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Stocks are Special Too: An Analysis of the Equity Lending Market

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Stocks are Special Too:
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Abstract

Stocks are Special Too: An Analysis of the Equity Lending Market

Short-sellers are generally obliged to borrow shares, and provide collateral as security. Lenders rebate interest they earn on the collateral, but the rebate shrinks as stocks grow scarce, i.e. go "on special." With daily rebate data from one of the highest-volume equity lenders, we characterize the equity lending market in general, and in three situations where the availability and cost of loans are potentially important: initial public offerings, merger speculation, and long-short "factor" portfolio construction. We find that IPOs are generally borrowable in the wholesale market, but are invariably on special at first. Specialness generally decreases with the float and increases with performance, but IPOs trading below their offering prices are also relatively more expensive to borrow. The market for borrowing a stock is significantly affected by the expiration of the 30-day restriction on lending by syndicate members, and also by the expiration of insider lockups. Merger arbitrage strategies lead to increased specialness in acquirers' stocks, especially when acquiring firms are small or target firms are large. Similarly, specialness is increasing the profitability of the arbitrage strategy, but the additional costs associated with borrowing special stock do not substantially decrease profits to merger arbitrage strategies. However, the inability to borrow acquirer's stock reduces profits by an economically, although not statistically, significant amount. Growth stocks are more than five times as expensive to borrow as value stocks and about three times as expensive as the average stock. However, the absolute cost of shorting growth stocks, large stocks or stocks with low momentum is not large economically and does not directly support the limits to arbitrage story explaining the persistence of premia associated with stocks along the value-growth, size and momentum dimensions. We find that while imposing these realistic constraints *ex ante* on popular equity factor models lowers the factor premia and increases their volatilities, their optimal Sharpe ratios do not fall much. Statistical rejection of the Fama-French (1993) and Carhart (1997) models is stronger when the constraints are imposed; however, it is only marginally stronger. Finally, while constraints appear not to alter estimates of mutual fund performance on average, they do significantly change portfolio style characterizations, especially along the dimension of value versus growth.

Stocks are Special Too: An Analysis of the Equity Lending Market

The equity-loan market is vital but obscure. It is vital because it permits negative equity exposure by providing shares for short-sellers to deliver. It is obscure because it clears within a network of private institutions that collectively report almost nothing to the public record. So while we know that equity loans can be crucial and can be expensive, we have seen little of the actual economics of equity-loan pricing. This paper brings the dynamics of equity-loan pricing to light with a large new daily database of individual transactions by one of the world's most active lenders.

In the typical equity loan, the borrower[1] delivers cash collateral to the lender, who invests it overnight and "rebates" some of the resulting interest to the borrower, so a high-cost loan is a low-rebate loan. On the typical day, most stocks go out at the same high rebate rate, just ¼% or so below the market overnight rate, but 100 to 200 are "specials" because their rebates trade below the high "general" rate, the shortfall being their "specialness." Why do stocks go on special, and what accounts for the cross section of specialness? The goal of this paper is to answer these questions.

The context where specialness is best understood is the Treasury-bond market. The incidence is quite predictable: on-the-run bonds (i.e. the most recently issued) are special, and the old bonds (i.e. second-most recently issued) often are too, but the remaining bonds are hardly ever special (see Keane (1996), Duffie (1996)). This is understood to reflect the higher liquidity of recent issues, which attracts short-term hedging and speculation. So in the

[1] Unless otherwise specified, "borrower" and "lender" refer to the equity-borrower and equity-lender, respectively.

Treasury-bond context, the specialness schedule is a straightforward product of the auction schedule. But equities promise to be more complicated.

Equities do have something like an auction schedule, in that an issue hits the market on its IPO day, and trades more intensely in its early days than it does later. But beyond that, the analogy to Treasury bonds is not very helpful. The circumstances of public corporations vary in a number of ways that could relate to demand for, or supply of, equity loans.

After a brief overview of equity-loan mechanics we begin our exploration of specialness with IPOs. New issues are found to be consistently on special, and the cross section of specialness is seen to relate significantly but non-monotonically to the performance of the IPO. In general, better performers are more expensive to borrow, but there is also an extra cost to borrow offerings trading at or below their offering prices. Smaller issues are also more expensive to borrow, as are the more heavily traded ones. We see that in the wholesale stock-lending market, borrowing IPOs is generally feasible but expensive. We also see a significant impact of the lapsing at 30 days of the lending restriction imposed on syndicate members, and at the lapsing of the insider lockup, usually at 180 days.

The next subject is merger speculation. In a sample of expected mergers, including merger plans that did not go through, we find that shorting the acquirer is expensive, and the expense increases for small acquiring firms and large target firms. Furthermore, as merger arbitrage profitability increases, so does the specialness in the acquiring firm's stock. These results are noisy, since we do not have useful information about the *ex ante* expected merger ratios, but they do make clear that the net profit from shorting the acquirer and buying the target is less than it would appear if specialness were not taken into account. However, the large profits available in merger arbitrage are not substantially reduced by the increased costs. Profits are reduced by the inability to borrow shares in the acquirer's stock. Even though the portfolio that short-sells only available shares is less profitable, the difference is not statistically significant.

Finally, we step back from discrete events and look at the relation between specialness and firm fundamentals, in particular the size, book-to-market and momentum characteristics that are prominent in the asset-pricing literature in general. We find borrowing costs as measured by specialness to vary significantly along the dimensions that these portfolio sort on, though the average expense due to shorting specials does not amount to much economically. This result is prima facie evidence that forming zero-investment trading strategies or factor-mimicking portfolios on the basis of return spreads induced by these sorting characteristics may not be prohibitively costly on the short side, although borrowing costs are relatively higher for low momentum and low book to market growth stocks. We also find that the mean returns of spread portfolios constructed on the basis of firm characteristics decrease and volatilities increase when we borrowing constraints indicated in our data. In addition, the Sharpe ratio of the optimal mean-variance portfolio formed from these spread portfolios as well as the value-weighted market portfolio is lower than when we form the portfolios without the constraints in place. However, it does not fall significantly either economically or statistically. Moreover, these realistic constraints do not appear to damage strongly the pricing properties of multifactor models. Pricing errors increase, but, again, not by much, and formal model tests reject this constrained model only marginally more strongly than unconstrained versions. Finally, the effects of incorporating equity borrowing costs and constraints on performance mutual fund performance attribution do not show up in palpable changes in fund alphas. Rather, they show up in style characterizations. We find that funds that appear to follow a value orientation actually have much lower value-factor sensitivities once the constraints are taken into account.

The rest of the paper is in seven sections. Section I gives some background on the microstructure of the equity-loan market, and Section II covers the relevant literature. Section III covers IPOs, Section IV covers mergers, Section V covers the relation between specialness and fundamentals, and Section VI summarizes and concludes.

I. Background on Equity Lending

A loan of equity shares transfers their legal ownership to the borrower. The usual motive for this transfer is delivery; the borrower acquires legal ownership in order to pass it on to a third party. There is an additional class of motives, wherein the borrower acquires legal ownership for some benefit that accrues to legal owners. In this scenario, the borrower acquires legal ownership in order to be the legal owner on the record date of the benefit. We briefly discuss the mechanics of an equity loan, particularly as they apply to our data, we define "specials" and "specialness" and then the issues related to the motives for equity-lending.

I.A Mechanics of Equity Loans and our Database

I.A.1 Summary of Our Data

Our data come from the "wholesale" equity-loan market. The lending agent is a large custodian bank lending shares held by its custodial clients, and the borrowers are major financial institutions, generally broker/dealers, which may be borrowing for their own use, or for the use of their customers. This is not the only venue for equity-lending. For example, many equity loans are in-house, where a broker loans shares from one account to another. Also, some institutions – mutual and pension funds, endowments, etc. – do their own lending, with no lending agent. The basic principles of equity lending apply to all venues but we focus here on the venue of our data supplier, and we describe our database along the way.

The data are the terms of every loan of U.S.-listed equities negotiated by the data provider between November 1, 1998 and October 31, 1999, a total of 249 trading days in the equity-loan market. We have the CUSIP, number of shares, initial interest rebate and subsequent adjustments to the rebate. There are 273,225 separate loans, representing 7144 different stocks. On an average day, loans of 3170 different stocks are outstanding. The median loan duration is three trading days.

I.A.2 Loan Mechanics

While a loan is outstanding, the beneficial owner (i.e. the owner of the portfolio the shares were lent from) is not the legal owner, and therefore not the owner of record for all distributions with record dates in the loan period. The borrower is obliged to reimburse these distributions to the lender, so the borrower reimburses the cash amount of any cash dividends, and the shares from any stock dividends. If the record date of a shareholder vote occurs during the loan then the beneficial owner misses that too, but votes are not reimbursed.[2]

The standard equity loan is a cash-collateral loan, and the standard collateral is 102% of the value of the shares. At the origination of a loan of n shares currently selling for S, the borrower remits $1.02nS$ in cash to the lender, while the lender simultaneously transfers legal ownership of n shares to the borrower. Over the course of the loan, collateral will be either increased or reduced as S varies. The lender and borrower will have negotiated the duration of the loan, and also the interest rebate. An interest rebate of r% means that the lender pays the borrower (r/100)(1/360) times the cash collateral it holds on a given day. The duration of the loan is generally "continuing," which means that the loan is open each day to re-negotiation or termination by either party, but otherwise continues on its current terms. Because loans are generally open to re-negotiation each day, we assume throughout the paper that on each day of a loan, its current terms are the current market terms, i.e. the terms that *would* have obtained if the loan had been originated that day.

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[2] In anticipation of a voting record date, the lending agent will ascertain how many shares his clients wish to vote, and ensure that at least that many shares are not loaned. In addition, ERISA accounts must have the option to call in shares for votes.

Some loans use securities, rather than cash, for collateral. In these cases, there is no interest to rebate. The lender will price the transaction instead by charging a lending fee, or "premium." Our data provider does not use negative interest rebates, and so uses this "in-kind" collateral structure for loans where the equity is so scarce that a zero-rebate loan would be too cheap. Loans of this sort account for less than 1% of the loans in the database.

There are substantial fixed costs to an equity loan, which result in volume discounting. Each lender presumably has its own in-house volume-discounting policy; our data provider sorts loans into Large, Medium and Small loans, and then applies the same volume discount to all Large loans (i.e. the relative size of two Large loans has no bearing on their relative pricing), and another (smaller) discount to all Medium loans. Small loans are priced case by case (so the relative size of two Small loans *can* differentiate their pricing). We know which loans are Large, Medium and Small.

I.B. "Specials" and "Specialness" Defined

Our analysis focuses primarily on "specials," which are stocks that are expensive to borrow due to scarcity, and "specialness," which is the amount by which they are more expensive. These can be calculated from rebate rates. In the repo market, most bonds are not scarce, and these bonds all go out on a given day at the same interest rate, known as the day's general rate. The bonds that go out at lower interest rates are said to be special, and the shortfall of their interest rates from the general rate is said to be their specialness. The same principle applies to equity loans; most equities are not scarce, and all Medium loans of these equities loan out at the same Medium general rate, and all Large loans go out at the same Large general rate. Because Small-loan rebates vary substantially (and unpredictably) due to loan size, they are not useful for estimating specialness. Accordingly, our method is to focus on the Medium and Large loans, and designate the equities that loan out on a given day *below* the general rates for their loan sizes as the day's specials, and designate the shortfall to be their specialness. For convenience, we say below (unless otherwise specified) that a stock is *loaned* on a given day if and only if there is at least one Medium or Large loan of the stock outstanding that day.

Before calculating specialness we have to estimate the correspondence between the premia of in-kind-collateral loans and the rebates of cash-collateral loans. The cost of a zero-premium loan is zero, as there is no foregone interest. The cost of a general-rebate loan is whatever spread the lender keeps for itself on these transactions, which we can not observe directly but estimate from trade publications to be about 20bp (bp = basis point, 1/100 of 1%). Consequently, we estimate that a premium of p corresponds to a rebate rate equal to the general rate minus (p-20bp), or in other words a specialness of p-20bp. For the rest of the paper we will translate the terms of in-kind-collateral loans in this way and when we refer to rebate rates and specialness we are including these loans.

Calculating the Large and Medium general rates on a given day is simple. Because the large majority of equities are not special, the general rates are easily apparent as the mode rebate rates for the day. For each day we calculate the fraction of all Large and Medium rebates that are below, at and above the mode rebates for their respective sizes that day. The results, in Table I, show 76.1% and 98.3% of Medium and Large loans, respectively, at the mode, and only a small fraction *above* the mode. [3] When we refer in the rest of the paper to the Medium or Large general rates, we are referring to these modes.

[3] We have investigated the incidence of rebates above the mode and learned that two situations are important: 1) the short rate changes during the day, perhaps due to the Fed, and 2) the borrower specifies a higher-risk collateral investment (e.g. P2-rated commercial paper) and contracts to bear the default risk. This would explain a higher incidence of higher rebates at quarter-ends, when the money market's risk premium is artificially high (see Musto (1997)).

Because we often have more than one loan of a given equity outstanding on a given day, our measure of the specialness of stock *s* on date *t* is the value-weighted average of the specialness of *all* loans of *s* outstanding on *t*. If our data provider had no loans of *s* outstanding on *t* then the specialness is regarded as missing.

I.C Borrowing to Deliver

When investor *A* sells *n* shares to investor *B*, he creates an obligation to deliver *n* shares to *B*. If *A* is short-selling then he expects to deliver shares he does not currently own, and the standard date for this delivery is *t*+3, i.e. 3 business days after the transaction. There are two principal ways to acquire shares to deliver. The first is to buy *n* shares on day *t*, so that he gets the shares for his short-sell settlement on *t*+3 from his purchase settlement. The second is to borrow shares on *t*+3 (equity loans settle same day). Once *A* transfers legal ownership to the third party, the third party's ownership is the same in every way as if *A* delivered shares he had *not* borrowed.[4] A related, but less frequent, reason for borrowing shares to deliver to third parties is failed deliveries. For example, an investor might buy and sell the same stock on *t*, and then find that the investor he bought from does not deliver on *t*+3 so he instead borrows the shares that he needs to deliver.

One consequence of these institutional features is that *if* a short sale obliges the short-seller to borrow shares, then the short-seller will generally borrow three business days later. It is important to note that the short-seller's initial loan may not last as long as his short sale. The initial loan can end, in which case the short-seller can keep his short position going by closing out the loan with shares borrowed from another institution. This implies that there is

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[4] A third way to acquire shares for delivery is non-standard settlement. The short-seller might buy on *t*+1 from an investor who is willing and able to deliver 2, rather than 3, days later.

no necessary correspondence between the origination dates of the loans in our database and the dates of the underlying short sales; they could have been three days earlier, or three months. The important point is that the rebate rates we observe indicate the realized cost of shorting three days earlier, whether or not the loans we observe are due to sales then.

Lenders such as our data provider may be particularly useful to investors interested in shorting initial public offerings (IPOs) in their first thirty days. This is because the brokers in an IPO syndicate are prohibited from lending the shares in that period,[5] so traders shopping for shares to deliver must turn to other sources, such as custodian banks.

I.D Borrowing for Legal Ownership

Depending on his circumstances, an investor might benefit from legal ownership of an equity on the record date of a dividend, even though the dividend's cash value must be reimbursed. For example, the stock may have an optional dividend-reinvestment plan (DRIP), so that the borrower – by participating in the DRIP – saves on transactions costs (reimburses \$*x* to the borrower, and gets \$*x* of shares). A bigger benefit accrues when the DRIP has a discount (borrower reimburses \$*x*, and gets more than \$*x* of shares; see Scholes and Wolfson (1989)). There is also a large cross-border market driven by international dividend arbitrage (the borrower is a taxpayer in a country with a tax credit for dividends from domestic firms, the loaned equity is one of those firms, and the lender can not get the credit). Lending volume is also significantly higher on voting record dates, which suggests borrowing for votes. These record-date issues are explored in Christoffersen, Geczy, Musto and Reed (2001).

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[5] *Wall Street Journal* (August 18, 1999 p. C1).

II. Related Literature

The sections of this paper describe several causes of expensive borrowing in the equity lending market: initial public offerings, merger arbitrage strategies, and fundamentals stock characteristics. Each section incorporates a brief review of the literature relevant to the section's topic, and this section describes the literature relevant to equity lending in general. Since equity borrowers are usually short-sellers, the short-selling literature is closely related to this work. However, this paper is fundamentally different. We find explanations for fluctuations in daily *prices* faced by short-sellers in the equity lending market, whereas the extant short-selling literature looks at the causes and consequences of the monthly *quantity* of short-loans outstanding. The study of specials in stock lending is the focus of this paper, just as Duffie (1996) explains how specialness can arise in treasury repo markets (see D'Avolio (2001) for an adaptation of the Duffie (1996) model to equities).

The literature has identified several explanations for the quantity of short-sales. MacDonald and Baron (1973) show that stocks with more idiosyncratic risk have higher short interest. Brent, Morse, and Stice (1990) find that stocks with traded options, convertible securities or high betas tend to have high short interest. In addition, as evidence of strategies using short-selling for tax purposes, they find that short interest follows a seasonal pattern. Gintschell (2000) documents an association between short interest on the NASDAQ stocks and the stocks' float. Dechow, Hutton, Meulbroek, and Sloan (2000) find stocks with low ratios of accounting performance measures to market value tend to have higher short interest. An increase short interest around the issuance of seasoned equity offerings is documented in Safieddine and Wilhelm (1996). Richardson (2000) finds no increase in the short interest of high accrual firms even though high accruals predict future underperformance.

