THE JOURNAL OF FINANCE • VOL. LXII, NO. 5 • OCTOBER 2007

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 2.98% 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.

AN ASSET'S BORROWING AND LENDING MARKET can have a large impact on its equilibrium price. For stocks, an active borrowing and lending market exists,[1] but its decentralized format and lack of transparency make isolating a direct link to stock prices difficult. The standard empirical approach to testing the relation between the shorting market and future returns relies on either (1) obtaining data on the direct costs of shorting from the stock loan market, as such costs provide a measure of the constraints on short selling,[2] or (2) 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, then one can measure the extent of overpricing or the extent of private information left

*Lauren Cohen is at the Yale School of Management; Karl B. Diether is at the Fisher College of Business, Ohio State University; and Christopher J. Malloy is at London Business School. We thank for helpful comments and suggestions Viral Acharya, Nick Barberis, Ron Bird, Menachem Brenner, John Cochrane, Doug Diamond, James Dow, Darrell Duffie, Gene Fama, Julian Franks, Ken French, Francisco Gomes, Tyler Henry, David Hirshleifer, Kewei Hou, Charles Jones, Andrew Karolyi, Owen Lamont, Paul Marsh, Toby Moskowitz, Yigal Newman, Ľuboš Pástor, Jay Ritter, Jeanne Sinquefield, Rob Stambaugh, Jeremy Stein, Ralph Walkling, Ingrid Werner, Karen Wruck, an anonymous referee, and seminar participants at the National Bureau of Economic Research, Western Finance Association, European Finance Association, Berkeley, University of Chicago, Harvard Business School, London Business School, Northwestern, Ohio State, Stanford, and Washington University. We also thank Gene Fama and Ken French for generously providing data.

[1] An active lending market exists in the U.S., but there is considerable variation in lending market activity internationally (see Bris, Goetzmann, and Zhu (2005)).

[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 (2004), among others.

out of the market. The idea behind looking at shorting supply is that shorting a stock requires that one first borrow the shares, and thus 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. 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, as it enables one to explicitly test which theoretical channel drives the relation between the shorting market and future returns.

Using a novel 4-year panel data set 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 a component of the intersection of supply and demand and using it to proxy for demand or supply (thereby 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 on loan (our measure of quantity) corresponds to at least an increase in shorting demand, as would be the case for 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, at least a demand shift outward *must* have occurred. By classifying shifts in this way, we are able to identify shifts in shorting demand and supply, and then explore the effect of these shifts on future stock returns.

Differentiating supply and demand is crucial for determining the channel through which, and thus the reason why, stock prices respond to activity in the shorting market. Mechanically, if shorting demand is the dominant channel, then the coupling of both increased (decreased) price (i.e., loan fee) and increased (decreased) quantity (i.e., short interest, or percentage of shares on loan) are important. Increased quantity, for instance, 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.[3] Either way, large short positions may require a 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. Overall, changes in shorting demand represent

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

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. Supply shifts are driven by changes in institutions' marginal cost of lending. For instance, because many lending institutions (including ours) also operate mutual funds, they have other incentives for holding stocks. Following a sale of the shares of a certain stock in its funds, a lending institution experiences an inward shift of its supply curve for the stock.[4] However, any movement in marginal costs will shift this curve. The interpretation and implications of shifts driven by contractions of shorting supply are therefore quite different from those of shifts 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 the additional market frictions and risks associated with shorting. Thus, 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 2.98% in the following month. Decreases in shorting supply play a more minor role. We also find that the loan fee is *not* a sufficient statistic for overpricing, as proposed in the previous literature. Rather, "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 investigate whether increased shorting demand signals informed trading (which then leaks out to the market and reduces prices), or whether it proxies for additional market frictions (which lead to higher expected returns for shorting, net of loan fees). To explore private information we exploit variation in the public information environment, and relate this to variation in the strength of the shorting market's ability to predict future returns. We then examine the 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. While in general we would not expect to find 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, then 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 not concentrated

[4] The new marginal cost of lending shares for that institution is then the cost of borrowing the shares in the market and relending them, and so is higher, as there are rents paid to the lender.

among stocks with high analyst coverage (a proxy for public information flow), nor is it driven by predictable shifts in shorting demand due to dividend capture borrowing. We also estimate the return to an investor who uses our identification strategy to form trading rules. *Net* of shorting costs, on average the investor makes over 47% per year. Even after incorporating trading costs such as commissions, bid-ask spreads, and price impact, a conservative estimate of the average return performance of the strategy still yields 4.5% per year. The Sharpe ratio of the strategy is about 2.5 to 3.5 times that of the market or *HML*. Thus, the 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.

The remainder of 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 large literature explores the theoretical link between short sale constraints and asset prices.[5] Miller (1977) posits that 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 that 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.[6] Diamond and Verrecchia (1987), in contrast, argue that rational uninformed agents take the presence of short sale constraints into account when forming their valuations, and thus that there is no overpricing conditional on public information as 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, however, 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 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

[5] See, for example, 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); Scheinkman and Xiong (2003); and Rubinstein (2004).

