of month $t-2$ to month $t-1$, and then measure the returns in month t to betting on these stocks in month $t-1$. We find 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 $t-1$ is -6.44% 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 notion that the lending market is an important mechanism 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 V, the strategy *DIN-DOUT* yields

3.48% per month.[27] Reforming the portfolio at the end of every month $t-1$ and holding it during month t gives roughly a 50.8% 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 47% average annual return (3.27% per month) net of explicit shorting costs.[28]

To incorporate other costs and risks of this strategy, we employ two methods.[29] First we estimate the other explicit transaction costs to this strategy using estimates of commissions, bid-ask spreads, and price impact from Keim and Madhavan (1997). Then, we create a Sharpe Ratio measure to compare the return of the strategy to other strategies per unit of risk. Keim and Madhavan (1997) estimate the cost to institutional traders of trading in stocks. They break up stocks into size of trade, market capitalization, and exchange. We can use these estimates to get an approximation of the trading costs of this *DIN-DOUT* strategy. The average monthly turnover of the portfolios *DIN* and *DOUT* are large, at 90% and 87%, respectively. Assuming that trade sizes are kept small, and looking at only trades in the smallest two quintiles of market cap, this implies an average monthly rebalancing cost for *DIN* of 1.46% and for *DOUT* of 1.44%.[30] Adding these together, the monthly cost of rebalancing the *DIN-DOUT* portfolio is 2.90%. Subtracting this from the return net of shorting costs yields a 3.27%-2.90%=0.37% per month return. So the return to this strategy net of shorting costs, commissions, and price pressure is estimated to be about 4.5% per year. However, as costs have probably decreased since the Keim and Madhavan (1997) sample of 1991-1993, we expect this to be a lower bound for the average net returns in our sample. Considering trading costs, though, does substantially reduce the profits from this strategy.

Another way to evaluate the returns on this strategy is to look at a return per unit risk, and compare this to a benchmark. To do this we will construct a Sharpe Ratio for the strategy using data in from Table V. As we do not have turnover data (or market capitalization data) to estimate transaction costs for the market or *HML*, which we use as two benchmarks, we will estimate

[27] 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.

[28] There is a confidence interval about this return, but even assuming that the lowest 10% bound of return is realized in every month (a return of 1.02% per month), the strategy still makes 9.31% per year net of shorting costs.

[29] Note that this analysis still excludes several indirect costs that are more difficult to measure. In the shorting market, these include the search process to find a party willing to lend shares, recall risk, and the short term marking to market of collateral (as price moves against the borrower). These costs may be large or small, and without a reliable way to measure them, we abstract from them here.

[30] An example of this calculation for *DIN* is Average cost = 2* turnover * ((% in Nasdaq)*(trading cost of Nasdaq)+(% in NYSE/AMEX)*(trading cost of NYSE/AMEX))=2*.9*((.72*.88)+(.28*.63))=1.46.

the Sharpe Ratio before transaction costs. The Sharpe Ratio of the *DIN-DOUT* strategy, from Table V is 0.338. Over this same time period, 1999-2003, the monthly market Sharpe Ratio was negative, so we use as a comparison the Sharpe Ratio from 1990-2003, which is 0.137. The Sharpe Ratio for *HML* over the same time interval (1990-2003) is .094. Comparing the three, the Sharpe Ratio of the *DIN-DOUT* strategy is about 2.5 times that of the market and over 3.5 times that of *HML*. Although this difference is likely to get closer as we include transaction costs into all three strategies, this test highlights that the strategy not only has larger absolute returns, but also has substantially larger returns per unit of volatility than do the market or *HML*.

Clearly indirect costs and risks of shorting would have to be quite large to explain the return on the *DOUT* strategy. We explore two such risks, arbitrage risk and recall risk, in Table VIII. As noted earlier, taking a large short position in a stock potentially subjects a short-seller to idiosyncratic risk that she cannot diversify away. If short-selling capital is limited, then the effect of *DOUT* should be concentrated in large stocks, since these require more arbitrage capital (Baker and Savasoglu (2002)). However, as shown in column 3 of Table VIII, the effect of *DOUT* is concentrated in small stocks, as the marginal effect of $ME_{small} * DOUT$ is strongly significant. This result indicates that the total effect of a *DOUT* shift for a stock below the 20th percentile of market capitalization is -6.31% (=-2.407+-3.903) next month. Further, the marginal effect of interacting *DOUT* with a measure of stock-level arbitrage risk ($IRISK_{high}$, a dummy variable equal to one if the stock's variance in market model residuals is above the 80th percentile (Wurgler and Zhuravskaya (2002)) is insignificant. Thus, the *DOUT* strategy does not appear to vary with arbitrage risk.[31]

The concentration of *DOUT*'s predictive ability in small stocks is consistent with a private information story, since information costs may be higher for small stocks (Malloy (2005)), but is also consistent with a view that recall risk may be larger in small stocks. Although we do not have data on recalls in our sample, D'Avolio (2002) reports that recall risk is rare (affecting only 2% of stocks) in his sample. He also reports that days on which stock-level recall risk is high are days in which trading volume is extremely high on these stocks. We test this idea by interacting *DOUT* with a dummy variable equal to one if the stock's volume is above the 80th percentile ($Volume_{high} * DOUT$). However, as shown in Table VIII, the marginal effect of

[31] Employing linear interaction terms, rather than percentile dummy interaction terms, yields identical conclusions.