In contrast to explaining the causes of short selling, a set of papers has examined the consequences of short-selling. The effect of short selling on stock prices has been examined in papers dating back to Seneca (1967) where high aggregate short interest is shown to be associated with lower returns for the S&P 500. Similarly, Figlewski (1981) finds that short interest is negatively correlated with future excess returns. Asquith and Meulbroek (1996) find that a portfolio of firms with high short interest underperforms the market over short and long horizons. In the very short-run, Senchack and Starks (1993) find an intra-daily decrease in stock prices after the announcement of higher than expected short interest. Using NASDAQ short interest, Desai, Thiagarajan, Ramesh, and Balachandran (2000) find similar results, and they find an increase in the probability of delisting for firms with high short interest.

Short sale constraints have also generated a long history of theoretical research. Miller (1977) and Figlewski (1981) both hypothesize that short-sale constraints lead to upward biases in stock prices as pessimistic investors are restricted from short-selling. Diamond and Verrecchia (1987)'s rational expectations model shows that stock prices won't be biased if market participants know that short-selling is restricted. However, since short sales are removed form the market, informational efficiency will be reduced in the presence of short-sale constraints. In a model where some investors' information is hidden, Hong and Stein (1999) show that large price movements and left-skewness can be a result of short-sale constraints.

Empirical work has verified many of the implications of the models. Jennings and Starks (1986) and Skinner (1990) show that informational efficiency is increased when options are available to circumvent short-sale constraints. In a paper closely related to this one, Reed (2001) uses the same equity lending database to examine the impact of costly short-selling on the informational efficiency of stock prices. The paper verifies Diamond and

Verrecchia (1987)'s hypothesis that short-sale restrictions lead to stock price distributions with larger absolute values and more left-skewness as information is announced.

Several recent papers have taken measurements of the equity-loan market. Ofek and Richardson (2001) demonstrate that rebates are generally lower for internet stocks in early 2000, Mitchell, Pulvino and Stafford (2001) show extremely low rebates for stocks in equity carve-out transactions, and D'Avolio (2001) relates the cross section of end-of-month specialness to a variety of stock-specific characteristics. A companion paper to this one explores the interaction of the equity-loan market with the record dates of corporate distributions and votes (Christoffersen, Geczy, Musto and Reed (2001)).

III. The Market for Borrowing IPO Shares

The goal of this section is to characterize the cost of borrowing IPO shares in terms of the usual variables of interest. We are particularly concerned with three subperiods of a stock's first months: the first few days, a window around 30 calendar days post-IPO, and a window around the expiration of insider lockups, usually at 180 days. The first few days are interesting because that is presumably the extreme market, the market for borrowing shares as soon as possible when speculative swings are strongest, and also because it is the period of price stabilization, an activity that short-selling would presumably complicate. Thirty days is when the restriction, mentioned above, on lending by syndicate members expires, so it is the moment when new supply hits the market. The point of exploring the days around the lockup expiration is to bring a new perspective to these events, which have attracted a great deal of attention in the financial press and have spawned a cottage industry in expiration-tracking. Before exploring those three subperiods we describe the data and provide a rough overview of the entire first half-year.

III.A IPO Data

We collect an IPO sample covering the 11/98 through 10/99 sample period, and also covering 5/98 through 10/98 to boost the population of offerings whose lockups expire in the sample period. Note that the 5/98 – 11/99 period saw many of the internet-related offerings that did extremely well at first, especially on the first day, then eventually very badly. Our method is to first list all stocks that first appeared in the CRSP stock-return data in those eighteen months, and then identify all that were 1) IPOs, 2) in the SDC database, and 3) not foreign, unit, or closed-end fund offerings. There are 534 offerings in the resulting sample. For each IPO we have the offering price, total offered shares (including the Green Shoe), and lockup-expiration date, as indicated by SDC. Following the advice of Aggarwal (2000), we examine the SEC filings of all sample firms for which SDC shows no Green Shoe shares, and add in any Green Shoe shares the filings report.

III.B Overview of the First Half-Year

Before focusing on subperiods, it is useful to see the entire half-year period in one picture. What we want is to track a panel of IPOs from their first trading day to about a half-year later, taking the average specialness on each event day (event day n is the n^{th} trading day of the IPO). Two considerations are important. First, we need a panel of IPOs that are covered by our data for their first half-year, so our panel is the 110 (of the 534) IPOs from our sample period whose first trading days are at least 125 trading days before the last trading day of the sample, so that our sample covers their first 126 trading days (which is about ½ year). Second, we can not observe the specialness of a stock on a day when our data provider had no loan of it outstanding. So our estimate of the average specialness of an IPO on its n^{th} trading day is the average across only those IPOs that happen to have been loaned.

For each IPO in the panel we calculate its specialness, as defined above, on each trading day out to its 126th, then we take the cross-sectional average, across the 110 IPOs in the panel, for each trading day. No IPO is loaned on its first or second day, and only three of the IPOs are loaned on their third days. The fourth day, which is when an investor would need shares to deliver for a short-sale on the first day, is the effective beginning of lending. We find that 79 of the 110 (72%) are loaned on the fourth day, and every one of the 79 is on special.[6] The number loaned drops to 46 (42%) by trading day 87, and is at 61 (55%) by day 126. The time series of average specialness is in Figure 1.

We see in Figure 1 that specialness is highest at the start, 3.22% is the point estimate, drops fairly steadily to somewhat above 1%, and is flat or slightly decreasing out to six months. This suggests a strong interest in shorting IPOs at first, which falls rapidly over the first month and then stabilizes. It also indicates a substantial piece of revenue that can be earned by those who hold on to their IPO shares. If we take these estimates from loaned IPOs as representative of all IPOs, they show a little more than a 1% annual rate for the first half-year, or a little more than ½% to add to the total return of the stock itself. Whether or not an investor can actually get this ½% depends on his access to the lending market.[7]

III.C The Cross Section of Borrowing Costs in the First Days

A stock's first days are intuitively a time of great uncertainty over its proper valuation, and therefore inviting to speculators. It is also a time when the microstructure of its trading is qualitatively different. The lead underwriter is especially active in making a market, and

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[6] There is an 80th IPO of which there are Small, but no Medium or Large, loans on event day four, and there typically are several such IPOs on each of the other event days as well.

[7] Of course, *somebody* is the legal owner of every share on every day, and therefore did not earn money by lending it.

price-stabilization activity is allowed and practiced (Ellis, Michaely and O'Hara (2000), Aggarwal (2000)). The availability and cost of shares for short-sellers to deliver during this period is an important but unexplored element of the strategic environment of market makers and traders. Of particular interest is the relation of borrowing cost to underpricing, since underpricing has been shown to influence subsequent market-maker activity.

For the purpose of studying the earliest days, we assemble a panel of all IPOs whose first 19 days are covered by our sample period, a total of 344 offerings. We choose 19 because it covers day 4, the first lending day, and 5, 10 and 15 trading days later. Some raw statistics on these IPOs are plotted in Figure 3, which shows both specialness and shares loaned (the average across the 344 IPOs of (Loaned Shares)/(IPO Shares)) steadily dropping over the period. Our goal is to explain the cross section of the specialness of these offerings on a given event day, but before that we characterize the selection bias in our observations with a probit model.

We can not observe the specialness of a stock on a day when our data provider did not lend it, so we should learn about the cross-sectional difference between stocks that are and are not loaned on a given event day, and we can do this with a probit model where the dependent variable is an indicator variable $LOANED_{s,t}$ for whether or not IPO s was loaned on its trading day t. The explanatory variables (which lag three days where appropriate, due to the settlement convention) are: $LRET_{s,t-3}$, the log-relative return on stock s from its offering price up to the close of its t-3rd trading day; $DOG_{s,t-3}$, which is 1 for stocks that closed below their offering prices on their t-3rd trading days, and 0 otherwise; $LSIZE_s$, the log of the offering size (offering price times shares); and $LVOL_{s,t-3}$, the log of one plus the number of shares of stock *s* traded on *t*-3, divided by the number of shares offered.[8]

We include *LRET* to represent the influence of IPO performance on secondary-market trading, and *DOG* to capture any special implication of trading below the offer price (see, e.g., Ellis et al. (2000) and Aggarwal (2000)). Since larger offerings would more likely be in the inventories of custodian banks we include *LSIZE*, and since stocks that are traded relatively more are presumably also shorted relatively more, we include *LVOL*. Probit results for *t* =4, 9, 14 and 19 are in Table II.

A positive coefficient indicates that the probability that the stock was loaned increases as the variable increases, and a negative coefficient indicates the opposite. The probit results show that one variable, *LSIZE,* is consistently and highly significant, but the others generally do not enter. The positive loading on *LSIZE* tells us that the offerings whose specialness we do *not* observe, about a quarter of the sample, are generally smaller than the offerings whose specialness we *do* observe, which is the intuitive relation. The insignificance of the other variables indicates that the performance and trading activity of the offerings do not relate significantly to whether or not they can be borrowed in the wholesale market.

Now we establish the cross-sectional dynamics of specialness by regressing the specialness of IPO *s* on its trading day *t*, $S_{s,t}$, on the same variables. But because the Probit model picked up a significant relation between selection to the sample (i.e. whether a stock was loaned) and our regressors, we are in the scenario addressed by the Heckman (1979) selection-correction two-stage model. For the cross-sectional regression for day *t* the first stage is the Probit for day *t* in Table II, and the second stage is an OLS regression on our

[8] We add one to the trading volumes before taking logs because a couple of the IPOs did not trade on one or more day in this period.

regressors *and* the 8-function of the fitted value (i.e. the Inverse Mills Ratio), from the Probit, of the observation.[9] So the selection-corrected regression model is

$$S_{s,t} = b_{0,t} + b_{1,t}LRET_{s,t-3} + b_{2,t}DOG_{s,t-3} + b_{3,t}LSIZE_{s} + b_{4,t}LVOL_{s,t-3} + b_{5,t}8_{s,t} + \gamma_{s,,t}$$

Results are in Table III.

The regression shows all of the variables entering consistently significantly, with 13 out of 16 p-values below 5%. Consistent with the indication from the Probit model that smaller offerings are in lower supply, we find specialness going up as the log of the initial value of the offering, *LSIZE*, goes down. But even though the log of the day *t*-3 value of the offering is *LSIZE+LRET*, we do *not* find that *LRET* enters like *LSIZE*. It enters oppositely; hotter offerings are more expensive to borrow. This could be due to investors sharing a belief that the hot offerings have lower subsequent returns, and in hindsight this may have been true for internet offerings, but it runs counter to the finding of Krigman, Shaw and Womack (1999) that hotter offerings have *higher* subsequent returns in the short term.

A better-fitting explanation is that of Miller (1977), who takes the view that investor beliefs are heterogeneous. He conjectures that insiders price IPOs at the mean of the distribution of expected future prices, and that IPOs are underpriced because among all possible investors, the investors who hold the small supply of IPO shares are those with the highest expectations of their future prices, i.e. those with expectations in the right tail of expectations. Assuming a symmetric distribution of expectations, and controlling for supply (which we do), an extreme right tail implies an extreme left tail, i.e. investors who think the IPO is very overvalued, and therefore view the expected return on shorting as very attractive. This would deliver the observed loading on *LRET*. An explanation for the decline of specialness in IPO time is also provided by Miller (1977). The arrival of more public

[9] See Greene (1993), p. 711 for a description and explanation.

information about the firm reduces heterogeneity of beliefs, bringing in the tails and thereby reducing the incidence of intense desires to short.

The relation between IPO performance and specialness is not monotonic, as *DOG* enters positively. The recent IPOs get cheaper to borrow as their performance goes down but those trading at or below their offering prices command a premium of around 40bp. This is consistent with investors arbitraging the price-support process. IPOs trading at or below their offering prices are presumably those whose prices the underwriting syndicate is trying hardest to prop up, but the propping-up is limited to the 30-day lifespan of the syndicate. If investors view the syndicate as willing to pay too much for shares, they would view short selling before 30 days as profitable and would therefore bid up the cost of loans, as we observe.

Finally, consistent with the intuition that *LVOL* proxies for shorting demand relative to supply, it enters positively, indicating that the IPOs whose shares trade more actively are more expensive to borrow. Also, the negative loading on 8 indicates that the bias associated with selection to the sample, i.e. being loaned, is negative; the IPOs that our data provider did not loan are generally more on special than those that it did loan. This means that the specialness numbers in Figure 3 for loaned IPOs are low-ball estimates of the average specialness across loaned *and* unloaned IPOs in the first days.

III.D Broker-Lending Restriction Expiration at Thirty Days

The lending restriction applied to brokers in the IPO syndicate releases at thirty calendar days, which suggests a change in the lending market across that moment. There is additional significance of 30 calendar days post-IPO, beyond this rule, as it constitutes the standard event horizon of an IPO. It is the usual expiration of the Green Shoe option, and appears, empirically, to mark the end of price support for dogs (Ellis et al. (2000)).[10] It is also when the Depository Trust Company turns off its IPO Tracking System (Aggarwal (2000)). So 30 days is when the market for lending an IPO and the market for trading it assume their long-term regulatory and organizational structures.

For studying this subperiod we assemble the 304 IPOs that are covered in the data from 10 trading days before to 10 trading days after 30 calendar days post-IPO. That is, for each IPO we identify event day 0, which is the first trading day that is on or after 30 calendar days after the IPO, and we track the IPO from event day –10 to event day +10 and there are 304 IPOs we can track. The evolution of specialness and lending activity across 30 days is plotted, analogously to Figure 4, as Figure 5. The graph shows a steady decline in specialness across the date, seemingly unaffected by the passing of any particular event day. But the graph also shows a pronounced drop in lending by our data provider between event days 0 and 5, and in particular between event days 2 and 4. The statistical significance of this drop is established in Table IV, which shows the first differences of loan volume in the ten days around event day 0. The drop of –0.245% of IPO shares between event days 2 and 3 is highly significant, and the drop of –0.138% over the next day is also significant.

It is interesting that the decline in lending volume occurs around three days *after* 30 calendar days, which suggests that the new lending by the formerly restricted syndicate members starts then, and not right at 30 calendar days. This could be a result of the procedure that brokers follow for determining whether a customer can short a stock. In our sample period, NASD rule 3370 allowed brokers to determine whether shares could be borrowed for a

[10] They find "…that for stocks trading below their offer price the underwriter accumulates substantial inventory positions, but this is not the case for stocks trading above the offer price. This inventory accumulation appears to continue for 21 [trading] days, suggesting a particular time dimension for his stabilization activities." Ellis et al. (2000), p. 1072.

requested short sale by referring to an "easy-to-borrow" list. If the stock was on the list, the broker could allow the order to go through. If it was not on the list the broker would have to take additional steps to ensure that the shares could actually be borrowed.[11] So it could be that brokers do not allow their customers to short IPOs at one to three days before 30 calendar days because the IPOs are *currently* hard to borrow, even though they will be easier to borrow by t+3.

The evidence in Ellis et al. (2000) that price support for dogs gives out at 21 trading days, and the extra cost of borrowing dogs in the early days reported in Table III, encourages us to break out the dogs from the sample and track them separately. Of the 304 offerings in this panel, 85 are classified as dogs because they closed at or below their offering prices on event day –13 (i.e. 3 trading days before the period in the graph), and the other 219 are not dogs. In Figure 5 we plot the same loan-volume time series from Figure 4, except for these two groups separately. We see a more pronounced effect for the dogs; they start out higher and finish lower, dropping by about 1% of IPO shares, as opposed to ½% of IPO shares for offerings that are not dogs.

We can gauge the statistical significance of the relation between IPO performance and loan-volume change across 30 days with a simple cross-sectional regression. The dependent variable is the percent change in shares loaned, divided by IPO shares, from event day –10 to event day 10, $DELSHRS_s$, and the explanatory variable is $LRET_s$ the log-relative return from the offering price to day !13 (t-statistics are below, in parentheses):

$$DELSHRS_s = \underset{(-8.64)}{-0.0112} + \underset{(3.07)}{0.0068 LRET_s} + \gamma_s \qquad \underset{N=304}{R^2=3.0\%}$$

The relation is easily significant in the predicted direction.

Finally, we run the same two-stage selection-corrected regression model from above on this 30-day panel. The first stage is not reported; the second-stage results for event days –10, -5, 0, 5 and 10 are in Table V. The notable result here is that the explanatory power breaks down after the 30-day IPO period, with widespread significance before 30 calendar days, and widespread insignificance afterward. The evidence that loan volume drops more across 30 days for weaker offerings supports the argument that investors are especially eager to short the bad performers during the price-support period. To close the circle it would be gratifying to see the loading on *DOG* decline across 30 days, but although *DOG* no longer enters significantly after 30 days, the point estimates are similar to before.

III.E Insider-Sales Lockup Expiration

Though the law does not require lockups on insider sales, the vast majority of offerings have them. For each offering with a lockup, SDC reports the expiration. The direct effect of the expiration, which usually occurs 180 calendar days post-IPO, is presumably whatever effect there is of new shares hitting the market. Previous research (e.g. Field and Hanka (2001), Ofek and Richardson (2000), Brav and Gompers (2001)) has shown an abnormally large negative return across expiration, and a spike in trading volume that settles down at 40% above the pre-expiration level. These are consistent with a burst of sales pushing investors down a sloping demand curve and providing more shares for investors to trade in the future.