[6] 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.

costs, a variety of studies exploit the fact that an 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 30% of mutual funds are allowed by their charters to sell short and only 2% 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, which signal an increase in the amount of negative information withheld from the market, lead to negative subsequent abnormal returns on average during the sample period, 1979 to 1998. Similarly, Nagel (2005) uses residual institutional ownership as a proxy for shorting demand (again assuming low residual institutional ownership signals that negative information is being withheld from stock prices) and finds that underperformance in growth stocks and high dispersion stocks is concentrated among stocks with low institutional ownership. However, Nagel (2005) also finds that when he combines his sample period with that in Chen, Hong, and Stein (2002), there is no longer a reliable pattern during the 1980 to 2003 period between breadth of mutual fund ownership and future returns. Residual institutional ownership may also proxy for shorting supply, since low institutional ownership restricts the supply of available shares on loan. As in Chen, Hong, and Stein (2002), 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 driven by nonshorting considerations such as investment style.

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 et al. (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. For example, a low level of short interest may not indicate low shorting demand: Stocks that are impossible to short could have a huge shorting demand, 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.[7] Alternatively, Desai et al. (2002) argue that 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 by low future returns. For example, Asquith and Meulbroek (1995) and Desai et al. (2002) find significant abnormal returns for stocks with high short interest on,

[7] Strictly speaking, as noted in Desai et al. (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.

respectively, the NYSE and Nasdaq exchanges for 1976 to 1993 and 1988 to 1994.[8] Boehme, Danielsen, and Sorescu (2006) 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 (2006) 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 the dispersion in analysts' forecasts. Finally, Aitken et al. (1998), Angel, Christophe, and Ferri (2003), and Diether, Lee, and Werner (2006) look at daily short sales and subsequent returns and find 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. They 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 points per month during the 1988 to 2002 period 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 interpretation problems 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 into the part 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).[9] The most commonly used metric is the rebate rate, in particular, the spread between the rebate rate and the market interest rate. 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 is often referred to as the loan fee. The rebate rate serves to equilibrate supply and demand in the stock lending market, much

[8] See also Figlewski and Webb (1993); Figlewski (1981); and Dechow et al. (2001) for evidence that stocks with high short interest experience low subsequent returns.

[9] 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 (2004); and Mitchell, Pulvino, and Stafford (2002).

like the "repo" rate in the fixed income market.[10] Obviously, if every investor were willing and able to lend shares in a competitive market, the lending fee would be close to 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. Using a database from a single lender from April 2000 through September 2001, D'Avolio (2002) reports that only 9% 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% typically have loan fees around 20 basis points per annum. In other words, the rebate rate is typically about 20 basis points less than the Federal Funds rate. He does find that stocks on special have higher short interest. Using a sample of rebate rates from a single lender from November 1998 through October 1999, Geczy, Musto, and Reed (2002) conclude that short sale constraints are unable to explain anomalous patterns in stock returns. Meanwhile, using proprietary data from July 1999 to December 2001, Ofek, Richardson, and Whitelaw (2004) document that stocks on special are more likely to violate put-call parity.[11] Finally, using a small database of rebate rates hand-collected from the *Wall Street Journal* from 1926 to 1933, Jones and Lamont (2002) find that stocks with low rebate rates (high loan fees) experience low subsequent returns. However, the effect is modest; the authors only find large negative size-adjusted returns (−2.52% in the following month) among stocks that are both expensive to short and new to the loan crowd (another proxy for high shorting demand).

Virtually all existing papers also fail to address the exact mechanism that causes the observed movement in stock prices. However, the problem of causation is 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 (2005) find no evidence that investors take disproportionately 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 attempt to address the endogeneity of shorting indicators explicitly.

[10] 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.

[11] 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.

II. Research Design

A. Data

We use 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. The data include daily contract-level data on rebate rates, the number shares on loan, collateral amounts, collateral/market rates, estimated income from each loan, and broker firm names for the entire universe of this firm's lending activity from September 1999 to August 2003.

The rebate rate is the portion of the collateral account interest rate that the short-seller receives back.[12] 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 therefore determines the 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. While each stock may have multiple lending contracts on a given day, the loan fees are almost always very similar. 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 the number of shares on loan divided by the number of 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 on loan as our measure of quantity instead.

Panel A of Table I presents lending activity examples from our sample. A typical large stock such as 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, such as Atlas Air, the loan fee can be very high (7.25% per year), and our institution may lend out a large share (almost 5%) of the total shares outstanding. Our lender is a large presence in the small cap market, owning 5% or more in over 600 small cap stocks throughout the sample period, and owning at least a small stake in the vast majority of stocks below the NYSE median market cap. Further, it is more active in the small stock lending market, making an average of 11.79 loans per stock per day across all small cap stocks as opposed to 4.64 for large stocks.

Untabulated statistics indicate that our lender accounts for a substantial fraction of overall market lending in small cap securities. For example, among stocks below (above) the NYSE median market capitalization that are also on loan by our lender, the average ratio of our fund's percentage on loan to the total short interest is 26% (2%); in 13.6% of the observations the fund is responsible for at least 67% of the short interest, and in 7.5% of the observations the fund is responsible for all of the short interest. On the other hand, our lending institution seems to be a relatively less important lender in the large cap lending market.

[12] 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.