$Volume_{high} * DOUT$ is insignificant in our sample.[32] We conclude that the profits generated by the $DOUT$ strategy are unlikely to represent a risk premium above and beyond the loan fee.

V. Conclusion

Our goal in this paper is to isolate the channel through which activity in the shorting market affects stock prices. 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 economically large and statistically 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. However, we do not find strong evidence that shifts in shorting supply are linked to future returns. These findings suggest that private information and/or additional non-price costs of shorting are important aspects of the link between the shorting market and stock prices, while the short-run effects of relaxing/tightening short sale constraints are less important. We also show that the cross-sectional relation between high shorting costs and future negative returns, documented previously in the literature, is only present when shorting costs are driven by increases in shorting demand.

We find that the effect of shorting demand on future returns is still large, and in some cases even larger, in those environments where other information is scarce. By contrast, predictable increases in shorting demand which are *not* related to private information (such as those around stock splits and dividends) do not influence future returns. A trading strategy based on our shift identification yields on average over 47% per year *net* of shorting costs. After incorporating conservative estimates of additional trading costs such as commissions, bid-ask spreads, and price impact, the strategy still yields 4.5% per year. Further, the Sharpe Ratio of the strategy is about 2.5-3.5 times that of the market and HML. These results indicate that indirect costs/risks of shorting would have to be very large to subsume this return. However, we find little evidence that the profits to the shorting demand strategy vary with proxies for recall risk or stock-level arbitrage risk. Overall, our results cast doubt on the view that the primary link between the shorting market and future stock returns is due to costly market frictions. Our findings suggest that the shorting market is,

[32] Note that both *Volume* and *IRISK* are commonly used measures of differences of opinion, and are often used to test the Miller (1977) story (see, for example, Boehme, Danielsen, and Sorescu (2004)). However, in our sample we find little evidence that the effect of shorting demand on future returns varies with proxies for differences of opinion.

most importantly, a mechanism for private information revelation into stock prices.

There are a number of directions for future research in this area. For example, 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. Ultimately, discovering the source of the apparent information advantage of short sellers while at the same time explaining the persistent lack of short selling in the stock market is necessary.

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Table I
Lending Activity Examples and Sample Summary Statistics

Panel A reports lending activity examples from our sample of proprietary stock lending data on a single date (July 29, 2003). For a given stock-day observation we use the rebate rate of the largest short-sale contract (largest = most shares on loan). Market Rate refers to the collateral account interest rate. The loan fee (Fee) is the difference between the market rate and the rebate rate, and is the interest rate the lender receives from the short-sale. %On Loan is the total number of shares on loan by our lender expressed as a percentage of total 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 B reports summary statistics for our entire sample (September 1999 to August 2003).

Panel A: Lending Activity Examples (July 29, 2003)

Stock	Rebate Rate	Market Rate	Fee	%On Loan	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 Sample Summary Statistics

All Stocks	Mean	Median	25 Ptile	75 Ptile
Rebate Rate	0.55	0.25	-0.00	1.10
Market Rate	3.15	1.94	1.37	5.22
Fee	2.60	1.82	0.14	4.20
%On Loan	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
Rebate Rate	1.75	1.53	1.09	1.64
Market Rate	2.14	1.69	1.23	1.92
Fee	0.39	0.13	0.10	0.16
%On Loan	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
Rebate Rate	-0.17	0.00	-0.01	0.12
Market Rate	3.77	3.86	1.72	5.62
Fee	3.94	3.93	1.99	5.30
%On Loan	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 Statistics

This table reports summary statistics for shifts in shorting supply and shorting demand from the universe of NYSE, AMEX, and Nasdaq stocks with lagged market capitalization below the NYSE median and lagged price greater than or equal to \$5. Panel A presents means, and Panel B presents medians. Shifts are constructed as follows. The last trading day of month t we check if there was a shift in shorting supply or shorting demand during the month (based on changes in loan fees and changes in the percentage of 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 lagged price greater than or 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 %On Loan* is the number of shares on loan by our lender before the shift occurs as a percentage of shares outstanding. *New %On Loan* 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 %On Loan	1.09	0.78	0.98	0.79
New %On Loan	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 %On Loan	0.58	0.40	0.58	0.34
New %On Loan	0.35	0.63	0.30	0.62

Table III
Cross Sectional Regressions: Monthly Abnormal Returns

The table reports estimates from pooled, cross-sectional regressions of the monthly abnormal returns (in percent) of all NYSE, AMEX, and Nasdaq stocks with market capitalization below the NYSE median with lagged share prices above \$5 on supply and demand shift dummy variables and a host of control variables. We characteristically adjust the left-hand side returns for size and book-to-market using 25 equal-weight size-BE/ME portfolios. DIN is a dummy variable for an 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 month's 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. 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 parentheses. The intercept is estimated but not reported.