What could a lockup expiration mean for the lending market? An increase in the number of shares floating would intuitively increase the supply of shares to loan, which we should see to the extent that the shares settle down in an account at our custodian bank. As

[11] In 2000 the rule was amended so that brokers could instead confirm that the stock was *off* their *hard*-to-borrow

before, IPO performance should be a factor, since the incentive for insiders to sell shares would intuitively vary with performance. The sample for this study is all the IPOs, of the 534, whose lockup expirations occur between day 11 and day 239 of our 249-day sample period, so we can track their loan activity from 10 days before to 10 days after expiration. There are 198 such IPOs. Analogously to the previous subsection, we define the expiration day to be event day 0, so we track from day –10 to day 10.

We begin by replicating the cumulative-return study of previous research on our sample. Field and Hanka (2001) find evidence, which they attribute to the “disposition” effect (Shefrin and Statman (1985), Odean (1998)) wherein investors sell winners more quickly, of more insider selling at expiration time of the hotter IPOs. In their 1988-97 sample, hotter offerings show more abnormal trading volume around the expiration, and (insignificantly) worse abnormal returns. Accordingly, we sort our sample by performance to event day –13 into three groups: the 85 that closed at or below their offering prices (the Dogs), the 44 that closed above two times their offering prices (the Stars), and the 69 in between (the Betweens). The average cumulative abnormal return[12] (CAR) of each group, from day –13 to day 7 (i.e. days !10 through 10, lagged 3 days) is in Figure 6.

The graph shows a big cross sectional variation in the lockup effect. The Stars plummet, the Dogs drift upward, and the Betweens are between. We can establish statistical significance with the same simple regression as above, where the dependent variable $LRETX_s$ is the log-relative CAR of IPO *s* from event day –13 to event day 7, and the explanatory variable $LRET_s$ is the log-relative return from offering to day !13:

$$LRETX_s = -0.0150 \quad - 0.0889 LRET_s \quad + \gamma_s \qquad R^2=4.1\%$$

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list, rather than *on* their *easy*-to-borrow list.

[12] As in Field and Hanka (2001), if a stock’s return on a given day is *r* and the value-weighted market index return is r_{VW}, then the stock’s CAR that day is $(1+r)/(1+r_{VW})-1$.

(-1.63) (2.91) N=198

Using instead the standard 2-day (day –1 and day 0) event-study return measurement period for $LRETX_s$, we get

$$LRETX_s = -0.0056 - 0.0278 LRET_s + \gamma_s \qquad R^2=4.0\%$$
$$(-1.91) \qquad (2.86) \qquad N=198$$

Either way, the relation is significant, indicating more negative effect for the better performers.

Moving to the loan market, we plot the lockup-expiration analog of Figure 5 as Figure 7, which shows the loan volume of the Dogs unaffected by expiration, the loan volume of Stars increasing substantially, and the Betweens in the middle. Again, we can run a simple regression, where the dependent variable is $DELSHRS_s$, the percentage change in (Loaned Shares)/(IPO Shares) from event day –10 to event day 10:

$$DELSHRS_s = 0.3201 + 1.409 LRET_{s,t-13} + \gamma_s \qquad R^2=5.1\%$$
$$(2.46) \qquad (3.26) \qquad N=198$$

If we instead define $DELSHRS_s$ to be the change from event day 1 to event day 3, to coincide with the CAR in event days –1 and 0, we get

$$DELSHRS_s = 0.0541 + 0.5605 LRET_{s,t-13} + \gamma_s \qquad R^2=5.8\%$$
$$(1.11) \qquad (3.48) \qquad N=198$$

In both specifications, the change in lending across the expiration date increases significantly with the lifetime price change of the IPO.

Finally, Figure 8 depicts the evolution of specialness for the three groups, showing a wide and steady dispersion pre-expiration, with the Stars most expensive to borrow, the Dogs least expensive, and the Betweens splitting the difference. Around event day 2, the dispersion starts to shrink, and it is largely gone by event day 10. To see if this shrinkage is statistically significant, we regress the change in specialness, $S_{s,t+10} - S_{s,t-10}$, on $LRET_{s,t-13}$, bearing in mind that both $S_{s,t+10}$ and $S_{s,t-10}$ must exist for *s* to be included in the regression. We get:

$$S_{s,t+10} - S_{s,t-10} = \underset{(1.78)}{0.3168} \; \underset{(-3.77)}{-0.7090} LRET_{s,t-13} + \gamma_s \qquad R^2=16.5\% \quad N=74$$

The relation, across the 74 of the 198 IPOs that were loaned on both day –10 and day+10, is strongly negative.

Taken together, the results on lockup expiration indicate that the hot offerings are relatively scarce in the lending market before expiration. This is unlikely to result from borrowing to short across the expiration day, since specialness is steady back at least as far as event day –10, two weeks before expiration. It is more likely due to a more general desire for short exposure, possibly by insiders who can not sell their own shares, or by investment banks that sold downside insurance, such as puts, to the insiders. Again, the relation between IPO performance and demand for short exposure is consistent with the disposition effect. At expiration, insiders of hot offerings quickly sell many shares, pushing out the supply of shares to loan and pulling down their own demand for short exposure, thereby driving down the cost of borrowing.

IV. Merger Arbitrage and Specialness

Merger arbitrage strategies can generate large profits. In these strategies, shares of acquiring firms are sold short in the expectation that the share prices of acquiring and target firms will converge by the time the merger is effective. Evidence suggests that acquiring firms' shares decline by less than target firms' shares rise (see Jensen and Ruback (1983) or Asquith (1983)). However, merger arbitrage can lock in *any* profit arising from discrepancies by short-selling shares of the acquiring firm and covering the short loan with shares of the target firm on the date of the merger. Results presented here indicate that even though the cross section of borrowing costs are heavily influenced by the specifics of merger arbitrage deals, the increased borrowing costs do not wipe out merger arbitrage profits.

Even though arbitrage strategies take advantage of the likely convergence of merger the acquirer and target stock prices, uncertainty about deal terms makes merger arbitrage strategies risky. As discussed in Jindra and Walkling (2001), there is always a substantial risk that a merger will not go through. Furthermore, the terms of the exchange are subject to change before the merger takes place. In particular, the ratio at which equities are exchanged is the key to determining the profitability of an arbitrage opportunity, and the ratio can change or be announced for the first time between the merger announcement date and the effective date.

Furthermore, practical obstacles can reduce merger arbitrage profits. The profitability of a merger arbitrage strategy depends on the ability of the arbitrageur to short-sell and therefore borrow acquiring firms' stock. As in the case of relative valuation discrepancies (e.g. Lamont and Thaler (2001)), merger acquirers' stock can be difficult to borrow. Since specialness often increases substantially when a stock is a merger acquirer, merger arbitrage profits from raw returns can be substantially more than the profits available in practice.[13] It is also important to point out that some stocks may not be available for borrowing at all; the inability to borrow shares can reduce the profitability of merger strategies and increase the risk of an arbitrage portfolio.

IV.A The Effect of Merger Arbitrage on Specialness

To describe the relationship between specialness and potential profits from merger arbitrage, we construct a sample of stock-swap mergers with announcement dates between

[13] Here's a quote from Mellon Global Securities Lending Market Update Report March 1-12, 1999: ''Adelphia Communication's intention to purchase Century Communications caused Adelphia to trade at a margin of 775 basis [sic] as traders locked in spreads for this cash, stock and debt deal."

October 28, 1998 and September 28, 1999 using data from Securities Data Corporation (SDC). This date range allows us to measure specialness from 3 to 23 days after the announcement of a merger for all of the mergers in the sample and it allows us to keep our sample size relatively stable for 20 days after the announcement. After matching with CRSP data, we end up with a sample of 226 mergers over this period. We design an experiment to minimize any forward-looking bias by using only information available on day t to predict day t+3 specialness. In particular, we include 27 *ex-post* unsuccessful mergers in the sample, and we use only day-t stock price differences instead of a measure of potential merger arbitrage profits that relies on the rate at which equities are eventually exchanged.

Table VI presents results from the following regression:

$$Special^{A}_{t+3} = a + b\ln(Mktcap^{A}) + c\ln(Mktcap^{T}) + d(P^{A}_{t} - P^{T}_{t}) + \varepsilon_t$$

Since the dependent variable is no less than zero, we employ a left-censored regression technique as described in Greene (1993). We use t+3 to estimate the specialness a short-seller would actually face if he were to short sell the acquirer's stock on day t. Since merger arbitrage strategies involve trading in both the target and the acquirer, the maximum size of a strategy might be limited by either the long position or the short position[14]. As evidence that arbitrage strategies involving small target firms generate less demand for acquirer's stock, the target firm's market capitalization, $\ln(Mktcap^{T})$, is positively related to specialness with a significant coefficient of 0.3819. As expected, the market capitalization of an acquiring firm, $\ln(Mktcap^{A})$, is negatively related to specialness; the statistically significant coefficient is –0.8166. The profitability of merger arbitrage strategies is also an important determinant of the

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[14] According to a representative of Mellon's Global Securities Lending Group, when Chase Manhattan, Corp. entered into an agreement to acquire J.P. Morgan via a stock swap, the supply of Chase shares was large enough to satisfy borrowing demand without trading at a premium.

specialness of an acquiring firm's stock. The coefficient of the acquirer-target price difference is 0.0114, indicating that mergers with larger potential price convergences lead to more expensive borrowing. Even though the measures of profit used here, stock price differences, are crude in light of the fact that many merging firms exchange equity at ratios other than one, the significant results here are consistent with the intuition that prices in the equity loan market are driven only by information available on that day, and the results rely only on information available on day t.

The regression results discussed above are from a cross-sectional regression on the day of the merger announcement. We also run the cross-sectional regression 5, 10, 15 and 20 days after the announcement. More acquiring firms are on special three days after the day of the announcement than later days; 62 firms are on special three days after the announcement, while 44 to 53 firms are on special 8, 13, 18 and 23 days after the announcement. Furthermore, the regressions' intercepts are decreasing monotonically as we increase the number of days since the merger announcement. Jensen & Ruback (1983) summarize evidence indicating merger announcement days are the most profitable days for merger arbitrage strategies, and our evidence supports the hypothesis that demand for borrowing stock is highest on these profitable announcement days.

IV.B Merger Arbitrage Portfolios

In addition to determining which aspects of merger arbitrage influence specialness, it is important to ask whether merger profits exist after taking borrowing costs into account. We form daily portfolios based on announced stock-swap mergers from the SDC database. Daily portfolio returns are equally-weighted averages of as few as 9 or as many as 111 individual merger arbitrage positions. Each position is the equivalent of a long position in the target firm's stock and equally valuable short position in the acquiring firm's stock; day t returns for merger position i are $r_{i,t} = r_{T,t} - r_{A,t}$.

Unlike Baker and Savasoglu (2000)'s method of constructing arbitrage portfolio returns, we do not use the exchange ratios of the stock-swap mergers for two reasons. First, the exchange ratios reported in SDC may not be available to arbitrageurs on the announcement date, and if the ratio changes or is announced after the merger announcement but before the merger is completed or withdrawn, an arbitrage portfolio using the reported exchange ratio would not be feasible. Second, as a practical matter, very few exchange ratios are reported in SDC; using SDC exchange ratios would substantially reduce the sample size.

To estimate the effects of short-selling expenses and difficulty on merger arbitrage profits, we compute portfolio returns where specialness and availability are taken into account. In the first portfolio, "All With Specialness", day t returns for merger position i are $r_{i,t} = r_{T,t} – r_{A,t} – S_{A,t+3}$ where $S_{A,t+3}$ is the specialness of the merger acquirer three days after the long-short position is taken. If our database does not have $S_{A,t+3}$ for merger position i on day t, we set $S_{A,t+3}$ to zero. This return construction is meant to capture the increased costs from specialness and explicitly disregard the fact that some acquiring firms aren't available for borrowing. Of course, specialness is only a small component of the total costs incurred by the short-seller. Since we can measure it precisely in the wholesale market, we focus only on this cost. Specialness indicates the increase in cost that a short seller would face to borrow the acquirer's stock as opposed to any other stock. Furthermore, since actual short-selling costs vary across market participants, total short-selling costs are not measurable without restrictive assumptions. Even though Mitchell and Pulvino (1999) show commissions and price impact can substantially reduce profits of merger-arbitrage strategies, we do not try to account for transactions costs other than the unusual cost that may arise from short-selling.

In a second portfolio, "Feasible With Specialness", we account for the fact that some acquirers' stocks may be difficult to borrow. The return for merger position i is still $r_{i,t} = r_{T,t} - r_{A,t} - S_{A,t+3}$, but the return is only computed if specialness exists on t+3. In other words, if our loan database does not have any loans in the acquirer's stock for merger position i on day t+3, then position i's return is not included in the portfolio return. The fact that our loan database does not indicate a loan in the acquirer's stock does not necessarily mean the stock could not be borrowed, it just means it wasn't lent by our lender. Since we don't know whether the shares were available or not, we take the conservative approach; by removing stocks that weren't lent from the arbitrage portfolio we ensure that all positions remaining in the portfolio were feasible for at least one market participant.

As shown in Figure 9, merger arbitrage profits are large, but they are reduced when borrowing costs and borrowing feasibility are taken into account. We compute portfolio returns starting two days after the announcement date to exclude announcement effects and to be sure the strategy is feasible. Table VII shows cumulative arbitrage portfolio returns are 64.287% without accounting for short-selling issues. The additional cost incurred to a borrower for borrowing special acquirer stocks is small; if we assign zero specialness for all stocks even if they don't show up in the database, our estimate of the cumulative returns is 64.057%. However, when we take account of borrowing costs *and* borrowing availability, portfolio returns are reduced to 44.302%. The reduction in cumulative returns is economically significant, 19.985%, but the reduction is not statistically significant because the daily portfolio return differences are small on average, 0.0513%, and volatile. With the 251 trading days in our sample, we are unable to reject the hypothesis that the feasible portfolio has the same average return as the ideal portfolio.

The feasible portfolio accounts for short-selling details and excludes announcement-day returns. Nevertheless, the Sharpe Ratio for the portfolio is well above that of the S&P 500, 58.533 versus 14.448. Computing 4-factor alphas from a daily regression, we see that the merger arbitrage strategy performs very well on a risk-adjusted basis. The intercept in the regression is equivalent to a 94.733% annual return, and it is statistically significant. As we saw with the average returns, even though the difference between the "All" portfolio's alpha and the "Feasible With Specialness" portfolio's alpha is large, 36.75%, the difference is not statistically significant because we have 251 daily portfolio differences that are relatively volatile (p-value is 13.492%). The inability to borrow stocks reduces profits by an economically, but not statistically, significant amount. The risks involved in merger-arbitrage strategies are highlighted by the fact that *ex-post* unsuccessful merger strategies perform significantly worse than strategies that used only *ex-post* successful mergers. The cumulative return of the portfolio of successful mergers is 82.505% while the portfolio of failed mergers has a –34.764% cumulative return.

Even if a loan shows up in our database, we can't say the acquirer's stock is available for short selling in general because our database only reflects the wholesale market for borrowing shares. Furthermore, since shares can be borrowed from a number of sources for any short-seller, it would be difficult to obtain estimates on the general level of availability. For this reason, we present results for an even more feasible portfolio, one where merger profits are earned only by a long position in the target's stock, $r_{i,t} = r_{T,t}$. Table VII shows that the returns to this strategy are better than the returns to the long-short strategy; the strategy earns 99.013% over the one year period with a Sharpe Ratio of 96.421. Since the long-short portfolio return is computed as $r_T - r_A$, the fact that the long only portfolio has better returns than the long-short portfolio implies that merger acquirers have positive returns on average.

This is consistent with some of the earlier work summarized in Jensen and Ruback (1983). Of course, the long only strategy loses one of the primary benefits of merger arbitrage portfolios; the strategy is not immune to market fluctuations. However, when we compute 4-factor alphas, we see that the long only portfolio still out performs the long-short portfolio on a risk-adjusted basis; the annualized alpha is 157.036% for the long only portfolio and 94.733% for the long-short portfolio. The alphas, although statistically significant, rely on one-year of daily data; a different time-period could yield a different result.

V. *Firm Fundamentals*

The controversy surrounding patterns in equity returns associated with stock-specific characteristics arises in part because empirical evidence on the types of equities that garner premiums may be interpreted from either a rational, risk-related view or from a investor-irrationality, behavioral perspective. It is of interest to members of both camps whether and by how much the cost of borrowing securities is systematically related to patterns in the cross-section of expected stock returns.

One approach to creating characteristic-based factor-mimicking portfolios is to do the experiment of shorting equities in the tail of the cross-sectional firm characteristic distribution having the lowest premium and investing the proceeds in the part of the distribution that enjoys highest premia. For instance Fama and French (1993) create a portfolio, HML, that shorts a dollar's worth of an equal-weighted portfolio comprised of stocks in the bottom three deciles of book-to-market ratios and invests the proceeds in an equal-weighted portfolio containing the top three deciles of book-to-market ratio stocks. Carhart (1997) forms a portfolio based on price momentum in a similar fashion. What the cost of shorting is and whether it is even possible to short such securities are currently open questions.