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 (August 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 (August 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

	Mean	Median	25 Ptile	75 Ptile
		All Stocks		
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*		
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*		
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

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, analyst coverage from I/B/E/S, and quarterly institutional holdings 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). We restrict our sample to stocks with lagged ($t - 1$) price greater than or equal to \$5. First, this ensures 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. 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 160 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 over the 2000 to 2003 period for small-cap stocks, compared to 20, 68, 249, and 350 over the same period for large-cap stocks. Therefore, the large-cap sample is concentrated at the end of the sample period, when market interest rates were lower. To avoid this calendar clustering in our sample, to focus our analysis on the area in which 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 evaluate the effect of shifts in the supply and demand for shorting on future stock returns. To do so, we must first isolate clear shifts in the supply and demand for shorting. 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 on loan (i.e., quantity) corresponds to an increase in shorting demand, as would be the case for 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 correspond 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*), and at least a supply shift in (*SIN*). More precisely, stocks in *DOUT* have seen both their loan fee and their loan amount rise (over the designated horizon), stocks in *DIN* have seen both their loan fee and loan quantity fall, stocks in *SOUT* have seen their loan fee fall but their loan quantity rise, and stocks in *SIN* have seen their loan fee rise but their loan quantity fall.[13] 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. First, the horizon over which these shifts is measured may be potentially crucial. For instance, one could observe an increase in the loan fee followed by a decrease in the loan fee, but over some horizon the net change might be zero. We therefore experiment over a variety of possible horizons. Second, by placing a stock into only one of the four quadrants at any point in time, we are restricting our attention to cases in which there is "at least" a shift of the type described. Clearly, a stock placed in the *DOUT* quadrant may also have experienced an increase in shorting supply over the designated period. While both shifts imply an increase in the quantity on loan, only *DOUT* implies an increase in the loan fee. Thus, if we observe an increase in quantity and fee, irrespective of all other shifts, we know that at least a demand shift out has occurred. 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, while the empirical literature on overpricing largely abstracts from the issue of timing, 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 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 to 3 years after firms' battles with short-sellers. Of course, there is no theoretical reason why this should be the case, and since we have no clear priors regarding what exactly is the "short-run" versus the "long-run," our preferred approach is to let the data speak for itself. In our data, the median stock lending contract is held for around 3 weeks. Thus, to mirror this fact we use 1-month holding periods for

[13] Shifts in which 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 in which 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.

most of the tests in the paper. In Section III.B, we examine shorter and longer horizons as well.

HYPOTHESIS 1: *DOUT predicts negative future returns.*

DOUT captures the case in which both the cost of shorting (i.e., loan fee) and the amount that investors are willing to short at this higher cost increase. Effectively, 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)).[14] 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. Nonprice marginal costs of shorting such as recall risk may then be increasing in quantity. In both views, *DOUT* predicts negative returns.

HYPOTHESIS 2: *DIN predicts positive future returns.*

DIN captures the case in which both shorting costs and the amount that investors borrow at this lower price decrease. *DIN* predicts positive future returns: Even though shorting costs decrease, investors are willing to allocate less capital to 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 more directly (and 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 future returns, 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 coupled with a decrease in the amount that investors are willing to short at this higher price. With less shares being shorted at a higher cost, the constriction in the supply of lendable shares represents a tightening of the constraint on shorting. Facing this higher cost, investor capital leaves the shorting market, which leads stocks to become more overpriced. Note that this conjecture contrasts with

[14] Although high shorting costs will generally reduce the number of liquidity short-sellers and hedgers, the cost could be related to the demand for shorting for any reason; if demand were not driven by information, we would not expect a large price reaction following *DOUT* shifts. We explore cases such as these in Section IV.B.

Chen, Hong, and Stein (2002), who argue that decreases in breadth of ownership (i.e., the tightening of short sale constraints) should lead to low returns. However, 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 future returns: 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 coupled with an increase in the amount investors are willing to borrow at this lower rate. Because the lowering of the cost makes it possible for more investors to enter the market, increased shorting at this lower price 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.[15]

D. Shift Characteristics

Summary statistics of the effect of each type of shift on both loan fee (price) and the quantity on loan are presented 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 basis point decrease on average. The average change in shares on loan as a percentage of shares outstanding 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 that are designed to analyze the extent to which our results are sample specific.

One potential caveat with regard to 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 demand shift out, when in fact there has been no increase in the shorting demand for 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, as noted in Section II.A, our lender comprises a substantial fraction of overall market lending for small cap stocks, making up on average 26% (but up to all) of the total short interest for the stocks on loan by the institution

[15] 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 average stock returns, we do not test this prediction.

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*). *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 6 months. The time period is September 1999 to August 2003.