	[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]
DIN	0.325	0.502	0.299					0.502		-0.149
	(0.50)	(0.97)	(0.59)					(0.96)		(0.31)
$DOUT$	-2.860	-2.538	-2.983					-2.364		-2.485
	(2.85)	(3.32)	(3.96)					(3.27)		(3.19)
SIN	0.240	0.348	-0.063					0.443		0.176
	(0.21)	(0.43)	(0.08)					(0.69)		(0.22)
$SOUT$	-0.829	-0.628	-0.820					-0.569		-1.225
	(1.04)	(0.91)	(1.23)					(0.85)		(1.81)
r_{-1}		-0.009	-0.012	-0.012	-0.012	-0.012	-0.012	-0.012	-0.013	-0.012
		(0.35)	(0.49)	(0.50)	(0.49)	(0.48)	(0.48)	(0.48)	(0.51)	(0.50)
$r_{-12,-2}$		0.004	0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
		(0.69)	(0.83)	(0.84)	(0.84)	(0.84)	(0.83)	(0.82)	(0.85)	(0.82)
IO		0.728	0.309	0.320	0.317	0.276	0.278	0.255	0.419	0.317
		(1.16)	(0.44)	(0.48)	(0.47)	(0.41)	(0.40)	(0.37)	(0.59)	(0.45)
Volume		-0.120	0.018	-0.004	0.001	0.004	0.006	0.019	-0.024	0.018
		(0.41)	(0.05)	(0.01)	(0.00)	(0.01)	(0.02)	(0.06)	(0.07)	(0.05)
Fee > 3.0%				-0.767	-0.557					
				(0.94)	(0.61)					
Fee > 5.0%						-2.025	-1.585	-1.596		
						(2.09)	(1.66)	(1.63)		
Quantity					-0.138		-0.044			
					(0.48)		(0.19)			
Quantity(Fee > 3.0%)					-0.134					
					(0.34)					
Quantity(Fee > 5.0%)							-0.582			
							(1.05)			
Δ(Fee)									-0.920	-0.912
									(1.95)	(1.76)
ΔQuantity									-0.907	-0.343
									(2.45)	(0.77)
Observations/month	2639	2626	2098	2098	2098	2098	2098	2098	2098	2098

Table IV
Cross Sectional Regressions: Large Shifts and High Loan Fees

The table reports estimates from pooled, cross-sectional regressions of the monthly abnormal returns (in percent) of all NYSE, AMEX, and Nasdaq stocks with market capitalization below the NYSE median with lagged share prices above \$5 on supply and demand shifts and a host of control variables. We characteristically adjust the left-hand side returns for size and book-to-market using 25 equal-weight size-BE/ME portfolios. We also interact the supply and demand shifts with loan fee and quantity changes. DIN, $DOUT$, SIN, $SOUT$ are shift dummy variables defined as in Table III. $Fee > 3\%$ is a dummy variable that equals one of the loan fee is greater than 3%. ΔFee^{+}_{big} (ΔFee^{-}_{big} is dummy variable that equals one if the change in the loan fee for month $t-1$ was greater than (less than or equal to) the 90th (10th) percentile. $\Delta Quantity^{+}_{big}$ is dummy variable that equals one if the change in quantity on loan (as a percentage of shares outstanding) for month $t-1$ was greater than the 90th percentile. The control variables r_{-1}, $r_{-12,-2}$, IO, and Volume are defined as in Table III. All regressions include calendar month dummies, and all standard errors take into account clustering by calendar date. The time period is October 1999 to September 2003. T-statistics are in parentheses. The intercept is estimated but not reported.