In addition, an underpinning of the behavioral take on the evidence that firm characteristics drive return premiums is that barriers to arbitrage permit long-lasting equity mispricing to persist. For instance, it is possible that the historical difference between the returns on large growths stocks and small value stocks has remained on average because shorting high-flying growth stocks is difficult or expensive and that a portfolio designed to capture this premium following the steps above is thus not possible to construct profitably. Sheleifer and Vishny (1997) argue that limits to arbitrage at least in this spirit can cause associated premia to persist, even in an anomaly setting.

We show below that such limits are not obviously reflected in the implied cost of shorting, although the results are not necessarily at odds with the idea and in fact relative borrowing costs line up with the limits story. For instance, growth stocks are more than five times as expensive to borrow as value stocks and about three times as expensive as the average stock. However, the absolute ‘abnormal’ cost of shorting growth stocks is not economically very large.

We first focus on three firm-specific equity characteristics shown in the literature to be associated with equity premiums: firm market capitalization, book-to-market ratio and recent price momentum. To explore the relationship between specialness and firm characteristics, we create independent weekly allocations of NYSE/AMEX/NASDAQ stocks into book-to-market, size and momentum tricile portfolios. Portfolio assignments occur on Wednesdays or the first trading day thereafter and use NYSE breakpoints. Book-to-market is defined as the ratio of book common equity to firm market capitalization at the beginning of a week, size is market capitalization, and momentum is defined as the return over the prior half-year not including the most recent month. These definitions mirror those in Fama and French (1993) and Zhu (2001) and to some degree those in Carhart (1997) and Grundy and Martin (2001).

Table VIII reports average firm and firm-specific equity loan characteristics for our sample firms, firms that were loaned but that were not on special and firms that were on special. The final column in Table VIII presents firm characteristics for the entire CRSP universe, including loan firms, during the same period for reference.[15] The average firm that was loaned during the period of study was on special at a rate of 6.7 basis points per year, while conditional on being special the average was 67.5 basis points per year.

Moreover, we report in the table the average annualized weekly return in the week following a given loan. The average weekly return for the loan sample annualized is 12.32%, while for firms not on special it is 11.96% and for firms on special, it is 16.12%. The return differential between off special and on special firms is statistically positive at the 5% level. The weekly, annualized firm return is 8.87% for the entire CRSP sample, which contains loan sample firms. Clearly, for firms that are relatively more expensive to borrow, returns over the subsequent week are greater than the average.

To get an initial view of what sort of firms are loaned and are on special, Table VIII also reports average annualized return momentum for the four sample sub-classifications, calculated as the average raw cumulated return for sample stocks over the previous 26 weeks. In addition, the table provides average firm book-to-market ratios using book values from the most recently available annual report with a three month reporting lag built in and market values from beginning of a given week. For the loan sample, market value (firm size) used in book-to-market calculations and reported alone is calculated as of the beginning of a week in which loans were made for a given firm. Finally, the table gives the average annualized weekly return volatility for the various samples calculated over the 26 weeks preceding a given loan for the loan sample and at the beginning of a week for the overall sample.

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[15] A methodological inconsistency exists in the calculation of the numbers in the fourth column since only loan

The summary statistics in Table VIII first suggest a notable difference in the momentum (or price run-up) characteristics of loaned and special firms, especially as compared to the average firm in the CRSP sample during this our sample time frame. The annualized 26-week return preceding a given firm getting loaned out is –6.8%. For firms loaned not on special, the prior return is –7.6% while firms on special have a much higher previous return of –1%; the 6.6% difference is statistically significant at the 5% level. In other words, firms that are borrowed in our sample on average have a surprising negative return over the half-year prior to the loan instead of a positive return as intuition might suggest. Even more surprising is that the average CRSP firm had an annualized 26-week prior return of over 20%. While these univariate momentum measures clearly do not control for other firm characteristics, they run counter to the intuition that the average borrowed stock has been a recent (half-year) high-flyer and that short sellers have reacted by shorting.

The remaining results in Table VIII in fact suggest a more refined story. The average CRSP sample firm has a book-to-market value of 0.738, consistent with results for the significantly longer time period reported in Fama and French (1992), about 0.80. However, the average loaned firm in our sample has a book-to-market ratio of 0.673, and the average stock on special has a book-to-market ratio of 0.494, suggesting strongly that the average borrowed stock is a growth stock. In addition, the average special stock is even more of a growth stock than the average loaned stock and much more of a growth stock than the average CRSP universe stock. It is worth repeating here that the values reported in Table VIII for the overall CRSP universe sample are in a sense contaminated with respect to the current exercise as they contain only the firms that are loaned during our sample period. The average CRSP firm not on loan would have an even higher book-to-market ratio (and momentum return as

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firms had given points at which they were observed to be loaned out.

well). Finally, the results on size suggest that while the average loaned firm is smaller in size (about $2.06 Bn) than the average CRSP firm in our time frame ($2.2 Bn), the average special firm is larger than both ($2.8 Bn). This characteristic emerges again when we look at the average specialness of univariate and trivariate sorts on the basis of firm size, book-to-market and momentum characteristics.

Table IX presents these arithmetic average specialness values calculated for independent tricile portfolios based on Size, B/M and recent price momentum. We also report the average loan value and number of shares in each tricile. Each tricile is formed weekly (at a week's beginning) throughout the sample period. Roughly speaking, examining spreads in average specialness across characteristic triciles allow us to examine the relative and absolute costs associated with forming zero-cost portfolios in the spirit of Fama and French (1993), Lakonishok, Shleifer and Vishny (1994), Carhart (1997) and others, which are designed to capture average premia associated with the characterisitcs. Our examination makes no direct presumption on the underlying source of these return premia, yet has potentially strong implications for the very admissibility and effectiveness of these trading strategies in practice. For example, one might view the spread between small and large firms size triciles as a proxy for the Fama-French (1993) size factor-mimicking portfolio, SMB, and their value-growth spread portfolio, HML, to be reflected generally in the spread between our high and low book-to-market groups. Moreover, the momentum spread of Carhart (1997) may be examined by viewing our high momentum group in comparison to our low momentum group. The costs of borrowing stocks on the short sides of these strategies, along with their inherent riskiness and various other trading costs, will help determine their true profitability and, in fact, whether they are feasible at all.

The table shows that the average specialness has an inverted U-shape in the size dimension. For the smallest third of our sample, specialness is 5.3 basis points per year, and for the largest third specialness is only 3.9 basis points per year, both below the specialness of the average firm. In contrast, the average specialness for the middle size tricile is about 8.6 basis points per year, over twice the specialness for large firms. Nonetheless, the differences in specialness across firm size are not remarkably different economically.

From the book-to-market tricile sorts we find that specialness is by far the greatest for the growth stocks in the lowest tricile, 11.3 basis points, while it is lowest for value stocks in the highest book-to-market tricile, about 2.7 basis points. In fact, this spread in the cost of shorting induced by the distinction between growth and value is the strongest of all three sorting variables we consider, indicating that, among the zero-cost spreads of Fama-French and Carhart, the value-growth portfolio has the highest cost. However, economically speaking, the cost is not prohibitive and does not directly support the spirit of arbitrage limits described by Shleifer and Vishny (1997). A corresponding pattern appears for average loan size and, to a lesser extent, for the average number of shares loaned (and therefore in the average price of a loaned stock).

The simple momentum sorts in Table IX reveal a U-shaped pattern in specialness. For the lowest momentum firms, specialness is 6.97 basis points, just above the average value for all loaned stocks. High momentum stocks have slightly lower specialness, 6.09 basis points, while medium momentum firms have an average specialness of 3.83 basis points per year. However, this U-shape is not reflected in average loan value, although it appears in the average number of shares loaned. Average loan values are about $6.6 million, $7.8 million and $10.6 million for low to high triciles while the average number of shares loaned are 239,674, 215,905, 265,593, respectively. On rank, the cross-sectional variation in premiums documented in Carhart (1997), Grundy and Martin (2001) and Zhu (2001) is not reflected in the absolute cost of borrowing. Thus, there do not appear to be any obvious limitations on arbitrage or on forming the types of portfolios discussed above for any of the characteristics that we examine and which are associated in the literature with economically significant return premia. And only in the relative cases of growth vs. value and small vs. large firm size do borrowing costs line up with the limits argument.

One important caveat must be made here, however. While the results in Table IX are informative about the average absolute and relative costs of borrowing a security under the parameters of our study, they do not directly characterize stocks that are not available to borrow at all or that appear on 'hard-to-borrow' lists facing even fairly large retail investors. As described earlier, our results effectively focus on the wholesale loan market. The average retail customer almost surely would not be able to borrow at the same rates as wholesale customers. Nonetheless, we are comforted by the fact that we do observe extremely expensive loans in the database, indicating that even though the supply constraints embodied in hard-to-borrow lists that have become nearly mythical among academics may exist – yet which are perhaps unobservable in our sample – we do witness its likely manifestation in the form of extreme specialness for a good number of stocks. The relevant point for characterizing borrowing costs as they relate to arbitrage limits[16], however, is that these costs simply do not appear prohibitive for wholesale investors, those who are either themselves important marginal investors or whose clients are important marginal investors like hedge funds and arbitrageurs.

While Table IX introduces evidence on equity loans as they relate to firm characteristics, it does so from a univariate perspective, leaving open the door for

[16] Or barriers on the formation of zero-costs factor mimicking portfolios.

combinations of characteristics to be jointly associated with various – possibly economically large – specialness rates. In Table X we examine the distribution of average specialness across jointly assigned tricile portfolios, 3 for Size, 3 for B/M and 3 for momentum (27 portfolios in all). The basic patterns that emerge in Table X remain in table IX. Namely, medium sized firms are the most expensive to borrow on average, growth stocks are more expensive to borrow than both the average stock and the average value stock, and with one key notable exception, spreads in the specialness across momentum categories are fairly flat. The interesting pattern that emerges in Table IX is that some categories of stocks are relatively much more expensive to borrow than indicated in Table X. Specifically, low momentum growth stocks of medium size have specialness of about 16.8 basis points per year, and small growth stocks with low momentum have specialness of about 13.9 basis points per year. In contrast, small, medium-momentum value stocks, medium size-medium book-to-market stocks and large value stocks have generally low (not distinguishable from zero) specialness rates. In addition, average loan sizes and number of shares vary significantly across the 27 (3x3x3) firm characteristic categories with small growth stocks having both the smallest average loan value (just over one million dollars) and smallest number of average shares loaned (about 72,000). We see the greatest number of shares borrowed and the largest loan values for large, high-momentum growth stocks, which have an average size of over $31 million at 562,864 shares.

VI. Pricing

To study more formally the implications of borrowing constraints for portfolio construction and multifactor models, we compare factor-mimicking portfolios from the four-factor model with and without these constraints. We create daily mimicking portfolios for the

NYSE/AMEX/NASDAQ value-weighted market, the Fama-French (1993) SMB and HML portfolios and the Carhart (1997) momentum portfolio from the entire CRSP universe but using NYSE breakpoints. A typical expression of this 4-factor model is

$$R_i - R_{RF} = \alpha_i + b_i\, RMRF + h_i\, HML + s_i\, SMB + m_i\, MOM + \varepsilon_i.$$

Here, i indexes the ith security or portfolio being regressed on the factor-mimicking spread portfolios. RF references the daily return on the 3-month T-Bill, RMRF denotes the daily excess return on the value-weighted CRSP market portfolio, HML and SMB reference our versions of the Fama-French (1993) value-growth and small-large factor-mimicking portfolios, and MOM refers to our version of the Carhart (1997) zero investment portfolio (PR1YR) capturing the premium and covariation associated with high and low previous returns. HML and MOM are formed by investing $1 in a portfolio comprised of the 30% of the equity universe with the highest book-to-market ratios an momentum based on NYSE cutoffs while shorting $1 in the lowest 30% of book-to-market ratios and momentum firms, respectively. In our case, as previously noted, momentum is calculated over 26 weeks preceding weekly portfolio formation, which occurs on Wednesdays or the first trading day thereafter.

We also create a set of parallel mimicking portfolios that have the same long component as the full CRSP-based factors but that have short sides created from a universe of firms that are *ex ante* not on special and therefore are unlikely to be difficult to borrow for shorting purposes. We match firm returns on day t with firm specialness as of the statutory share delivery date, day t+3, where t+3 ranges from Nov 2, 1998 through October 31, 1999 in our sample. The thought experiment is simply one in which someone trying to construct and trade the factors form the long side but have difficulty finding certain shares to borrow on the short side and thus does not even attempt to do so. We are conservative in two senses. First, we have data from only one lender. If a trader cannot obtain shares to short (proxied by any specialness at all for the stock) from our lender, he is presumed not to be able to find it elsewhere, almost surely not the case in reality. Second, we do not focus on extremely small stocks. However, we are able to compare our loan sample on one day to that of Dimensional Fund Advisors (DFA), a money management firm historically specializing in small stock investing and in many ways acting as a market maker in small stocks (see Keim, 2000). We find that in our sample on December 31, 1998, our database shows 3289 stocks on loan. The DFA database indicates 499 mostly small stocks on loan. 344 of those 499 stocks in the DFA loaned sample appear in our database, while 155 appear solely in the DFA sample. Our experiment would automatically classify those 155 stocks as unloanable and thus is conservative by overemphasizing the constraint in this way.

The first comparisons are found in Table XI where we tabulate mean excess returns, volatilities and cross-correlations of the full CRSP-based and the non-special, constrained factors. We denote the full CRSP-based factors with a c subscript (e.g., SMBc) and the factors whose short sides do not contain stocks on special with an s subscript (e.g., SMBs). In Table XI, the returns on the value-weighted market, SMBc, and MoMc are positive (11, 9 and 25 b.p. per day, respectively). While the market premium is not significantly different from zero, qualitatively similar to results in Fama and French (1993), premia on the remaining mimicking portfolios are indeed statistically distinguishable from zero at the 95% level. For HMLc, the underperformance of value stocks and overperformance of growth stocks relative to historical averages during this period in general is apparent with the mean value-growth spread being negative, approximately -7 basis points per day.

The mean excess return and volatility patterns of the specialness-constrained zero-investment portfolios SMBs, HMLs and MoMs run quite parallel to those of the unconstrained mimicking portfolios. However, the means of the constrained mimicking portfolios are each marginally smaller than the means of the corresponding unconstrained portfolios. For instance, the returns on MoMc and MoMs are 25 b.p. and 24. b.p., respectively. The average return for the unrestricted SMBc is 8.9 b.p., while the constrained portfolio has an average return of 8.6 b.p. In addition, the average daily return of HMLc is -7 b.p., while the constrained portfolio return is about -11 b.p. per day. Nonetheless, *none* of the average differences are statistically different from each other at the 95% level.

In all cases except HMLc vs. HMLs, the volatilities of the constrained factors are larger than the unconstrained counterpart. The volatility of SMBc and SMBs are 63 b.p. and 67 b.p., respectively. In addition, the standard deviation of MoMc is 67.2 b.p. and the standard deviation of MoMs is 74.5 b.p. Finally, HMLc has a volatility of 44.5 b.p., while we estimate the volatility of the constrained portfolio, HMLs, as 44.2 b.p. Thus, while on rank the total volatility of the constrained factors has risen as expected when compared to the unconstrained factors, this increase in variability is not large.

The correlations among the factors reported in Table XI in general run parallel to those reported by Carhart (1997) as well, with the exception of SMB. For instance, Carhart estimates a negative correlation between the value-weighted market and HML, a positive correlation between SMB and HML and a negative correlation between the momentum spread and HML using monthly data over thirty years. We too estimate a negative correlation between the daily value-weighted market return and HML (-69% for HMLc and –70% for HMLs), a positive association between HML and SMB (19% between HMLc and SMBc and 4% between HMLs and SMBs), and a negative correlation between HML and MoM (-21% for the unconstrained factors and –4% for the constrained factors). However, it is more interesting to note in Table XI is that the correlation between each unconstrained factor mimicking portfolio and its constrained counterparts is quite high. For instance, the correlations between the unconstrained and constrained versions of SMB, HML and MoM are 95%, 92%, and 92%, respectively.

With the means of the Fama-French and Carhart constrained and unconstrained factor portfolios not being markedly different, their volatilities being close, and correlations being high, the evidence that borrowing constraints do not significantly matter is strong. Moreover, the Sharpe ratios of the optimal minimum-variance portfolios formed from the two sets of factors are 0.42 and 0.39 for the unconstrained and constrained versions, respectively. As expected, adding constraints brings the Sharpe ratio down. However, the decrease is neither economically nor statistically significant. We thus conclude that we find no initial evidence that imposing realistic borrowing constraints on the short side of these zero-investment portfolios changes their behaviors.