	DIN	*DOUT*	*SIN*	*SOUT*
Panel A: Mean				
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

that are below the NYSE median market cap. Second, as described below, we run additional tests that attempt to exploit variation in our lender's market share. For example, we run regressions that interact the shift variables 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, 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 variables in *predicting* future returns. To control for the well-known effects of size (Banz (1981)), book-to-market (Rosenburg, 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 we control for past returns on the right-hand side.[16]

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 (week) $t-1$ we check if there was some kind of shift in supply or demand during the month (based on changes in loan fees and shares on loan). We define *DIN* as a dummy variable equal to one 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. We include last month's (week's) return to control for reversals, and the prior year's return to control for the momentum effect. We include institutional ownership to control for how widely held the security is by the most probable security lenders (institutions). In addition, we include trading volume, as it may proxy for a number of effects including liquidity, recall risk, or general disagreement among investors about a firm's price (Miller (1977)). The variable *Loan Fee* is a continuous variable measuring the spread between the market rate and rebate rate, *Quantity* equals the end-of-month/week ratio of shares on loan 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 month.

The baseline model takes the form

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

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.

[16] The horizon of past returns will depend on the horizon of the returns being considered as the dependent variable in the regression.

The regressions include calendar month dummies, and the standard errors take into account clustering by month employing a robust cluster variance estimator. Note that we 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 and 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 -2.98% in the following month ($t = -3.96$). We also see from column 2 that both institutional ownership, which proxies for ease of shorting a stock, and volume, which could proxy for a number of effects including recall risk, disagreement, and liquidity, do not significantly affect abnormal returns after controlling for the shifts.

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 magnitude of each of the shifts themselves in terms of loan fee and quantity (from 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 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 3 to 7 in Table III. Consistent with a number of recent papers (Jones and Lamont (2002); Reed (2002); and Geczy, Musto, and Reed (2002)), we find that high shorting costs, specifically *Loan Fee* $> 5\%$ per annum, predict future negative returns. However, when we include the shift variables in column 7, the conditional effect of these high costs is no longer significant, while *DOUT* remains large and

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/book-to-market 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 one if the loan fee is greater than *x* and zero otherwise. *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]
DIN	0.281	0.299					0.502		−0.149
	(0.43)	(0.59)					(0.96)		(0.31)
DOUT	−3.144	−2.983					−2.364		−2.485
	(3.20)	(3.96)					(3.27)		(3.19)
SIN	0.006	−0.063					0.443		0.176
	(0.01)	(0.08)					(0.69)		(0.22)
SOUT	−0.869	−0.820					−0.569		−1.225
	(1.11)	(1.23)					(0.85)		(1.81)
r_{-1}		−0.012	−0.012	−0.012	−0.012	−0.012	−0.012	−0.013	−0.012
		(0.49)	(0.50)	(0.49)	(0.48)	(0.48)	(0.48)	(0.51)	(0.50)
$r_{-12,-2}$		0.005	0.005	0.005	0.005	0.005	0.005	0.005	0.005
		(0.83)	(0.84)	(0.84)	(0.84)	(0.83)	(0.82)	(0.85)	(0.82)
IO		0.309	0.320	0.317	0.276	0.278	0.255	0.419	0.317
		(0.44)	(0.48)	(0.47)	(0.41)	(0.40)	(0.37)	(0.59)	(0.45)
Volume		0.018	−0.004	0.001	0.004	0.006	0.019	−0.024	0.018
		(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)
Δ*Quantity*								−0.907	−0.343
								(2.45)	(0.77)
Observations/ month	2,100	2,098	2,098	2,098	2,098	2,098	2,098	2,098	2,098

significant ($-2.36\%, t = 3.27$).[17] The quantity level is uninformative; as shown in columns 4 and 6, 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 either a supply shift out or a demand shift out (and decrease because of a supply shift in or a demand shift in), while the loan fee can increase because of an supply shift in or a demand shift out (and decrease because of a supply shift out or a demand shift in). We compute quantity changes (Δ*Quantity*) and loan fee changes (Δ*Fee*) at month $t - 1$, and test their predictive ability for next-month returns in columns 8 and 9 of Table III. Column 8 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, the conditional effect of Δ*Quantity* decreases. Also, *DOUT* remains negative and highly significant ($-2.49\%, t = -3.19$). In fact, our results suggest that quantity 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. The results in Table III 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*)

[17] 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* > 5% 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.

in week $t - 1$ lead to large negative abnormal returns on average in week t. For example, when we regress weekly abnormal returns (size/book-to-market adjusted) on the four shift variables the coefficient on *DOUT* is -0.56%, statistically significant ($t = -2.24$). Compounding this result to monthly returns yields 2.26%, which is similar to the monthly results discussed in Table III. 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. This allows us to evaluate the speed with which prices adjust after each of the types of shifts individually. For example, in the top two graphs of Figure 1 we regress characteristically adjusted daily returns on *DIN*, *DOUT*, *SIN*, *SOUT*, yesterday's return, and a constant for each lag length from