	[1]	[2]	[3]	[4]	[5]	[6]
DIN	0.299	0.297	0.298	0.294	0.365	-0.613
	(0.59)	(0.58)	(0.59)	(0.58)	(0.69)	(1.01)
$DOUT$	-2.983	-2.649	-2.649	-2.458	-2.866	-0.769
	(3.96)	(2.66)	(2.81)	(2.95)	(3.40)	(0.97)
SIN	-0.063	-0.062	-0.063	-0.059	0.038	0.655
	(0.08)	(0.08)	(0.08)	(0.07)	(0.05)	(0.88)
$SOUT$	-0.820	-0.819	-1.175	-1.136	-0.744	-0.624
	(1.23)	(0.98)	(1.53)	(1.53)	(1.17)	(0.95)
$DOUT * \Delta Fee^{+}_{big}$		-1.253				
		(0.69)				
$SOUT * \Delta Fee^{-}_{big}$		-0.015				
		(0.01)				
$DOUT * \Delta Quantity^{+}_{big}$			-1.138			
			(0.67)			
$SOUT * \Delta Quantity^{+}_{big}$			1.169			
			(1.02)			
$\Delta Fee^{+}_{big} * \Delta Quantity^{+}_{big}$				-4.480		
				(2.32)		
$\Delta Fee^{-}_{big} * \Delta Quantity^{+}_{big}$				2.633		
				(1.32)		
Fee > 3%					-0.219	0.175
					(0.24)	(0.24)
(Fee > 3%)*DIN						2.798
						(1.82)
(Fee > 3%)*DOUT						-4.144
						(2.69)
(Fee > 3%)*SIN						-1.691
						(0.93)
(Fee > 3%)*SOUT						-0.710
						(0.42)
Observations/month	2098	2098	2098	2098	2098	2098
Control Variables	r_{-1}, $r_{-12,-2}$, IO, Volume, and calendar month dummies					

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

This table presents average monthly returns (in percent) on shorting supply and shorting demand shift portfolios from the universe of NYSE, AMEX, and Nasdaq stocks with lagged market capitalization below the NYSE median and lagged price greater than or equal to \$5. Excess Returns are average monthly returns in excess of the one-month Treasury bill rate. Abnormal Returns are computed by characteristically adjusting returns 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 greater than or equal to 5 dollars. The last trading day of month $t-1$ we check if there was a shift in shorting supply or shorting demand during the month (based on changes in loan fees and changes in the percentage of 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. The time period is October 1999 to September 2003.

Panel A: Excess Returns						
	DIN	$DOUT$	SIN	$SOUT$	$DIN-DOUT$	$SIN-SOUT$
Equal-Weight						
Mean	1.65	-1.82	0.84	-1.12	3.48	1.96
T-stat	0.79	-1.02	0.49	-0.57	2.34	1.55
Value-Weight						
Mean	0.53	-0.53	0.42	-2.15	1.06	2.57
T-stat	0.27	-0.27	0.23	-1.09	0.65	1.92
Panel B: Abnormal Returns (Benchmark Portfolios: 25 Size-BE/ME Portfolios)						
	DIN	$DOUT$	SIN	$SOUT$	$DIN-DOUT$	$SIN-SOUT$
Equal-Weight						
Mean	0.84	-2.34	0.48	-1.81	3.18	2.28
T-stat	0.67	-2.52	0.56	-1.43	2.17	1.81
Value-Weight						
Mean	-0.12	-1.05	0.01	-2.63	0.93	2.65
T-stat	-0.12	-0.88	0.01	-2.23	0.56	1.94
Panel C: Abnormal Returns (Benchmark Portfolios: 75 Size-BE/ME-Mom Portfolios)						
	DIN	$DOUT$	SIN	$SOUT$	$DIN-DOUT$	$SIN-SOUT$
Equal-Weight						
Mean	0.76	-2.11	0.08	-1.63	2.87	1.72
T-stat	0.72	-2.15	0.11	-1.36	2.21	1.34
Value-Weight						
Mean	-0.26	-0.88	-0.29	-2.41	0.61	2.12
T-stat	-0.28	-0.75	-0.30	-2.15	0.41	1.58

Table VI
Cross Sectional Regressions: Robustness Tests

The table reports estimates from pooled, cross-sectional regressions of the monthly abnormal returns (in percent) of all NYSE, AMEX, and Nasdaq stocks owned by the lender with market capitalization below the NYSE median and lagged share prices above $5 on supply and demand shift dummy variables and a host of control variables. We characteristically adjust all left-hand side returns for size and book-to-market using 25 equal-weight size-BE/ME portfolios. DIN, $DOUT$, SIN, $SOUT$ are shift dummy variables defined as in Table III. In columns 1 – 4, the loan quantity used to define shifts is the number of shares on loan by our lender divided by total shares outstanding (*%On Loan*), and returns are measured at the month's end; in column 5, loan quantity equals total monthly short interest divided by total shares outstanding (*Short Int*), and monthly returns are measured using closing prices from the 16th of the month. Market Power is the number of shares lent out by our lender in month $t-1$ divided by short interest (*SI*) 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 control variables r_{-1}, $r_{-12,-2}$, IO, and Volume are defined as in Table III. All 5 columns include calendar month dummies, and the first column also includes industry dummies (using Fama and French's (1997) 48-industry classification scheme). All standard errors take into account clustering by calendar date. The time period is October 1999 to September 2003 for columns 1–4 and November 1999 to September 2003 for column 5. T-statistics are in parentheses. The intercept is estimated but not reported.