However, while the evidence thus far is strongly suggestive that realistic borrowing constraints do not substantially penalize factor-mimicking portfolios from the popular model we study, the *pricing performance* of the model might be denuded by the constraints. To examine the relative pricing implications of the restricted factors, we construct daily excess returns on test portfolios reflecting the three dimensions of firm size, book-to-market values, and 26-week return momentum, the dimensions from the trivariate sorts of Table X. We use the twenty-seven resulting portfolios (3 size x 3 book-to-market x 3 momentum) in tests based on the following regression for both sets of factor mimicking portfolios:

$$R_i - R_{RF} = a_i + b_i RMRF + h_i HML + s_i SMB + m_i MOM + e_i$$

Table XII presents means and volatilities for these 27 test portfolios. As expected, the return patterns found in the previous univariate and trivariate sorts in Tables IX and X are reflected in the average excess returns of Table XII. Typically, smaller stocks have higher average returns than large stocks, and 26-week winners have higher returns than losers. Again, though, the spread across the value-growth dimension reflects the underperformance of that spread during our sample period except for stocks with low momentum. That is, growth stocks (those with relatively low B/M values) beat value stocks (those with relatively high B/M values). In addition, the daily excess return volatilities of the test portfolios clearly vary across the sorting dimensions of size, book-to-market and growth, and return momentum. Generally, value stocks have higher total variabilities than growth stocks. However, perhaps surprisingly, small stocks during our sample period have lower daily volatilities than large stocks.

Table XIII, Panel A presents the parameter estimates and corresponding t-statistics for multivariate regressions of the 27 test portfolios on the 4-factor model estimated using the unconstrained versions of HML, SMB, and MoM along with the excess value-weighted market return. The pricing errors embodied in the intercepts from those regressions in Panel A are not particularly favorable to the 4-factor model during the time frame of our investigation. While alphas are not uniformly economically large across all test portfolio strata, the 4-factor model does have apparent trouble pricing small stocks and growth stocks in general. While this characteristic is not unexpected and to some degree follows the pattern documented in Fama and French (1993) and especially that in Brav, Geczy and Gompers (2000), pricing the type of high-flying technology stocks and IPOs famous in this period in market history is weak with this model. In addition, the well-known property of this model to have difficulty pricing growth stocks in general and small growth stocks in particular documented in Brav, Geczy and Gompers (2000) is also apparent in Panel A (and Panel B).

Moreover, the factor loadings in Panel A– b for the market, s for SMBc, h for HMLc, and m for MoMc – also reflect a pattern documented in the literature. Small stocks load positively and large stocks load negatively on SMBc across the dimensions of growth-value and momentum. Value stocks (those with high values of B/M) load positively on HML, and growth stocks generally load negatively on HML. Moreover, winners load positively on MoM, while losers load negatively. Finally, 4-factor market betas (b's) in Table XIII, Panel A generally are lower than in Brav, Geczy and Gompers (2000), who find using monthly data that market betas for equity portfolios formed similarly to ours but using monthly data and estimated using the 4-factor model have an average value of approximately one.

Panel B of Table XIII presents results similar to those in Panel B except that we use the constrained versions of zero investment portfolios in the 4-factor model. Again the 4-factor model pricing is poor for small stocks and growth stocks, and factor loadings reflect the expected pattern across test portfolio sorting criteria. However, once again the most interesting result in Table XIII emerges from the comparison between the results from the unconstrained and constrained factor regressions. Most notably, a reliable pattern of pricing error (intercept) differences is not readily apparent beyond the fact that the constrained model produces eighteen out of twenty-seven intercepts that are larger in value the unconstrained model. Also clear however is that the economic differences in the pricing errors from the two versions of the 4-factor model are not unexpectedly large. Thus, while imposing borrowing constraints on the factors apparently damages the pricing capabilities of the model, it does not appear to destroy them, although, of course, the model is still prone to the poor-performance "bad model problem" of Fama (2000).

Finally, we formally test the null pricing hypothesis that the optimal linear combination of the two sets of factors lies on the *ex ante* mean-variance frontier formed by the 27 test portfolios. We compute the Hotelling T^2 test of Gibbons, Ross and Shanken (GRS, 1989) to do this. The GRS statistic for the test involving the unconstrained factors yields a rejection of the 4-factor model with a P-value of 9.21%. Similarly, Fama and French (1993) reject their monthly 3-factor and 5-factor models using the GRS statistics, both of which include the value-weighted market, HMLc and SMBc, with p-values of approximately 4%. The GRS test likewise rejects the constrained 4-factor model with a P-value of 6.09%. Thus, the bulk of the evidence suggests that accounting for borrowing constraints in constructing zero-investment, factor-mimicking portfolios marginally lowers their average premia and increases their volatilities. However factor Sharpe ratios and model pricing characteristics do not deteriorate significantly either statistically or economically.

VII. Mutual Funds and Performance Attribution

The final question we address is whether realistic constraints imposed on the equity short sides of the zero-cost factor portfolios alter conclusions about the performance of mutual funds. To do this, we regress nine mutual fund "style" indices on the four factors. Lipper produces these indices, the daily returns for which are reported in the *Wall Street Journal*. These indices reflect a 3x3 sort of constituent Lipper-tracked funds into Small-Cap, Mid-Cap, Large-Cap and Value, Core, Growth styles. See Carhart, et al. (2001) for a related discussion. Results for these regressions are reported in Table XIV.

Unconditionally, the returns on growth funds beat those of value and core funds by large margins during our sample period, a result consistent with those in Table X. For instance, the mean excess returns of small-, medium and large cap value mutual funds reported in Panel A are 1 b.p., 4 b.p. and 8 b.p., while the average excess returns of the corresponding growth styles are 15, 19 and 15 basis points respectively. This pattern, although greatly flattened, persists in the alphas from unconstrained 4-factor model regressions reported in Panel B of the table. There, the strongest statistically reliable evidence of positive performance is in the Large-Cap style where growth funds have an average alpha of 2 basis points per day with a t-statistic of 1.99. In addition, Large-Cap Core and Large-Cap Value funds have negative and statistically significant alphas of –5 b.p. and –3 b.p. with t-statistics of –2.98 and –3.01, respectively. The pattern of statistical reliability in the performance estimates is not unsurprising given the decreases in residual volatility typically associated with the capitalization of underlying equity investments made by the funds in the Large-Cap style.

The unconditional mean excess returns associated with variation in style are absorbed by the four unconstrained factors as evidence by the factor loadings also reported in Panel B of Table XIV. For instance, market betas are generally smallest for the Small-Cap style funds and increase from about 0.45 (0.35, 0.40 and 0.61 for Small-Cap Growth, Core and Value, respectively) to approximately 1.00 for the Large Cap sector (0.91, 1.05, and 1.21 for Large-Cap Value, Core and Growth respectively). Similarly, value factor loadings range from large (above 1.0) for value funds to strongly negative for growth styles (approximately as high as 1.2 to as high as low as –0.30), in line with the loadings spread across value categories in Table XII.

Panel C presents alphas and factor loadings for the mutual fund style indices using the restricted factors. Apparent from the panel is that the pricing comparisons reported in Table XIII continue to be present for mutual fund style indices. That is, alphas estimated using the restricted factors are not obviously different from those estimated using the unrestricted model. However, differences appear in factor loading point estimates, most notably with respect to the value-growth factor, HML. Specifically, for the Small- and Mid-Cap Value Core, and Growth styles, HML loadings for the constrained model decrease significantly and, in some cases, even switch sign. For instance, we estimate h, the loading on HMLc, for Small-Cap Value funds at 1.12 with a t-statistic of 9.79. However, the corresponding value of h loading on HMLs is only about 0.40, with a t-statistic of 3.79. The bootstrap p-value on test for equality of these two values is 0.087. In addition, for Mid-Cap Growth, h from the unconstrained model is 0.30 with a t-statistic of 3.59 while the corresponding value from the constrained factor model is –0.0092 (t-statistic –0.13). In all cases, the constraints on the factors appear to lower loadings on the value-growth spread. None of the other factor loadings are substantially different across models.

On rank then, the mutual fund performance results bolster our conclusions that accounting for equity borrowing constraints associated with large growth firms with low momentum qualities does not significantly alter the portfolio construction, pricing and performance attribution qualities of the Fama-French (1993) and Carhart (1997) models with the exception of affecting managed portfolio sensitivities to value versus growth. This last observation should be tempered however, as the value-growth spread estimated to be approximately 46 basis points per month by Carhart (1997) actually reversed strongly during our sample period and become negative. We also conclude that the type of limits to arbitrage possibly attendant to the zero-investment operations used to construct these factor models is not significant. And if one takes an anomaly perspective on the source of return spreads associated with firm characteristics like firm size, book-to-market and return momentum, the kinds of constraints one might anticipate on the short sides of those spreads do not seem to prohibitive.

VI. Summary and Conclusion

Short sales require equity loans, so the feasibility and expense of short positions reflect availability and pricing in the equity-loan market. We characterize availability and pricing for stocks in the IPO and merger-arbitrage markets, and also the stocks that are short in the asset-pricing "factors," with a 12-month database of all equity loans by a major lender.

We find that stocks begin life on special. For a borrower in the wholesale market, IPOs are generally available but not cheap. Smaller offerings are less available, but availability does not depend on other potentially relevant factors, such as performance. We find that the better performers are generally more *expensive*, though the offerings that are struggling to exceed the offering price are also expensive. The higher cost of shorting better performers is consistent with the heterogeneous-beliefs model of Miller (1977), and the higher cost of shorting those near or below their offering prices is consistent with investors arbitraging the price support documented by Ellis et al. (2000) and Aggarwal (2000). The lending market is significantly affected by the passing of 30 calendar days post-IPO, and also by the expiration of insider lockups. The decline in borrowing cost across expiration is strongest for the hottest offerings, consistent with the disposition effect of Shefrin and Statman (1985) and Odean (1998).

In the case of mergers, we find that merger acquirers are more likely to be on special when the profit opportunities from the merger arbitrage are large. Furthermore, since the arbitrage implementation is potentially limited by the ability to purchase shares of the target's stock, we find that mergers with larger target firms have more specialness in the acquirer's stock. We also find that larger acquiring firms have lower specialness. Even though merger profits can drive specialness, we find that the costs of borrowing do not significantly reduce the large profits of merger arbitrage strategies. The reduction comes from the inability to borrow shares of acquirers' stock. Even though the reduction is relatively large, it is noisy. Statistically, the difference between the feasible portfolio and the unconstrained portfolio is not significant.

In addition, with the costs of shorting the short side of the Fama-French and Carhart factor portfolios there are significant differences in shorting costs along the dimensions these portfolios sort on. However, while firms on special tend to covary on average with small, high-momentum growth stocks, the specialness of short portfolios is not so large as to prevent traders from forming typical characteristic-based trading strategies designed to capture associated premia. We find that while imposing realistic and even conservative characterizations of borrowing constraints *ex ante* on zero-investment factor-mimicking portfolios reduces their means and increases their volatilities, their optimal Sharpe ratios do not markedly fall. In addition, we find that while imposing these constraints on the 4-factor model does indeed produce some increases in average pricing errors, their overall effect is small. And while statistical rejection of the 4-factor model is stronger when the constraints are imposed, it is only marginally stronger. Finally, and perhaps most interestingly, while the constraints appear not to alter estimates of excess performance of mutual fund managers on average, they do appear to change significantly portfolio style characterizations. What looks like value-style management from the perspective of the unconstrained model may look substantially different once borrowing constraints are accounted for.

The goal of this paper is to bring to light some of the important elements of the obscure equity-loan market. We have established some basic facts about shorting stocks for which there would intuitively be strong shorting demand: IPOs, acquirers, and the short-side of the zero investment factor-mimicking portfolios. Much of the equity-loan market is still unexplored, offering a wide range of topics for future research.

Bibliography

Aggarwal, Reena, 2000, Stabilization Activities by Underwriters after Initial Public Offerings, *Journal of Finance* 55, 1075-1103

Asquith, Paul, 1983, Merger Bids, Uncertainty, and Shareholder Returns, *Journal of Financial Economics* 11, 51–83.

Asquith, Paul, and Lisa Meulbroek, 1996, An Empirical Investigation of Short Interest, Working Paper, Harvard Business School.

Baker, Malcolm and Serkan Savasoglu, 2000, Limited Arbitrage In Mergers and Acquisitions, Working Paper, Harvard Business School.

Brav, Alon, and Paul A. Gompers, 2001, The role of lockups in initial public offerings, Working Paper, Duke and Harvard Universities.

Brav, Alon, Christopher C. Geczy and Paul A. Gompers, 2000, Is the abnormal return following equity issuances anomalous, *Journal of Financial Economics*, V6, n2, pp. 209-249.

Brent, Averil, Dale Morse, and E. Kay Stice, 1990, Short Interest: Explanations and Tests, *Journal of Financial and Quantitative Analysis* 25,
273–289.

Carhart, Mark, 1997, On persistence in mutual fund performance, *Journal of Finance*, v52, n1, pp. 57-82.

Carhart, Mark, Ron Kaniel, David K. Musto and Adam V. Reed, 2001, Leaning for the tape: Evidence of gaming behavior in equity mutual funds, *Journal of Finance*, forthcoming.

Christoffersen, Susan E. K., Chris Geczy, David K. Musto and Adam V. Reed, 2001, The Market for Legal Ownership of Equities, McGill University and University of Pennsylvania Working Paper.

D'Avolio, Gene, 2001, The market for borrowing stock, Harvard University Working Paper.

Dechow, Patricia M., Amy P. Hutton, Lisa Meulbroek, and Richard G. Sloan,
2000, Short-Sellers, Fundamental Analysis and Stock Returns, Forthcoming, *Journal of Financial Economics*.

Desai, Hemang, S. Ramu Thiagarajan, K. Ramesh, and Balachandran, 2000, An Investigation of the Informational Role of Short Interest in the Nasdaq Market, Working Paper, Southern Methodist University.

Diamond, Douglas W., and Robert E. Verrecchia, 1987, Constraints on Short-Selling and Asset Price Adjustment to Private Information, *Journal of Financial Economics* 18, 277–311.

Duffie, Darrell, 1996, Special Repo Rates, *Journal of Finance* 51, 493–526.

Ellis, Katrina, Roni Michaely and Maureen O'Hara, 2000, When the Underwriter is the Market Maker: An Examination of Trading in the IPO Aftermarket, *Journal of Finance* 55, 1039-1074.

Fabozzi, Frank J., 1997, *Securities Lending and Repurchase Agreements*. (Frank J. Fabozzi Associates New Hope, PA).

Fama, Eugene, 1998, Market efficiency, long-term returns and stock returns, *Journal of Financial Economics*, v49, n3, pp. 283-306.

Fama, Eugene and Kenneth French, 1992, The cross-section of expected stock returns, *Journal of Finance*, v47, n2, pp. 427-465.

Fama, Eugene and Kenneth French, 1993, Common risk factors in the returns on stock and bonds, *Journal of Financial Economics*, v33, n1, pp. 3-56.

Field, Laura C., and Gordon Hanka, 2001, The Expiration of IPO Share Lockups, *Journal of Finance*, 56(2), pp. 471-500.

Figlewski, Stephen, 1981, The Informational Effects of Restrictions on Short Sales: Some Empirical Evidence, *Journal of Financial and Quantitative Analysis* 4, 463–476.

Gintschell, Andreas, 2000, Short Interest on NASDAQ, Working Paper, University of Rochester.

Greene, William H., 1993, Econometric Analysis, Second Edition. (Macmillan Publishing Company, New York).

Heckman, James, 1979, Sample selection as a specification error, *Econometrica* 47, 153-161.

Hong, Harrison and Jeremy Stein, 1999, Differences of Opinion, Rational Arbitrage and Market Crashes, Working Paper, MIT.

Jennings, Robert, and Laura Starks, 1986, Earnings Announcements, Stock Price Adjustment, and the Existence of Option Markets, *Journal of Finance* 41, 107–125.

Jensen, Michael C., and Richard S. Ruback, 1983, The Market for Corporate Control, *Journal of Financial Economics* 11, 5–50.

Jindra, Jan and Ralph A. Walkling, 2001, Speculation Spreads and the Market Pricing of Proposed Acquisitions, Working Paper, Ohio State University.

Keane, Frank, 1996, Repo rate patterns for new treasury notes, *Current Issues in Economics and Finance* 2.

Keim, Donald, 2000, An analysis of mutual fund design: The case of investing in small-cap stocks, *Journal of Financial Economics* 51, 173-194.
Krigman, Laurie, Wayne Shaw and Kent Womack, 1999, The persistence of IPO mispricing and the predictive power of flipping, *Journal of Finance* 54, 1015-1044

Lakonishok, Joseph, Andrei Shleifer and Robert Vishny, 1994, Contrarian investment, extrapolation and risk, *Journal of Finance*, v49, n5, pp. 1541-1578.

Lamont, Owen A. and Richard H. Thaler, 2001, Can the market add and subtract? Mispricing in tech stock carve-outs. Working Paper, The University of Chicago.

MacDonald, John G., and Donald C. Baron, 1973, Risk and Return on Short Positions in Common Stocks, *Journal of Finance* 28, 97–107.

Mitchell, Mark and Todd Pulvino, 1999, Characteristics of Risk and Return in Risk Arbitrage, Working Paper, Northwestern University.

Mitchell, Mark, Todd Pulvino and Erik Stafford, 2001, Limited arbitrage in equity markets, Working Paper, Harvard Business School.

Musto, David K., 1997, Portfolio Disclosures and Year-End Price Shifts, *Journal of Finance* 52, 1563-1588.

Odean, Terrance, 1998, Are investors reluctant to realize their losses? *Journal of Finance* 53, 1775-1798.

Ofek, Eli, and Matthew Richardson, 2000, The IPO lock-up period: implications for market efficiency and downward sloping demand curves, Working Paper, New York University.