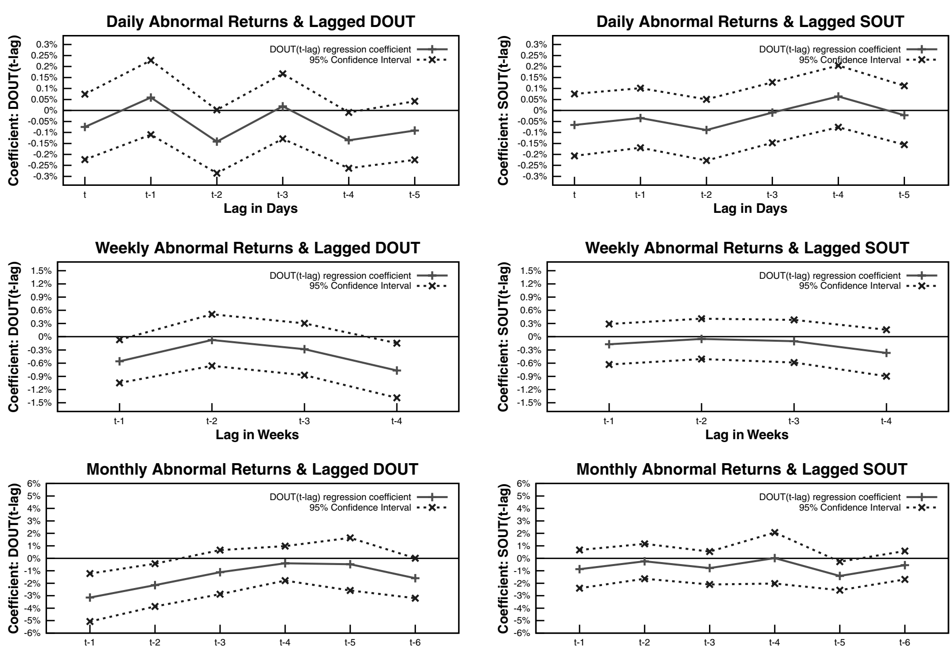

Figure 1. Daily, weekly, and monthly abnormal returns. In the top row we regress the daily abnormal returns (in percent) of all stocks owned by the lender with market capitalization below the NYSE median and lagged share prices above \$5 on daily supply and demand shifts and lagged daily returns. In row 2 (row 3) we regress the weekly (monthly) abnormal returns (in %) of the same universe of stocks on weekly (monthly) supply and demand shifts. We include all the shifts in the regressions (*DIN*, *DOUT*, *SIN*, and *SOUT*), but only report the coefficients for *DOUT* and *SOUT*. *DOUT*($t - lag$) is a dummy variable for an outward demand shift lag days (weeks, months) ago, and *SOUT*($t - lag$) is a dummy variable for an outward supply shift lag days (weeks, months) ago. We proxy for expected returns characteristically using 25 equal-weight size/book-to-market portfolios. We run separate regressions for each lag length. The regressions include calendar time dummies, and the standard errors take into account clustering by calendar date.

the first day up to the fifth day.[18] We provide plots for *DOUT* and *SOUT* in the figure; *DIN* and *SIN* effects on returns are weaker and insignificant at each horizon.[19] Starting with daily *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 5-day average (not shown), are marginally significant. None of the other shifts, however, produce reliably significant effects at a daily frequency. 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 (as is the 5-day average).

Turning to a weekly horizon, the middle set of graphs indicate that increases in shorting demand lead to low average abnormal returns during the next 4 weeks. The total effect for the first 4 weeks is about -1.68% and is significant (result computed but not shown in figure).[20] Abnormal returns following *SOUT* shifts are slightly negative for every lag length, but neither the individual lags nor the total effect are significant.

The bottom set of graphs in Figure 1 examine monthly abnormal returns out to 6 months. The lag 1 values in the figure correspond to the regression coefficients in column 1 of Table III. The *DOUT* coefficient is negative for each of the 6 months following a shift, and is economically and statistically significant for the first 2 months. The *SOUT* coefficient is negative for virtually every lag length, but is significant only for the fifth lag, with the combined effect over the 6 months insignificant. 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 3 months also yields an insignificant coefficient on the supply shift variable. In summary, prices respond mainly to increases in shorting demand, and this price adjustment seems to occur at a weekly frequency, and even more strongly at a monthly frequency. This fits well with our empirical observation that the average lending contract position in our sample lasts for nearly 1 month. As a result, we concentrate on this monthly horizon 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 explore the extent to which large shifts in shorting supply and demand may be more informative/predictive than small shifts. For example, Desai et al. (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.

[18] We also control for returns lagged 1 day in these figures to control for bid-ask bounce in daily returns.

[19] Graphs for *DIN* and *SIN* are available upon request.

[20] The total effect over 4 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 1-week shifts are much smaller shifts on average.

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* solely large increases in loan fees *or* large increases in quantity are insignificant. In contrast, column 4 shows that the marginal effect of large increases in fees *coupled with* large increases in quantity, which capture large *DOUT* shifts ($=\Delta Fee^{+}_{big} \times \Delta Quantity^{+}_{big}$), is large 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 = $\Delta Fee^{-}_{big} \times \Delta Quantity^{+}_{big}$) 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.[21] As noted earlier, a number of papers find that the cost of shorting (loan fee) is correlated with future returns. In the regressions of Table III, we also find evidence of such a link. We argue that the supply and demand shift categorization is important in understanding future return implications from higher costs in the shorting market. Specifically, there are two ways that a high cost of shorting can develop: via a ceteris paribus demand shift outward for borrowing shares (*DOUT*), or via 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 maintain that the information content of *DOUT* and *SIN* differ. In particular, given the evidence above, we expect the flow of private information and/or nonprice risks of shorting captured by *DOUT* to have more predictive power for future returns. This is especially true considering

[21] Jones and Lamont (2002, pp. 207–239.) argue with respect to their findings 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."