	[1]	[2]	[3]	[4]	[5]
DIN	0.206	0.273	0.196	0.356	0.215
	(0.41)	(0.53)	(0.34)	(0.69)	(0.42)
DOUT	-3.030	-3.014	-2.389	-2.741	-1.262
	(4.05)	(3.94)	(3.03)	(3.52)	(2.06)
SIN	-0.172	-0.067	0.156	0.009	-0.950
	(0.22)	(0.08)	(0.18)	(0.01)	(1.22)
SOUT	-0.888	-0.804	-0.731	-0.803	-0.793
	(1.35)	(1.21)	(1.17)	(1.25)	(1.48)
(Market Power)**DIN*			0.585		
			(0.25)		
(Market Power)**DOUT*			-5.642		
			(1.26)		
(Market Power)**SIN*			-1.537		
			(0.56)		
(Market Power)**SOUT*			-0.683		
			(0.24)		
(Market Power>2/3)**DIN*				-1.446	
				(0.77)	
(Market Power>2/3)**DOUT*				-8.361	
				(2.38)	
(Market Power>2/3)**SIN*				-1.296	
				(0.57)	
(Market Power>2/3)**SOUT*				0.050	
				(0.01)	
Observations/month	2098	2095	2095	2095	2097
Loan Quantity	*%On Loan*	*%On Loan*	*%On Loan*	*%On Loan*	*Short Int*
Industry Dummies	Yes	No	No	No	No
Control Variables	r_{-1},$r_{-12,-2}$, IO, Volume, and calendar month dummies always included				

Table VII
Cross Sectional Regressions: Analyst Coverage and Predictable Demand

The table reports estimates from pooled, cross-sectional regressions of the monthly abnormal returns (in percent) of all NYSE, AMEX, and Nasdaq stocks with market capitalization below the NYSE median with lagged share prices above \$5 on supply and demand shift dummy variables and a host of control variables. We characteristically adjust the left-hand side returns for size and book-to-market using 25 equal-weight size-BE/ME portfolios. DIN, $DOUT$, SIN, $SOUT$ are shift dummy variables defined as in Table III. $RCOV_{t-1}$ 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. $SPLIT$ is a dummy variable equal to 1 if there was a stock split or stock dividend in month $t-1$, and DIV is a dummy variable equal to 1 if there was a dividend in month $t-1$. The control variables r_{-1}, $r_{-12,-2}$, IO, and Volume are defined as in Table III. All regressions include calendar month dummies, and all standard errors take into account clustering by calendar date. The time period is October 1999 to September 2003. T-statistics are in parentheses. The intercept is estimated but not reported.

	[1]	[2]	[3]	[4]	[5]
DIN	0.299	0.303	0.300	0.285	0.286
	(0.59)	(0.60)	(0.59)	(0.56)	(0.56)
$DOUT$	-2.983	-2.936	-3.003	-3.096	-3.113
	(3.96)	(4.30)	(4.04)	(3.91)	(3.98)
SIN	-0.063	-0.059	-0.064	-0.075	-0.076
	(0.08)	(0.08)	(0.08)	(0.10)	(0.10)
$SOUT$	-0.820	-0.813	-0.821	-0.835	-0.835
	(1.23)	(1.22)	(1.23)	(1.26)	(1.26)
$RCOV_{t-1}$		0.019			
		(0.26)			
$RCOV_{t-1}$*$DOUT$		0.052			
		(0.24)			
$SPLIT$			0.522		0.546
			(0.47)		(0.50)
$SPLIT$*$DOUT$			2.839		2.663
			(0.30)		(0.28)
DIV				-0.347	-0.350
				(1.09)	(1.11)
DIV*$DOUT$				2.251	2.209
				(0.94)	(0.92)
Observations/month	2098	2098	2098	2098	2098
Control Variables	r_{-1}, $r_{-12,-2}$, IO, Volume, and calendar month dummies				

Table VIII
Cross Sectional Regressions: Indirect Costs and Risks of Shorting

The table reports estimates from pooled, cross-sectional regressions of the monthly abnormal returns (in percent) of all NYSE, AMEX, and Nasdaq stocks owned by the lender with market capitalization below the NYSE median and lagged share prices above $5 on supply and demand shift dummy variables, proxies for indirect risks and costs of shorting, and control variables. We characteristically adjust the left-hand side returns for size and book-to-market using 25 equal-weight size-BE/ME portfolios. DIN, $DOUT$, SIN, $SOUT$ are shift dummy variables defined as in Table III. The control variables r_{-1}, $r_{-12,-2}$, IO, and Volume are defined as in Table III. $Volume_{high}$ is a dummy variable that equals if the average daily exchange-adjusted share turnover during the previous 6 months is greater than the 80th volume percentile of all stocks in the regression. ME_{small} is a dummy variable that equals one if lagged market-cap is less than or equal to the 20th lagged market-cap percentile of all stocks in the regression. $IRISK$ is idiosyncratic risk measured as the standard deviation of market model residuals using one year of past daily returns. The market model regression is $r_{it} = \alpha_i + \beta_{1i} r_{Mt} + \beta_{2i} r_{Mt-1} + \varepsilon_{it}$ where r_{it} is the return on stock i for day t and r_{Mt} is the return on the market portfolio (CRSP value-weight index) for day t. $IRISK_{high}$ is a dummy variable that equals one if IRISK is less greater than the 80th $IRISK$ percentile of all stocks in the regression. All regressions include calendar month dummies, and all standard errors take into account clustering by calendar date. The time period is October 1999 to September 2003. T-statistics are in parentheses. The intercept is estimated but not reported.