Ofek, Eli and Matthew Richardson, 2001, DotCom Mania: A Survey of Market Efficiency in the Internet Sector, Working Paper, New York University.

Reed, Adam V. 2001, Costly Short-Selling and Stock Price Reactions to Earnings Announcements, Working Paper, University of Pennsylvania.

Richardson, Scott, 2000, Accruals and Short Selling: An Opportunity Forgone?, Working Paper, University of Michigan.

Safieddine, Assem, Jr. and William J. Wilhelm, 1996, An Empirical Investigation of Short-Selling Activity Prior to Seasoned Equity Offerings, *Journal of Finance* 51, 729–749.

Scholes, Myron S., and Mark A. Wolfson, 1989, Decentralized Investment Banking: The case of discount dividend-reinvestment and stock-purchase plans, *Journal of Financial Economics* 24, 7-35.

Senchack, A. J., and Laura T. Starks, 1993, Short-Sale Restrictions and Market Reaction to Short-Interest Announcements, *Journal of Financial and Quantitative Analysis* 28, 177–194.

Seneca, Joseph J., 1967, Short Interest: Bearish or Bullish?, *Journal of Finance* 22, 67–70.

Shefrin, Hersh, and Meir Statman, 1985, The disposition to sell winners too early and ride losers too long: Theory and evidence, *Journal of Finance* 40, 777-790.

Shleifer, Andrei and Robert Vishny, 1997, The limits of arbitrage, *Journal of Finance*, v52, n1, pp. 35-55.

Skinner, Douglas J., 1990, Options Markets and the Information Content of Accounting Earnings Releases, *Journal of Accounting and Economics* 13, 191–211.

Zhu, Xiaoting, 1997, Investigating the source of momentum profits: risk factors or market inefficiencies?, Working paper, The Wharton School.

Table I
General Rebate Rates and Specialness

The daily general rebate rate is defined as the mode of rebate rates for a given loan category each day. Panel A shows the percentage of loans below, at, or above the general rate. Panel B shows specialness, or the difference between loan rates and general rates on a value-weighted and equal-weighted basis. Loan values are used as weights.

Panel A: Percentage of Loans at the General Rate

	—Percentage of Loan Rates—			
Loan Size	Below General	General	Above General	Total
Medium	21.76%	76.10%	2.15%	29.08%
Large	1.05%	98.30%	0.65%	70.92%
Medium and Large	7.07%	91.85%	1.09%	100.00%

Panel B: Specialness by Loan Size

Loan Size	Value-Weighted	Equal-Weighted
Medium	0.12744%	0.20338%
Large	0.01400%	0.01514%
Medium and Large	0.01968%	0.06988%

Table II
Probit Model for Whether an IPO was loaned

We construct a panel of 359 IPOs whose first 20 trading days occurred between November 1, 1998 and October 31, 1999 (the sample period). $LOANED_{s,t}$ is 1 if IPO *s* was loaned on its t^{th} trading day, and 0 otherwise. $LRET_{s,t-3}$ is the log-relative return of IPO *s* from its offering price to the close of its *t*-3rd trading day, $DOG_{s,t-3}$ is 1 if IPO *s* closed below its offering price on its *t*-3rd trading day, $LSIZE_s$ is the log of the offering price of IPO *s* times the number of shares offered, and $LVOL_{s,t-3}$ is the log of one plus the number of shares of *s* traded on *t*-3, divided by the number of shares of *s* sold in the IPO. The probit model estimates the probability that an IPO is not loaned as a function of the specified variables. A variable enters negatively if the probability that an IPO is *not* loaned decreases as the value of the variable increases. The model is estimated for four values of *t*: 4, 9, 14 and 19. P-values (in percent) for statistical significance are below the estimated coefficients, in italics. At the bottom of each column is the number of the 359 IPOs that were not loaned on that trading day.

Explanatory Variable	*IPO Trading Day*			
	t=4	*t=9*	*t=14*	*t=19*
Intercept	-21.273	-25.294	-21.023	-25.274
	<0.01	*<0.01*	*<0.01*	*<0.01*
$LRET_{s,t-3}$	0.163	0.293	-0.146	-0.689
	54.03	*36.81*	*59.07*	*0.81*
$DOG_{s,t-3}$	-0.027	-0.428	-0.413	0.164
	91.35	*11.56*	*12.54*	*55.42*
$LSIZE_s$	1.226	1.476	1.255	1.411
	<0.01	*<0.01*	*<0.01*	*<0.01*
$LVOL_{s,t-3}$	0.151	-0.010	0.137	-0.167
	24.88	*92.44*	*6.22*	*3.67*
Not Loaned:	91	72	84	89

Table III

Cross Section of IPO Specialness in the First Days

Model is

$$S_{s,t} = b_{0,t} + b_{1,t}LRET_{s,t-3} + b_{2,t}DOG_{s,t-3} + b_{3,t}LSIZE_{s} + b_{4,t}LVOL_{s,t-3} + b_{5,t}8_{s,t} + \gamma_{s,,t}$$

We construct a panel of 359 IPOs whose first 20 trading days occurred between November 1, 1998 and October 31, 1999 (the sample period). $S_{s,t}$ is the specialness (as defined in the text) of IPO *s* on its t^{th} trading day. $LRET_{s,t-3}$ is the log-relative return of IPO *s* from its offering price to the close of its *t*-3rd trading day, $DOG_{s,t-3}$ is 1 if IPO *s* closed below its offering price on its *t*-3rd trading day, $LSIZE_s$ is the log of the offering price of IPO *s* times the number of shares offered, and $LVOL_{s,t-3}$ is the log of one plus the number of shares of *s* traded on *t*-3, divided by the number of shares of *s* sold in the IPO. The Inverse Mills Ratio from running a Probit model for selection to the sample (i.e. whether or not the stock was loaned on *t*; the explanatory variables are *LRET*, *DOG*, *LSIZE* and *LVOL*) is denoted by $8_{s,t}$ (so this is the second stage of the Heckman (1979) 2-stage procedure). The model is estimated for four values of *t*: 4, 9, 14 and 19. P-values (in percent) for significant difference from zero are below, in italics. At the bottom of each column is the R^2 of the regression and the number of observations.

Explanatory		*IPO Trading Day*		
Variable	*t=4*	*t=9*	*t=14*	*t=19*
Intercept	5.2533	14.759	16.3903	15.439
	<0.01	*<0.01*	*<0.01*	*<0.01*
$LRET_{s,t-3}$	0.5730	0.3926	0.6351	0.0423
	<0.01	*0.50*	*0.12*	*86.53*
$DOG_{s,t-3}$	0.3198	0.4061	0.4839	0.4210
	0.12	*0.28*	*2.60*	*10.22*
$LSIZE_s$	-0.1416	-0.6342	-0.7440	-0.6622
	4.53	*<0.01*	*<0.01*	*<0.01*
$LVOL_{s,t-3}$	0.1405	0.1747	0.1351	0.3503
	1.10	*0.06*	*7.38*	*<0.01*
$8_{s,t}$	-0.0986	-1.2909	-1.1950	-1.147
	63.90	*<0.01*	*0.93*	*1.95*
R^2	31.4%	36.3%	25.6%	18.4%
# observations:	253	272	260	255

Table IV
Daily Change in Loan Volume around 30 Days Post-IPO

We construct a panel of 304 IPOs that are covered out to 10 trading days after 30 calendar days post-IPO by our November 1, 1998 to October 31, 1999 sample period. For a given IPO, event day 0 is the first trading day on or after 30 calendar days after the IPO date. On each event day *t* we measure $V_{s,t}$, the total shares of IPO *s* that our data provider loaned that day, divided by the number of shares of *s* sold at its IPO. For each event day from –5 to 4 we measure the average of $V_{s,t+1} - V_{s,t}$, and we calculate a t-statistic for significant difference from zero. We also count the number of IPOs for which $V_{s,t+1} - V_{s,t}$ is positive, and the number for which it is negative.

Event Days	*Average of* $V_{s,t+1} - V_{s,t}$	*T-Statistic*	*# with* $V_{s,t+1} > V_{s,t}$	*# with* $V_{s,t+1} < V_{s,t}$
-5 to –4	-0.042	-1.28	82	102
-4 to –3	0.061	1.33	76	105
-3 to –2	-0.095	-2.00	69	117
-2 to –1	0.008	0.25	77	106
-1 to 0	0.001	0.03	73	103
0 to 1	-0.060	-1.35	84	93
1 to 2	-0.057	-1.56	70	97
2 to 3	-0.245	-5.49	55	128
3 to 4	-0.138	-2.97	52	111
4 to 5	-0.053	-1.79	53	92

Table V
Cross Section of IPO Specialness around 30 Calendar Days Post-IPO

Model is

$$S_{s,t} = b_{0,t} + b_{1,t}LRET_{s,t-3} + b_{2,t}DOG_{s,t-3} + b_{3,t}LSIZE_{s} + b_{4,t}LVOL_{s,t-3} + b_{5,t}8_{s,t} + \gamma_{s,,t}$$

We construct a panel of 304 IPOs that are covered out to 10 trading days after 30 calendar days post-IPO by our November 1, 1998 to October 31, 1999 sample period. For a given IPO, event day 0 is the first trading day on or after 30 calendar days after the IPO's first trading day. $S_{s,t}$ is the specialness (as defined in the text) of IPO *s* on its event day *t*. $LRET_{s,t-3}$ is the log-relative return of IPO *s* from its offering price to the close of its event day *t*-3, $DOG_{s,t-3}$ is 1 if IPO *s* closed below its offering price on its event day *t*-3, $LSIZE_s$ is the log of the offering price of IPO *s* times the number of shares offered, and $LVOL_{s,t-3}$ is the log of one plus the number of shares of *s* traded on *t*-3, divided by the number of shares of *s* sold in the IPO. The Inverse Mills Ratio from running a Probit model for selection to the sample (i.e. whether or not the stock was loaned on *t*; the explanatory variables are *LRET*, *DOG*, *LSIZE* and *LVOL*) is denoted by $8_{s,t}$ (so this is the second stage of the Heckman (1979) 2-stage procedure). The model is estimated for five event days: -10, -5, 0, 5 and 10. P-values (in percent) for significant difference from zero are below, in italics. At the bottom of each column is the R^2 of the regression and the number of observations.

Explanatory			*Event Day*		
Variable	*-10*	*-5*	*0*	*5*	*10*
Intercept	16.7030	14.4019	13.0932	13.8799	7.0848
	<0.01	*<0.01*	*0.03*	*3.40*	*39.31*
$LRET_{s,t-3}$	0.6470	0.7133	0.1851	-0.4349	0.6929
	0.10	*0.63*	*50.99*	*32.99*	*31.38*
$DOG_{s,t-3}$	0.7154	0.4835	0.1979	0.2668	0.5132
	0.04	*6.63*	*53.55*	*46.46*	*24.44*
$LSIZE_s$	-0.7582	-0.6352	-0.5686	-0.5496	-0.331
	<0.01	*<0.01*	*0.33*	*8.96*	*41.26*
$LVOL_{s,t-3}$	0.1321	0.2461	0.2700	0.4919	0.0486
	6.36	*0.23*	*0.44*	*0.02*	*69.15*
$8_{s,t}$	-1.6260	-0.8537	-0.6857	-1.2581	-0.260
	<0.01	*8.00*	*25.20*	*21.60*	*84.40*
R^2	31.0%	24.6%	14.8%	14.6%	10.3%
# observations:	235	229	221	184	171

Table VI
The Specialness of Merger Acquirers

This table presents results from a regression of the specialness of merger acquirers on several explanatory variables.

$$Special^A_{t+3} = a + b\ \ln(Mktcap^A) + c\ \ln(Mktcap^T) + d\ (P^A_t - P^T_t) + \varepsilon_t$$

$Special^A_{t+3}$ is the difference between the rebate on loans of the acquirer on day t+3 and the typical rebate on day t+3. $\ln(Mktcap)^A$ is the natural log of the market capitalization of the acquirer at the end of the month before the month in which day t falls. $\ln(Mktcap)^T$ is the same measure for merger targets. $(P^A_{i,t} - P^T_{i,t})$ is stock price difference between the acquirer and target in merger on day t. We use mergers announced between October 28, 1998 and September 28, 1999. P-values and parameter estimates are based on the censored regression model.

Explanatory	*Trading Days Since Merger Announcement*				
Variable	*0*	*5*	*10*	*15*	*20*
Intercept	6.5501	6.1036	5.2245	3.9978	3.3442
	0.0005	0.0124	0.0198	0.1632	0.2320
$\ln(Mktcap^A)$	-0.8166	-0.6776	-0.8787	-0.5344	-0.3955
	<.0001	0.0025	0.0012	0.1144	0.2560
$\ln(Mktcap^T)$	0.3819	0.2689	0.5073	0.2409	0.1344
	0.0313	0.1543	0.0399	0.3991	0.6245
$(P^A_t - P^T_t)$	0.0114	-0.0009	0.0263	0.0075	0.0008
	0.0780	0.9328	0.0780	0.6378	0.9612
Observations					
Uncensored (Specials)	62	50	53	44	45
Total	226	225	224	224	223

Table VII

The Profitability of Merger Arbitrage when Short-Selling is Costly

We compute returns for a portfolio comprising a long position in the target firm and a short position in the acquiring firm. For the *"All"* portfolio, day t returns for merger position i are $r_{i,t} = r_{T,t} - r_{A,t}$ where $r_{A,t}$ and $r_{T,t}$ are day-t returns on the acquiring and target firms' stocks, respectively. For the *"All With Specialness"* portfolio, day t returns for merger position i are $r_{i,t} = r_{T,t} - r_{A,t} - S_{A,t+3}$ where $S_{A,t+3}$ is the specialness of the acquiring stock (as defined in the text) three trading days after day t. A merger pair is only included in the feasible portfolio if our database indicates the existence of a loan in the acquirer's stock on day t+3. "Average Daily Difference" is the average of the daily difference between the *"All"* portfolio and the *"Feasible With Specialness"* portfolio. At the 10% confidence level, the difference is not statistically different from zero except for the successful mergers where the p-value is 0.042. Portfolio returns do not include returns until two trading days after the announcement. In Panel B, day t returns for merger position i are $r_{i,t} = r_{T,t}$. There are between 9 and 111 merger observations in each day, over which we take the equal-weighted average. In the "Failures" portfolio, there are two days where there are no active deals, so the portfolio return is the federal funds rate. We compute the cumulative return over the 251 trading days between October 28, 1998 and October 26, 1999 period by compounding in the usual way. Sharpe ratios are computed using the average fed-funds rate over the period of 3.47%. 4-factor alphas are computed with the intercepts from the daily regression: $R_i - R_{RF} = \alpha_i + b_i RMRF + h_i HML + s_i SMB + m_i MOM + \varepsilon_i$ over the sample period and then annualized for each merger portfolio i (factor construction is described in the fundamentals section of the text). The alpha for the "Average Daily Difference" row is the alpha of a portfolio that is formed by taking the daily difference between *"All"* and *"Feasible With Specialness"* portfolios.

Portfolio		*Return 10/28/98-10/26/199*	*Sharpe Ratio*	*4-Factor Alpha (Annualized)*	*P-Value*
Panel A: Long-Short Portfolios					
All Mergers	*All*	*64.287%*	*97.531*	*94.733%*	*0.002%*
	All w/ Specialness	*64.057%*	*97.171*	*94.342%*	*0.002%*
	Feasible w/ Specialness	*44.302%*	*58.533*	*57.983%*	*0.842%*
	Average Daily Difference	*0.0513%*		*23.295%*	*13.492%*
Failures	*All*	*-34.764%*	*-11.229*	*-21.993%*	*76.807%*
	All w/ Specialness	*-34.787%*	*-11.236*	*-22.035%*	*0.053%*
	Feasible w/ Specialness	*-46.453%*	*-22.405*	*-58.103%*	*11.750%*
	Average Daily Difference	*0.1100%*		*85.910%*	*44.917%*
Successes	*All*	*82.505%*	*120.738*	*119.929%*	*<0.001%*
	All w/ Specialness	*82.228%*	*120.326*	*119.450%*	*<0.001%*
	Feasible w/ Specialness	*0.56688*	*72.850*	*75.778%*	*0.199%*
	Average Daily Difference	0.0604%*		25.162%	5.494%
Panel B: Long Only Portfolios					
All Mergers		*99.013%*	*96.421*	*157.036%*	*0.013%*
Failures		*-30.875%*	*-12.688*	*-25.555%*	*65.787%*
Successes		*124.263%*	*118.494*	*198.198%*	*0.002*
S&P 500		*0.20329%*	*14.448*		

Table VIII
Specialness and Firms Characteristics: Summary Measures

The table presents average firm characteristics for stocks in the CRSP universe during the paper's sample period, November 1, 1998 through October 31, 1999, for firms within that universe that appear in our loan database, and those within the database that are and are not on special.

Specialness is reported in %/year units. We compute daily annualized specialness averaged over a week. Average daily loan values are calculated on a given day and averaged over a week, as are the corresponding average numbers of shares loaned. The average annualized subsequent weekly return is the annualized return for the week following the week in which a given loan was made. For the CRSP Sample, this value and others are simply averages of all weekly characteristic variables. The CRSP Sample contains stocks on loan as well as stocks not on loan. The Previous Annualized Weekly Return (momentum) is the annualized return over the 26 weeks preceding a given loan, including time before the sample period begins. We calculate a firm's book-to-market ratio using the firm's (non-missing, non-negative) book value from the most recently available annual report assuming a 3-month reporting lag. Firm size used in both book-to-market ratios and the reported firm size variable is as of the beginning of a reference week. Finally, annualized weekly return volatility is calculated over the preceding 26 weeks using weekly data and then annualized.