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 control variables. We characteristically adjust the left-hand side returns for size and book-to-market using 25 equal-weight size/book-to-market portfolios. We also interact the supply and demand shifts with loan fee and quantity changes. *DIN* (*DOUT*) is a dummy variable for an inward (outward) demand shift last month, and *SIN* (*SOUT*) a dummy variable for an inward (outward) supply shift last month. $Fee > 3\%$ is a dummy variable that equals one if the loan fee is greater than 3%. ΔFee^{+}_{big} (ΔFee^{-}_{big}) is a dummy variable that equals one if the change in the loan fee for month $t-1$ is greater than (less than or equal to) the 90th (10th) percentile. $\Delta Quantity^{+}_{big}$ is a dummy variable that equals one if the change in quantity on loan (as a percentage of shares outstanding) for month $t-1$ is greater than the 90th percentile. r_{-1} is last month's return. $r_{-12,-2}$ is the return from month $t-12$ to $t-2$. *IO* is institutional ownership as a fraction of shares outstanding lagged one quarter. *Volume* is the average daily exchange-adjusted share turnover during the previous 6 months. 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)
$DOUT \times \Delta Fee^{+}_{big}$		−1.253				
		(0.69)				
$SOUT \times \Delta Fee^{-}_{big}$		−0.015				
		(0.01)				
$DOUT \times \Delta Quantity^{+}_{big}$			−1.138			
			(0.67)			
$SOUT \times \Delta Quantity^{+}_{big}$			1.169			
			(1.02)			
$\Delta Fee^{+}_{big} \times \Delta Quantity^{+}_{big}$				−4.480		
				(2.32)		
$\Delta Fee^{-}_{big} \times \Delta Quantity^{+}_{big}$				2.633		
				(1.32)		
$Fee > 3\%$					−0.219	0.175
					(0.24)	(0.24)
$(Fee > 3\%) \times DIN$						2.798
						(1.82)
$(Fee > 3\%) \times DOUT$						−4.144
						(2.69)
$(Fee > 3\%) \times SIN$						−1.691
						(0.93)
$(Fee > 3\%) \times SOUT$						−0.710
						(0.42)
Observations/month	2,098	2,098	2,098	2,098	2,098	2,098
Control Variables	$r_{-1}, r_{-12,-2}$, *IO*, *Volume*, and calendar month dummies					

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 still significantly affect the lending supply in many securities, however.

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 3% per annum 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*[22] for a given level of loan fee, when *DOUT* causes the higher loan fee, it has significant predictive power for subsequent abnormal returns that is over two 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 measure portfolio returns first by using returns in excess of the risk-free rate, and then by characteristically adjusted returns using either 25 size/book-to-market benchmark portfolios, or 75 ($3 \times 5 \times 5$) size/book-to-market/momentum benchmark portfolios. For example, when using the 75 size/book-to-market/momentum benchmark portfolios, we compute each stock's abnormal return as

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

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.[23] However, all the portfolio tests in the paper are robust to

[22] From Table II the average magnitude of loan fee moves in both *DOUT* and *SIN* are similar, at 42 and 40 basis points, respectively.

[23] See Daniel et al. (1997) and Grinblatt and Moskowitz (1999) for more details on characteristically adjusting returns.

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 1-month Treasury bill rate. Abnormal Returns are computed by characteristically adjusting returns using 25 equal weight size/book-to-market portfolios and 75 ($3 \times 5 \times 5$) equal weight size/book-to-market/momentum portfolios. The benchmark portfolios also contain the restriction that lagged price must be greater than or equal to $5. For 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.

	DIN	*DOUT*	*SIN*	*SOUT*	*DIN* − *DOUT*	*SIN* − *SOUT*
Panel A: Excess Returns						
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/Book-to-Market Portfolios)						
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/Book-to-Market/Momentum Portfolios)						
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

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 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/book-to-market portfolios and -2.11% per month when benchmarked relative to size/book-to-market/momentum portfolios.[24] The value-weight results for these outward demand shifts are smaller and insignificant. However, in unreported tests we find that if we 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 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 ($SOUT = -0.829, t = -1.04$). Both *DIN* and *SIN* shifts lead to positive (but insignificant) returns in the future. The trading strategy of buying stocks that have demand shifts inward and shorting stocks that have 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 similar 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 relation with future returns.[25] Overall, the portfolio results suggest a possible link between increases in shorting supply and future returns (which is not supported in our regression tests, however), and reinforce our earlier findings on the strong relation between increases in shorting demand and negative future 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. First, we augment our cross-sectional regressions in Table III by using industry dummy variables in addition to calendar time dummies, using 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

[24] Untabulated statistics reveal virtually identical results if we use factor loadings to compute abnormal returns instead. In particular, monthly alphas in four-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*($-1.65, t = -1.27$).

[25] 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.

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*) is a dummy variable for an inward (outward) demand shift last month, and *SIN* (*SOUT*) a dummy variable for an inward (outward) supply shift last month. In columns 1 to 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 two-thirds. r_{-1} is last month's return. $r_{-12,-2}$ is the return from month $t-12$ to $t-2$. *IO* is institutional ownership as a fraction of shares outstanding lagged one quarter. *Volume* is the average daily exchange-adjusted share turnover during the previous six months. All five 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 to 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	2,098	2,095	2,095	2,095	2,097
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				

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.