	[1]	[2]	[3]	[4]
DIN	0.299	0.266	0.297	0.284
	(0.59)	(0.53)	(0.58)	(0.55)
$DOUT$	-2.983	-3.015	-2.407	-2.155
	(3.96)	(3.00)	(2.90)	(3.15)
SIN	-0.063	-0.088	-0.063	-0.081
	(0.08)	(0.11)	(0.08)	(0.10)
$SOUT$	-0.820	-0.869	-0.824	-0.839
	(1.23)	(1.30)	(1.23)	(1.24)
$Volume_{high}$		0.500		
		(1.00)		
$Volume_{high} * DOUT$		-0.001		
		(0.00)		
ME_{small}			-0.126	
			(0.48)	
$ME_{small} * DOUT$			-3.903	
			(2.38)	
$IRISK_{high}$				0.111
				(0.13)
$IRISK_{high} * DOUT$				-1.766
				(1.04)
Observations/month	2098	2098	2098	2098
Control Variables	r_{-1}, $r_{-12,-2}$, IO, Volume, and calendar month dummies			

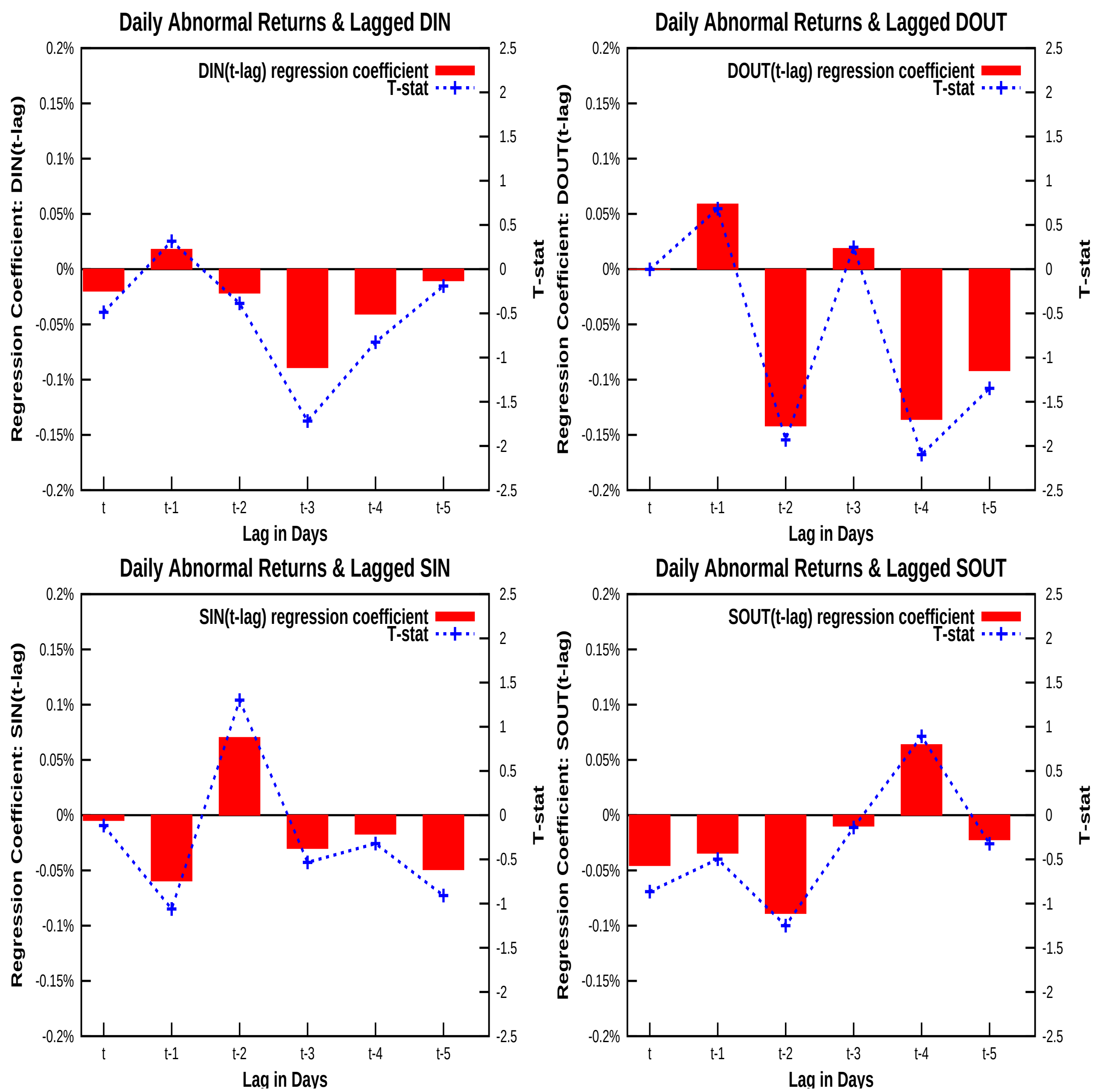

Figure 1: Daily Abnormal Returns And Lagged Shifts

We regress the daily abnormal returns (in percent) of all NYSE, AMEX, and Nasdaq stocks owned by the lender with market capitalization below the NYSE median and lagged share prices above $5 on supply and demand shifts and lagged daily returns. We proxy for expected returns characteristically using 25 equal