Characteristic	*Loan Sample*	*Firms Not on Special*	*Firms on Special*	*CRSP Sample*
Specialness (\%/year)	0.067	0.000	0.675	NA
Average Loan Value	$8,023,610	$7,224,157	$10,353,812	NA
Average Number of Shares Loaned	225,422	200,038	297,776	NA
Average Annualized Subsequent Weekly Return	12.32%	11.96%	16.12%	8.87%
Previous Annualized Weekly Return (Momentum)	-6.80	-7.60	-1.00	20.02
Book-to-Market Ratio	0.673	0.694	0.494	0.738
Firm Size (000's)	$2,058,158	$1,968,609	$2,834,032	$2,207,833
Annualized Weekly Return Volatility	12.26%	12.14%	12.29%	12.21%

Table IX
Specialness and Firm Characteristics: Univariate Sorts

The table presents average firm characteristics for stocks in the CRSP universe during the paper's sample period, November 1, 1998 through October 31, 1999, for firms within that universe that appear in our loan database. In each panel of the table, these firms are assigned independently to one of three groups on the basis of three corresponding sorting variables, firms size, book-to-market ratio and return momentum. The assignations occur weekly, and the values reported in the table are simple averages across weeks and firms.

Specialness is reported in %/year units. We compute daily annualized specialness averaged over a week. Average daily loan values are calculated on a given day and averaged over a week, as are the corresponding average numbers of shares loaned. We calculate a firm's book-to-market ratio using the firm's (non-missing, non-negative) book value from the most recently available annual report assuming a 3-month reporting lag. Firm size used in both book-to-market ratios and the reported firm size variable is as of the beginning of a reference/group assignation week.

		Size	
	Small	*Medium*	*Large*
Specialness (%/year)	0.053	0.086	0.039
Average Loan Value	$926,136	$5,168,697	$19,362,002
Average Number of Shares	71,382	230,446	444,668
		Book-to-Market	
	Low	*Medium*	*High*
Specialness (%/year)	0.114	0.031	0.027
Average Loan Value	$10,772,622	$5,682,802	$4,395,684
Average Number of Shares	279,522	205,528	188,235
		Momentum	
	Low	*Medium*	*High*
Specialness (%/year)	0.070	0.038	0.061
Average Loan Value	$6,566,125	$7,802,682	$10,611,545
Average Number of Shares	239,674	215,905	265,593

Table X
Specialness and Firm Characteristics: Trivariate Sorts

The table presents average firm characteristics for stocks in the CRSP universe during the paper's sample period, November 1, 1998 through October 31, 1999, for firms within that universe that appear in our loan database. In each panel of the table, these firms are assigned independently to one of three groups on the basis of three corresponding sorting variables, firms size, book-to-market ratio and return momentum. The assignations occur weekly, and the values reported in the table are simple averages across weeks and firms. The table reports averages for groups formed by the intersection of these assignations, producing 27 (3 x 3 x 3) different categorizations. Averages across any given dimension in the table appear in the previous table.

Specialness is reported in %/year units. We compute daily annualized specialness averaged over a week. Average daily loan values are calculated on a given day and averaged over a week, as are the corresponding average numbers of shares loaned. We calculate a firm's book-to-market ratio using the firm's (non-missing, non-negative) book value from the most recently available annual report assuming a 3-month reporting lag. Firm size used in both book-to-market ratios and the reported firm size variable is as of the beginning of a reference/group assignation week.

			Small Size	
		Low Momentum	Medium Momentum	High Momentum
Low Book-to-Market	*Specialness*	0.139	0.098	0.110
	Average Loan Value	$1,111,118	$1,000,634	$1,319,560
	Average Number of Shares	72,007	71,140	83,146
Medium Book-to-Market	*Specialness*	0.039	0.019	0.033
	Average Loan Value	$916,410	$587,096	$598,714
	Average Number of Shares	78,477	46,463	43,472
High Book-to-Market	*Specialness*	0.027	0.007	0.039
	Average Loan Value	$879,783	$565,872	$687,377
	Average Number of Shares	94,849	49,722	61,179
			Medium Size	
		Low Momentum	Medium Momentum	High Momentum
Low Book-to-Market	*Specialness*	0.168	0.123	0.130
	Average Loan Value	$6,861,740	$5,132,421	$6,543,568
	Average Number of Shares	300,659	200,671	226,429
Medium Book-to-Market	*Specialness*	0.06441	0.01276	0.01596
	Average Loan Value	$4,328,969	$3,715,521	$4,731,633
	Average Number of Shares	248,728	175,799	194,570
High Book-to-Market	*Specialness*	0.06524	0.02922	0.03323
	Average Loan Value	$3,187,936	$3,532,183	$3,253,088
	Average Number of Shares	219,712	150,060	208,756
			Large Size	
		Low Momentum	Medium Momentum	High Momentum
Low Book-to-Market	*Specialness*	0.064	0.055	0.049
	Average Loan Value	$20,540,793	$18,109,604	$31,085,686
	Average Number of Shares	497,662	373,694	562,864
Medium Book-to-Market	*Specialness*	0.00200	0.02827	0.00989
	Average Loan Value	$12,858,149	$13,670,619	$15,660,891
	Average Number of Shares	400,598	339,072	408,550
High Book-to-Market	*Specialness*	0.03641	0.02206	0.01516
	Average Loan Value	$13,505,454	$12,960,643	$17,981,127
	Average Number of Shares	426,605	371,104	567,795

Table XI
Unconstrained and Constrained Spread Portfolio Summary Statistics

The table presents summary measures for four factor-mimicking portfolios during the paper's sample period offset by three days to accommodate equity lending delivery dates: October 28, 1998 through October 26, 1999 (251 trading days). RMRF is the excess return on the value-weighted CRSP market index less the T-bill return. SMBc and HMLc are daily versions of Fama and French's (1993) mimicking portfolios for size and book-to-market equity constructed using the entire CRSP universe (with NYSE breakpoints). MoMc is a daily version of Carhart's (1997) equity momentum spread portfolio also constructed using the entire CRSP universe of stocks and NYSE breakpoints. SMBs, HMLs and MoMs are versions of the preceding three zero-investment portfolios in which stocks that are on special on delivery date (t+3) are presumed to be unborrowable and therefore are eliminated from the short side of the spread *ex ante*. For all six versions of SMB, HML and MoM, portfolio assignments are made weekly on Wednesdays or on the first trading date thereafter. Momentum is calculated as cumulative return over the 26 weeks prior to portfolio assignment.

				Factor Correlations						
Factor Portfolio	Daily Excess Return	Std. Dev.	t-stat for mean=0	VW MRT	SMBc	HMLc	MoMc	SMBs	HMLs	MoMs
RMRF	0.0011	0.0111	1.51	1.00						
SMBc	0.0009	0.0063	2.23	-0.62	1.00					
HMLc	-0.0007	0.0045	-2.60	-0.69	0.19	1.00				
MoMc	0.0025	0.0068	5.84	0.22	0.02	-0.21	1.00			
SMBs	0.0009	0.0067	2.03	-0.61	0.95	0.18	0.05	1.00		
HMLs	-0.0011	0.0044	-3.97	-0.70	0.25	0.92	-0.16	0.24	1.00	
MoMs	0.0024	0.0075	5.02	0.04	0.16	-0.07	0.92	0.21	0.04	1.00

Table XII
Summary Statistics for 27 Unconstrained and Constrained Test Portfolios Formed on Size, Book-to-Market Equity and 26-Week Return Momentum

The table presents means and standard deviations for 27 portfolios formed by sorting firms into groups according to firm charac teristics. Firms are assigned independently to one of three groups on the basis of three corresponding sorting variables, firm size (small, med. and large), book-to-market ratio (B/M) and return momentum (loser vs. winner). The assignments occur weekly on Wednesdays or the first trading day thereafter. The table reports returns means and standard deviations for groups formed by the intersection of these assignments that produce27 (3 x 3 x 3) different daily portfolio return series during the period October 28, 1998 through October 26, 1999, 251 trading days.

		Means			**Standard Deviations**		
		Small	Med	Large	Small	Med	Large
	Low B/M	-0.00014	-0.00005	-0.00023	0.00916	0.01158	0.01218
Loser		0.00004	-0.00058	-0.00039	0.00743	0.0092	0.0118
	High B/M	0.00017	-0.00133	-0.00101	0.00736	0.00983	0.01156
	Low B/M	0.00133	0.00051	0.00069	0.00684	0.0089	0.00964
		0.00063	0.00024	0.00046	0.0044	0.00705	0.00897
	High B/M	0.00069	0.0000	0.00006	0.00444	0.00695	0.00777
	Low B/M	0.00338	0.00249	0.00217	0.01005	0.01173	0.01316
Winner		0.00319	0.00134	0.00131	0.00758	0.00806	0.00943
	High B/M	0.00272	0.00139	0.00093	0.00707	0.0081	0.00869

Table XIII, Panel A
Regressions of Excess Stock Returns on the 4-Factor Model Mimicking Returns with no Borrowing Constraints

The table presents parameter estimates from regressions of the 27 test portfolios from Table XII formed on the basis of size, book-to-market equity and 26-week return momentum on the *unconstrained* 4-factor model from Table XI: $R_i - R_{RF} = \alpha_i + b_i\,RMRF + h_i\,HMLc + s_i\,SMBc + m_i\,MOMc + \varepsilon_i$. The multivariate regression is estimate over the period October 28, 1998 through October 26, 1999.). RMRF is the excess return on the value-weighted CRSP market index less the T-bill return. SMBc and HMLc are daily versions of Fama and French's (1993) mimicking portfolios for size and book-to-market equity constructed using the entire CRSP universe (with NYSE breakpoints). MoMc is a daily version of Carhart's (1997) equity momentum spread portfolio also constructed using the entire CRSP universe of stocks and NYSE breakpoints.

		a			b			s			h			m		
		Small	Med	Large	Small	Med	Large	Small	Med	Large	Small	Med	Large	Small	Med	Large
	Low B/M	0.0010	-0.0001	0.0009	0.6629	0.6880	0.6118	0.6811	0.1403	-0.4734	-0.3287	-0.2309	-0.4384	-0.8123	-0.8171	-0.7715
		3.69	*-0.22*	*1.76*	*15.02*	*9.71*	*7.57*	*11.90*	*1.53*	*-4.52*	*-3.81*	*-1.67*	*-2.78*	*-20.76*	*-13.01*	*-10.77*
Loser		0.0009	0.0003	0.0018	0.5318	0.5265	0.5772	0.5206	0.0981	-0.5657	0.0974	0.2125	0.0113	-0.8297	-0.7246	-0.9527
		3.34	*0.74*	*4.52*	*12.33*	*7.82*	*9.23*	*9.31*	*1.12*	*-6.97*	*1.16*	*1.61*	*0.09*	*-21.70*	*-12.14*	*-17.18*
	High B/M	0.0006	0.0006	0.0010	0.5659	0.3738	0.3115	0.6314	0.0194	-0.5821	0.4655	1.3267	1.3033	-0.9293	0.8555	-0.8583
		1.64	*1.34*	*2.92*	*10.25*	*5.26*	*5.48*	*8.82*	*0.21*	*-7.90*	*4.31*	*9.56*	*11.73*	*-18.99*	*-13.58*	*-17.03*
	Low B/M	0.0006	0.0003	0.0010	0.4253	0.3766	0.3995	0.4541	-0.0890	-0.4795	-0.2691	-0.0665	-0.3584	-0.2582	-0.2779	-0.3294
		2.45	*0.81*	*3.23*	*11.65*	*6.30*	*7.82*	*9.59*	*-1.15*	*-7.23*	*-3.77*	*-0.57*	*-3.59*	*-7.97*	*-5.25*	*-7.27*
		0.0004	0.0005	0.0014	0.3200	0.3539	0.4592	0.3105	-0.1212	-0.5305	0.0415	0.0894	-0.0518	-0.2174	-0.2663	-0.4027
		1.77	*1.25*	*4.28*	*8.68*	*6.06*	*8.91*	*6.49*	*-1.60*	*-7.94*	*0.58*	*0.78*	*-0.51*	*-6.65*	*-5.15*	*-8.81*
	High B/M	0.0010	0.0002	0.0009	0.3726	0.3560	0.5704	0.3225	-0.1370	-0.4230	0.4733	0.6606	0.2808	-0.3448	-0.2029	-0.2969
		3.20	*0.40*	*3.57*	*7.10*	*5.41*	*14.26*	*4.74*	*-1.60*	*-8.15*	*4.61*	*5.13*	*3.59*	*-7.41*	*-3.48*	*-8.37*
	Low B/M	0.0012	0.0007	0.0006	0.5852	0.4184	0.3871	0.6612	-0.1101	-0.4891	-0.1650	0.0284	-0.3418	0.1205	0.0970	0.1891
		3.45	*1.59*	*1.48*	*10.30*	*6.20*	*5.78*	*8.97*	*-1.26*	*-5.64*	*-1.49*	*0.22*	*-2.61*	*2.39*	*1.62*	*3.19*
Winner		0.0016	0.0004	0.0005	0.5383	0.3859	0.5300	0.4891	-0.1357	-0.4100	0.1959	0.3427	0.0393	0.1148	0.1123	0.1872
		4.71	*1.14*	*1.56*	*9.64*	*6.69*	*10.21*	*6.75*	*-1.81*	*-6.09*	*1.79*	*3.04*	*0.39*	*2.32*	*2.20*	*4.07*
	High B/M	0.0011	0.0004	0.0004	0.6596	0.5296	0.8152	0.7098	0.0209	-0.2664	0.5974	1.0581	0.6638	0.1427	0.2636	0.2217
		2.86	*0.93*	*1.66*	*10.25*	*8.33*	*21.47*	*8.51*	*0.25*	*-5.41*	*4.75*	*8.51*	*8.94*	*2.50*	*4.67*	*6.58*

Table XIII, Panel B

Regressions of Excess Stock Returns on the 4-Factor Model Mimicking Returns with Borrowing Constraints

The table presents parameter estimates from regressions of the 27 test portfolios from Table XII formed on the basis of size, book-to-market equity and 26-week return momentum on the <u>*constrained*</u> 4-factor model from Table XI: $R_i - R_{RF} = \alpha_i + b_i RMRF + h_i HMLs + s_i SMBs + m_i MOMs + \varepsilon_{i.}$ The multivariate regression is estimate over the period October 28, 1998 through October 26, 1999.). RMRF is the excess return on the value-weighted CRSP market index less the T-bill return. SMBs and HMLs are daily versions of Fama and French's (1993) mimicking portfolios for size and book-to-market equity constructed using the CRSP universe (with NYSE breakpoints) while eliminating *ex ante* from the short sides stocks that are on special at date t+3. MoMs is a daily version of Carhart's (1997) equity momentum spread portfolio also constructed using the CRSP universe of stocks and NYSE breakpoints while eliminating *ex ante* from the short side stocks that are on special at date t+3.

		a			b			s			h			m		
		Small	Med	Large	Small	Med	Large	Small	Med	Large	Small	Med	Large	Small	Med	Large
	Low B/M	0.0010	0.0000	0.0007	0.6945	0.8111	0.6204	0.6446	0.2285	-0.4305	-0.3843	-0.5676	-0.3699	0.7170	0.7076	0.6822
		3.40	*0.04*	*1.40*	*16.87*	*13.49*	*8.85*	*10.65*	*2.59*	*-4.18*	*-4.93*	*-4.98*	*-2.79*	*17.55*	*11.86*	*9.80*
Loser		0.0009	0.0005	0.0017	0.6609	0.7197	0.7394	0.5231	0.1946	-0.4415	-0.1779	-0.2674	-0.3101	0.7315	0.6308	0.8274
		3.39	*1.11*	*4.31*	*15.95*	*12.18*	*13.24*	*8.59*	*2.24*	*-5.38*	*-2.27*	*-2.39*	*-2.93*	*17.78*	*10.76*	*14.93*
	High B/M	0.0006	0.0007	0.0010	0.7897	0.8154	0.6840	0.6595	0.1929	-0.4692	0.0150	0.3307	0.5600	0.8422	0.7459	0.7695
		1.63	*1.53*	*2.61*	*15.05*	*11.17*	*11.57*	*8.55*	*1.80*	*-5.40*	*0.15*	*2.39*	*5.00*	*16.17*	*10.29*	*13.11*
	Low B/M	0.0007	0.0005	0.0010	0.4115	0.4932	0.4026	0.4231	0.0403	-0.4163	-0.2623	-0.4515	-0.3695	-0.2394	-0.2221	-0.2921
		3.09	*1.50*	*3.25*	*13.11*	*10.07*	*9.43*	*9.17*	*0.56*	*-6.63*	*-4.41*	*-4.87*	*-4.57*	*-7.68*	*-4.57*	*-6.90*
		0.0006	0.0006	0.0013	0.3857	0.4936	0.5423	0.3287	0.0135	-0.4276	-0.1532	-0.3143	-0.2423	-0.1976	-0.2183	-0.3415
		2.61	*1.81*	*4.17*	*12.21*	*10.08*	*12.29*	*7.08*	*0.19*	*-6.60*	*-2.56*	*-3.39*	*-2.90*	*-6.30*	*-4.49*	*-7.80*
	High B/M	0.0012	0.0003	0.0008	0.5417	0.5838	0.6738	0.3607	0.0017	-0.3637	0.0624	0.0831	0.1041	-0.3163	-0.1551	-0.2773
		3.80	*0.75*	*3.22*	*11.42*	*9.86*	*19.42*	*5.18*	*0.02*	*-7.13*	*0.69*	*0.74*	*1.58*	*-6.72*	*-2.64*	*-8.06*
	Low B/M	0.0016	0.0009	0.0007	0.5827	0.4914	0.3655	0.6477	0.0010	-0.3919	-0.2546	-0.2755	-0.4113	0.0770	0.1297	0.1967
		4.47	*2.16*	*1.74*	*11.91*	*8.72*	*6.53*	*9.01*	*0.01*	*-4.76*	*-2.75*	*-2.58*	*-3.88*	*1.59*	*2.32*	*3.54*
Winner		0.0020	0.0007	0.0006	0.6408	0.5306	0.5695	0.5549	-0.0012	-0.3121	-0.1313	-0.1218	-0.1534	0.0796	0.1319	0.2122
		5.65	*1.78*	*1.86*	*13.36*	*10.71*	*13.07*	*7.87*	*-0.02*	*-4.88*	*-1.44*	*-1.30*	*-1.86*	*1.67*	*2.68*	*4.91*
	High B/M	0.0016	0.0007	0.0004	0.8425	0.8047	0.9254	0.7815	0.1893	-0.2189	0.0779	0.2716	0.3965	-0.1030	0.2920	0.2175
		3.67	*1.45*	*1.54*	*14.60*	*13.47*	*26.95*	*9.21*	*2.16*	*-4.34*	*0.71*	*2.40*	*6.10*	*-1.80*	*4.92*	*6.38*