Next, 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 expect that for those stocks for which our institution lends out most of the available shares our shift measures should be less noisy, and hence our results attributable to them should be even stronger. To test this idea we collect monthly short interest data on all the NYSE, AMEX, and Nasdaq stocks in our data set for which short interest data are publicly available. We then compute the *Market Power* of our lender in a given stock as the number of shares on loan 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 Power* with *DOUT* produces a large (-5.64% 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 two-thirds, the coefficient on this interaction term is large (-8.36% 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.

To overcome the shortcoming of having only one lender in our sample, we also 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 15$^{\text{th}}$ of every month or the last trading day before the 15$^{\text{th}}$. Since it usually takes three trading days to settle short sale trades, short interest includes short sale trades up to three trading days before the 15$^{\text{th}}$. 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 16$^{\text{th}}$ 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 and 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 2,098 stocks per month, of which 172 (8.2%) are eligible for a shift (since they are on loan at both the beginning and end of month $t-1$); of these 172 stocks, 125 (72.7%) experience a shift. On average, the number of stocks per month that experience at least an outward demand shift 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 38 (out of 3,760 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, together with our earlier finding that *DOUT* is significant even when we run our baseline regression on *all* stocks (rather than just those 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 that is posted. Again, this concern is alleviated in our sample, since our institution charges 102% 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 conclude that collateral-related issues do not appear to drive our results.

We also explore 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 in which lending activity increases from zero to a large amount, conditioning on our lender already owning a large amount (e.g., 5% of shares outstanding) so as to ensure that this lending activity is demand driven. Specifically, we look at the month-t returns of stocks that are on special in month $t - 1$, but that have zero lending activity in month $t - 2$. Although we can identify only 205 such shifts, untabulated results reveal that this type of demand shift is associated with a large (but insignificant) -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 endogeneity of commonly used shorting indicators. 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 refer to as "residual analyst coverage."[26] We compute residual analyst coverage for each stock as the residual from month-by-month cross-sectional regressions of $\ln(1+ \textit{number\_analysts})$ on $\ln(\textit{size})$. 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 so, we replicate our prior monthly regression results, but add residual analyst coverage (*RCOV*) as a control variable and interact it with *DOUT*. As column 2 of Table VII shows, the evidence for increases in shorting demand leading to large declines in future stock returns is *not* concentrated among 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.[27]

B. Times of Predictable Demand: Dividends

One concern is that stocks may experience a spike in borrowing and lending right around dividend dates for tax purposes, and that these spikes may be driving any empirical regularities. Indeed, Christoffersen et al. (2004) document a significant relation between the magnitude of the dividend and the amount on loan. Dividends also provide a nice test of the private information hypothesis, in that borrowing around dividend dates may result in *predictable* shifts in shorting demand (*DOUT*), which are unrelated to private information.

In our sample, untabulated results reveal that dividend payments are also positively related to demand shifts out. Column 3 of Table VII shows that the effect of *DOUT* is still negative and strongly significant after controlling for those *DOUT* shifts that occur in dividend months. The interaction term, $DIV \times DOUT$, is positive and insignificant. To explore a private information story, we want to test if predictable *DOUT* shifts (due to known dividend payment dates) forecast returns in future months. We therefore compute the combined effect, that is the interaction plus main effect. When adding the interaction term to

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

[27] 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.

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 owned by the lending institution with market capitalization below the NYSE median and lagged share prices above $5 on supply and demand shift dummy variables, residual analyst coverage, a dividend indicator variable, and a host of other control variables. We characteristically adjust the left-hand side returns for size and book-to-market using 25 equal-weight size/book-to-market portfolios. *DIN* (*DOUT*) is a dummy variable for an inward (outward) demand shift last month, and *SIN* (*SOUT*) a dummy variable for an inward (outward) supply shift last month. *RCOV* 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. This residual is defined as residual analyst coverage. *DIV* is a dummy variable equal to one if there was a dividend in month $t-1$. The control variables r_{-1} is last month's return. $r_{-12,-2}$ is the return from month $t-12$ to $t-2$. *IO* is institutional ownership as a fraction of shares outstanding lagged one quarter. *Volume* is the average daily exchange-adjusted share turnover during the previous six months. 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]
DIN	0.299	0.303	0.285
	(0.59)	(0.60)	(0.56)
DOUT	−2.983	−2.936	−3.096
	(3.96)	(4.30)	(3.91)
SIN	−0.063	−0.059	−0.075
	(0.08)	(0.08)	(0.10)
SOUT	−0.820	−0.813	−0.835
	(1.23)	(1.22)	(1.26)
RCOV		0.019	
		(0.26)	
RCOV × *DOUT*		0.052	
		(0.24)	
DIV			−0.347
			(1.09)
DIV × *DOUT*			2.251
			(0.94)
Observations/month	2,098	2,098	2,098
Control variables	$r_{-1}, r_{-12,-2}$, *IO*, *Volume*, and calendar month dummies		

the main effect, (*DOUT* + *DIV* × *DOUT* (=−0.845%)) is not significantly different from zero. Thus, demand shifts that are likely to be unrelated to private information are not significantly related to future returns. This is consistent with the hypothesis that the link between *DOUT* and future returns is driven by private information, with the link being broken when *DOUT* is driven by motives unrelated to private information.