weight size-BE/ME portfolios. DIN(t-lag) is a dummy variable for an inward demand shift lag days ago. DOUT(t-lag) is a dummy variable for an outward demand shift lag days ago. SIN(t-lag) is a dummy variable for an inward supply shift lag days ago. SOUT(t-lag) is a dummy variable for an outward supply shift lag days ago. We run separate regressions for each lag length. The regressions include calendar month dummies, and the standard errors take into account clustering by calendar date.

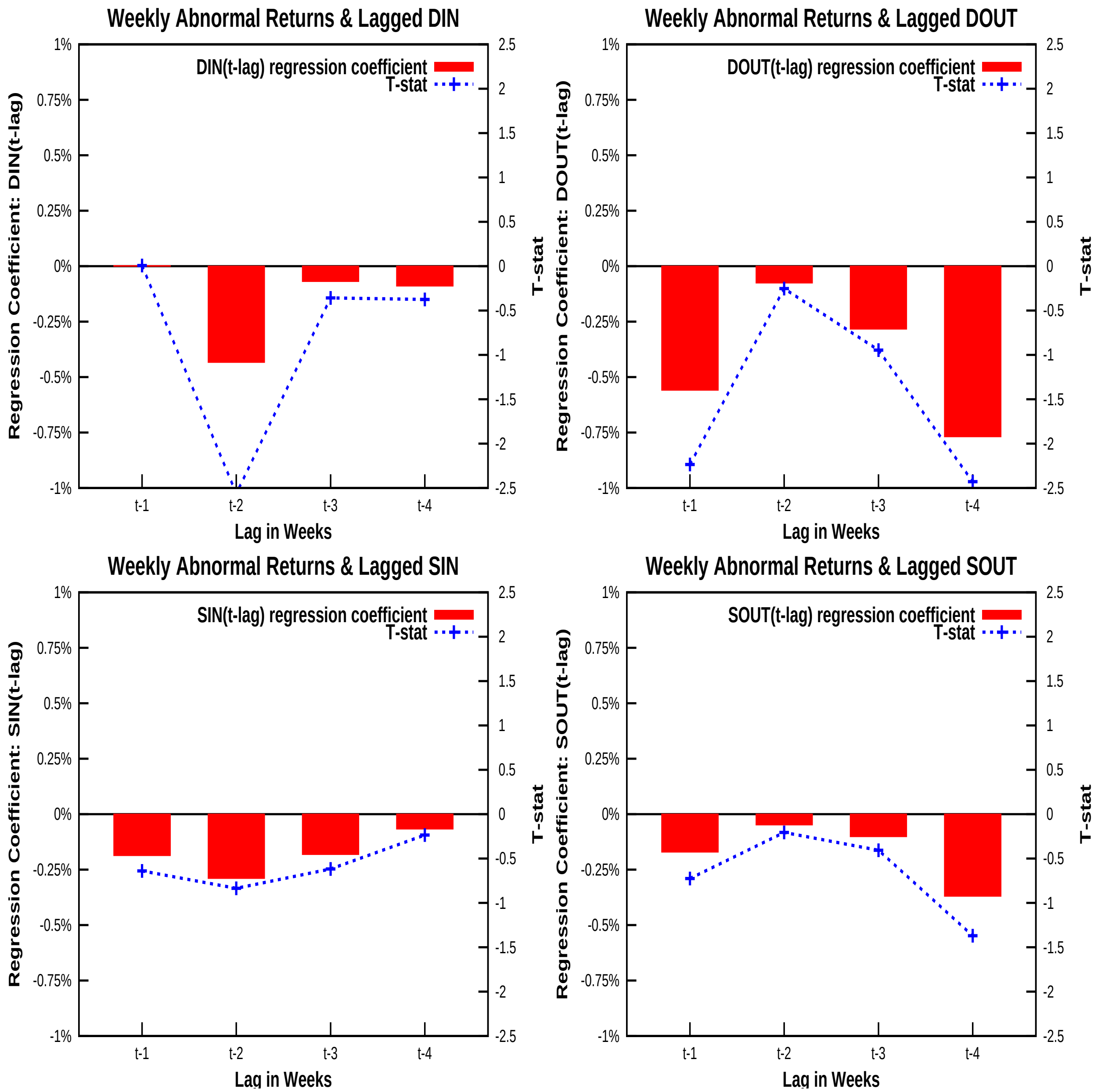

Figure 2: Weekly Abnormal Returns And Lagged Shifts

We regress the weekly abnormal returns (in percent) of all NYSE, AMEX, and Nasdaq stocks owned by the lender with market capitalization below the NYSE median and lagged share prices above $5 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 or equal to 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 regressions include calendar month dummies, and the standard errors take into account clustering by calendar date.