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 month-t returns to betting on these stocks in month $t - 1$. We find that when costs of shorting are high (*loan fee* >3% per annum), 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 a -6.44% average abnormal return next month, which is significant at the 0.01 level. This return is over twice as large as the return following an unconditional *DOUT* shift from Table III (-2.98%).

Another piece of evidence consistent with the notion that the equity 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.[28] 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.[29]

To incorporate other costs and risks associated with this strategy, we employ two methods.[30] 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). We then 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 categorize stocks by 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 only at 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%.[31] Adding these together, the monthly cost of rebalancing the

[28] 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.

[29] There is a confidence interval about this return, but even assuming that the lowest 5% bound is realized in every month (a return of 1.02% per month), the strategy still yields 9.31% per year net of shorting costs.

[30] 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.

[31] An example of this calculation for *DIN* is

$$\begin{aligned} \textit{Average cost} &= 2 \times \textit{turnover} \times ((\%\textit{in Nasdaq}) \times (\textit{trading cost of Nasdaq}) \\ &\quad + (\%\textit{in NYSE/AMEX}) \times (\textit{trading cost of NYSE/AMEX})) \\ &= 2 \times 0.9 \times ((0.72 \times 0.88) + (0.28 \times 0.63)) = 1.46. \end{aligned}$$

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. Thus, the return to this strategy net of shorting costs, commissions, and price pressure is estimated to be about 4.5% per year. Note that as costs have probably decreased since Keim and Madhavan's (1997) sample period of 1991 to 1993, we expect this to be a lower bound for the average net returns in our sample. Nonetheless, considering trading costs does substantially reduce the profits from this strategy.

Another way to evaluate the returns on this strategy is to look at the return per unit of risk and then to compare this measure to a benchmark. To do so, we construct a Sharpe ratio for the strategy using the data in Table V. Since 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 estimate the Sharpe ratio before transaction costs. The Sharpe ratio of the *DIN–DOUT* strategy based upon Table V is 0.338. Over this same time period, 1999 to 2003, the monthly market Sharpe ratio was negative, so as a comparison we use the Sharpe ratio from 1990 to 2003, which is 0.137. The Sharpe ratio for *HML* over the same time interval (1990 to 2003) is 0.094. 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 narrow as we add transaction costs to all three strategies, this test highlights that the demand shift-based trading strategy not only has larger absolute returns, but also has substantially larger returns per unit of volatility than does the market or *HML*.

Clearly, the 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 the larger stocks in our sample, since these require more arbitrage capital (Baker and Savasoglu (2002)). However, as column 3 of Table VIII shows, the effect of *DOUT* is concentrated in small stocks, as the marginal effect of $ME_{small} \times DOUT$ is strongly significant. This result indicates that the total effect of a *DOUT* shift for a stock below the 20$^{\text{th}}$ 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 80$^{\text{th}}$ percentile (Wurgler and Zhuravskaya (2002)) is insignificant. Thus, the *DOUT* strategy does not appear to vary with arbitrage risk.[32]

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 the view that recall risk may be larger among 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

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

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 five dollars 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/book-to-market portfolios. *DIN* (*DOUT*) is a dummy variable for an inward (outward) demand shift last month, and *SIN* (*SOUT*) a dummy variable for an inward (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 as a fraction of shares outstanding lagged one quarter. Volume is the average daily exchange-adjusted share turnover during the previous 6 months. $Volume_{high}$ is a dummy variable that equals one 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 1 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 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)		
$Volume_{high} \times DOUT$		−0.001		
		(0.00)		
ME_{small}			−0.126	
			(0.48)	
$ME_{small} \times DOUT$			−3.903	
			(2.38)	
$IRISK_{high}$				0.111
				(0.13)
$IRISK_{high} \times DOUT$				−1.766
				(1.04)
Observations/month	2,098	2,098	2,098	2,098
Control variables	r_{-1}, $r_{-12,-2}$, *IO*, *Volume*, and calendar month dummies			

stocks) in his sample. He also reports that the days on which stock-level recall risk is high are the days in which trading volume is extremely high for 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 ($Volume_{high} \times DOUT$).

However, as Table VIII shows, the marginal effect of $Volume_{high} \times DOUT$ is insignificant in our sample.[33]

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 of our estimates range between 2% and 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 nonprice 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 continues to be large, and in some cases is even larger, in those environments in which other information is scarce. By contrast, predictable increases in shorting demand that are *not* related to private information (such as those around 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. Even after incorporating trading costs such as commissions, bid-ask spreads, and price impact, a conservative estimate of the strategy is 4.5% per year. Further, the Sharpe ratio of the strategy is about 2.5 to 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, most importantly, a mechanism for private information revelation.

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.

[33] 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 (2006)). However, in our sample we find little evidence that the effect of shorting demand on future returns varies with proxies for differences of opinion.

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