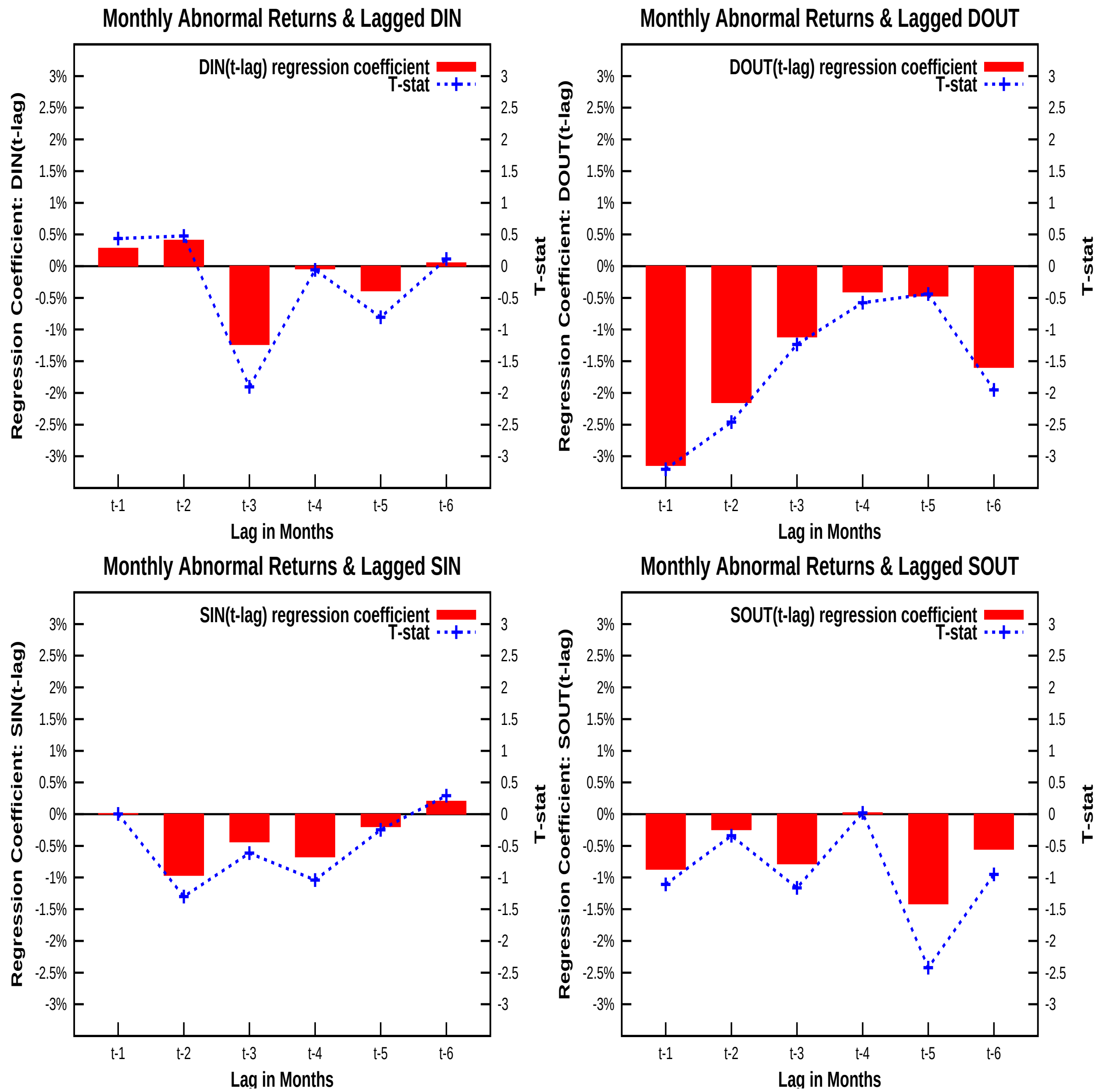

Figure 3: Monthly Abnormal Returns And Lagged Shifts

We regress the monthly abnormal returns (in percent) of all NYSE, AMEX, and Nasdaq stocks owned by the lender with market capitalization below the NYSE median and lagged share prices above $5 on supply and demand shifts. 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 regressions include calendar month dummies, and the standard errors take into account clustering by calendar date.