Table XIV
Regressions of Mutual Fund Style Portfolios on the 4-Factor Model with and without Borrowing Constraints

The table presents parameter estimates from regressions nine equal weighted mutual fund portfolios on both the *unconstrained* and *constrained* 4-factor models from Table XI: $R_i - R_{RF} = \alpha_i + b_i\, RMRF + h_i\, HML_{(c\ or\ s)} + s_i\, SMB_{(c\ or\ s} + m_i\, MOM_{(c\ or\ s)} + \varepsilon_{i.}$ The multivariate regression is estimate over the period October 28, 1998 through October 26, 1999.). RMRF is the excess return on the value-weighted CRSP market index less the T-bill return. SMBs and HMLs are daily versions of Fama and French's (1993) mimicking portfolios for size and book-to-market equity constructed using the CRSP universe (with NYSE breakpoints) while eliminating *ex ante* from the short sides stocks that are on special at date t+3. MoMs is a daily version of Carhart's (1997) equity momentum spread portfolio also constructed using the CRSP universe of stocks and NYSE breakpoints while eliminating *ex ante* from the short side stocks that are on special at date t+3. The mutual fund style indices are from Lipper.

Mutal Fund Style Portfolios

	Small-Cap Value	Small-Cap Core	Small-Cap Growth	Mid-Cap Value	Mid-Cap Core	Mid-cap Growth	Large-Cap Value	Large-Cap Core	Large-Cap Growth
	Means of Mutual Fund Style Portfolios								
Mean	0.0001	0.0006	0.0015	0.0004	0.0009	0.0019	0.0008	0.0010	0.0015
	Mutual Fund Style Portfolio Factor Loadings -- Unconstrained Factors								
a	-0.0003	0.0000	0.0002	-0.0003	0.0001	0.0003	-0.0005	-0.0003	0.0002
	-0.88	*-0.11*	*0.53*	*-0.91*	*0.19*	*0.98*	*-3.01*	*-2.98*	*1.99*
b	0.6106	0.3952	0.3480	0.7502	0.4907	0.4418	1.2094	1.0506	0.9058
	10.45	*8.20*	*6.97*	*13.26*	*10.85*	*10.34*	*44.22*	*69.33*	*46.92*
s	0.0685	-0.0360	-0.0721	0.0280	-0.2546	-0.2719	0.1672	0.0093	-0.1539
	0.90	*-0.58*	*-1.11*	*0.38*	*-4.34*	*-4.90*	*4.71*	*0.47*	*-6.15*
h	1.1184	0.5724	0.1596	1.1828	0.7460	0.2999	0.0872	-0.1155	-0.3078
	9.79	*6.08*	*1.64*	*10.69*	*8.44*	*3.59*	*1.63*	*-3.90*	*-8.16*
m	-0.0760	0.1172	0.2290	-0.1725	0.0535	0.1670	-0.1481	-0.0409	0.0914
	-1.47	*2.74*	*5.17*	*-3.44*	*1.33*	*4.41*	*-6.11*	*-3.04*	*5.34*
	Mutual Fund Style Portfolio Factor Loadings -- Constrained Factors								
a	-0.0001	0.0001	0.0003	-0.0002	0.0001	0.0003	-0.0005	-0.0003	0.0002
	-0.28	*0.38*	*1.01*	*-0.44*	*0.33*	*1.14*	*3.08*	*-3.29*	*1.39*
b	0.8773	0.5796	0.4716	1.0033	0.6759	0.5643	1.1886	1.0092	0.8551
	15.57	*13.12*	*11.05*	*18.41*	*15.83*	*14.96*	*52.16*	*75.75*	*48.74*
s	0.188	0.0668	0.0276	0.1327	-0.1644	-0.1797	0.1333	-0.0125	-0.1546
	2.27	*1.03*	*0.44*	*1.66*	*-2.62*	*-3.24*	*3.98*	*-0.64*	*-6.00*
h	0.4047	0.0788	-0.1862	0.5072	0.2824	-0.0092	0.1354	-0.0067	-0.1736
	3.79	*0.94*	*-2.30*	*4.92*	*3.49*	*-0.13*	*3.14*	*-0.26*	*-5.22*
m	-0.0545	-0.1667	-0.2299	0.041	-0.1059	-0.1734	0.1203	0.0472	-0.0459
	-1.05	*-4.27*	*-6.11*	*0.80*	*-2.76*	*-5.19*	*5.76*	*3.96*	*-2.78*

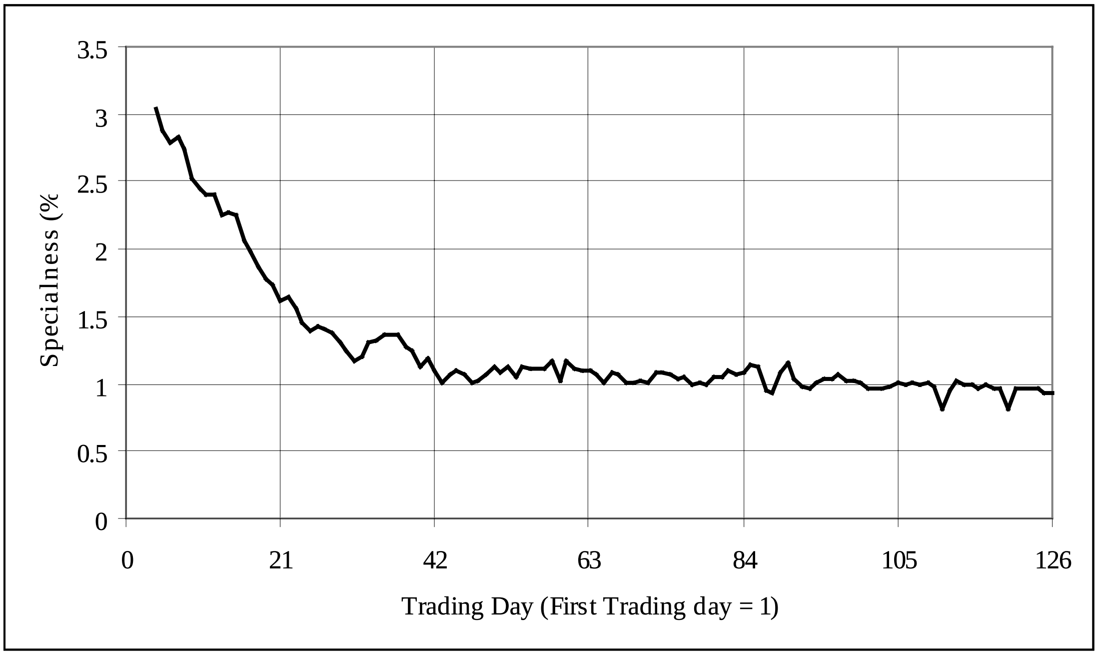

Figure 1. Time Series of IPO Specialness over the First 180 Days. The IPOs are the 110 IPOs in our sample which were covered by our equity-loan data out to their 126th trading days. The figure for Trading day *n* is the average specialness of all IPOs in the panel that were loaned on their respective *n*th trading days.

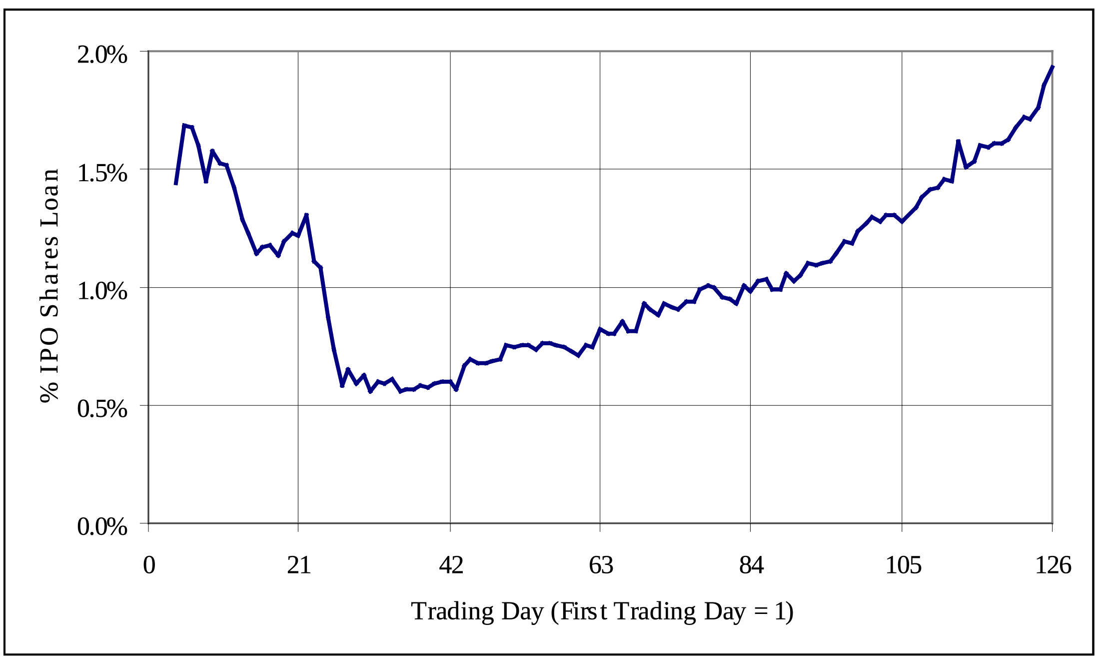

Figure 2. Time Series of IPO Shares Loaned by our Data Provider, as a Fraction of IPO Shares Issued. The IPOs are the 110 IPOs in our sample which were covered by our equity-loan data out to their 126th trading days. The figure for day *n* is the average of (Loaned Shares)/(Shares Offered at IPO) across all IPOs in the panel on their respective *n*th days, including the IPOs that were not loaned on day *n*.

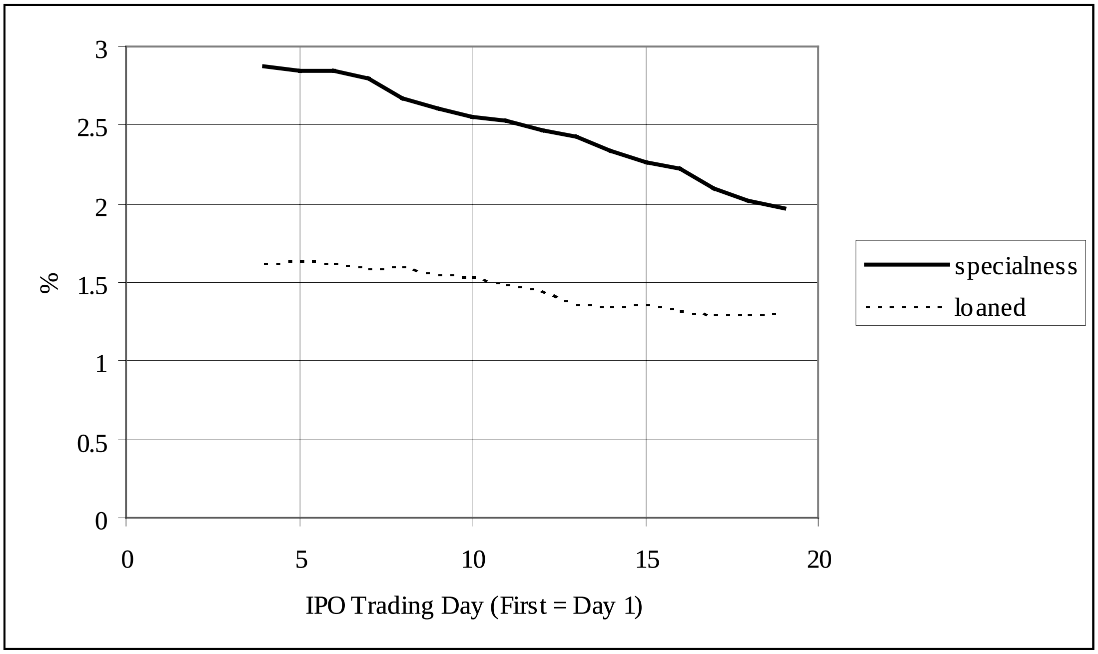

Figure 3. Average Specialness of Loaned IPOs, and Average % of IPO Shares Loaned across Loaned and Unloaned IPOs, in their First 19 Trading Days. The IPOs are the 344 IPOs in our sample which were covered by our equity-loan data out to their 19th trading days. The figures for Trading day *n* are the average specialness of all IPOs in the panel that were loaned (thick line), and the average of (loaned shares)/(IPO shares)x100 across all 344 IPOs (dashed line), on the IPOs' respective *n*th trading days.

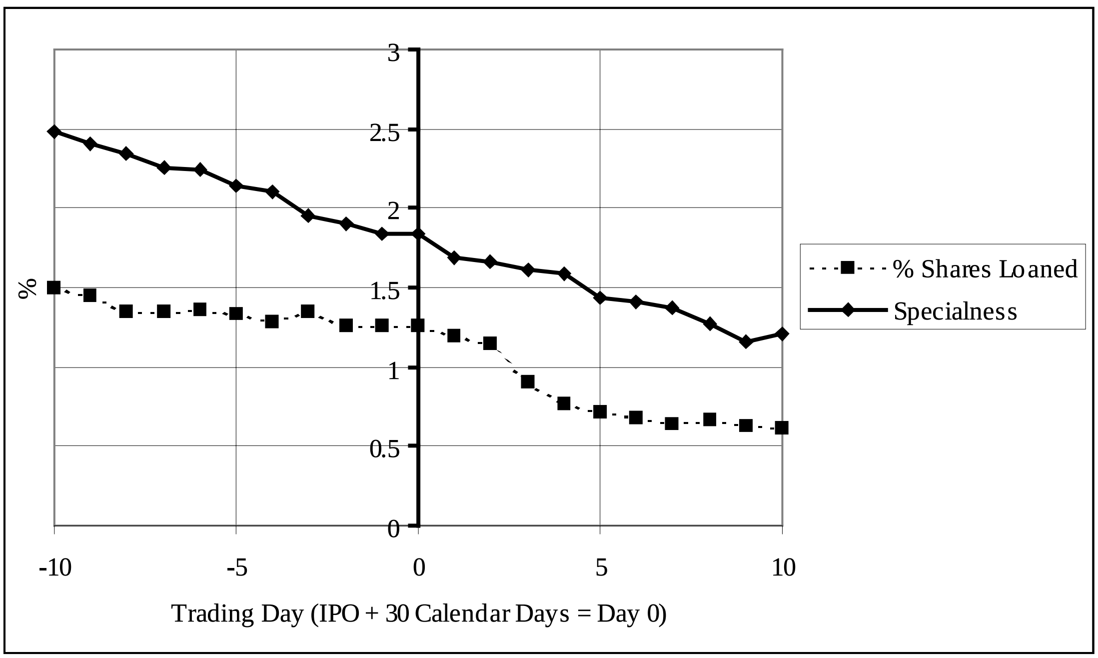

Figure 4. Average Specialness of Loaned IPOs, and Average % of IPO Shares Loaned across Loaned and Unloaned IPOs, in the 20 Trading Days around 30 Calendar Days post-IPO. The IPOs are the 304 IPOs in our sample which were covered by our equity-loan data out to 10 trading days after 30 calendar days post-IPO. The figures for Trading day *n* are the average specialness of all IPOs in the panel that were loaned, and the average of (loaned shares)/(IPO shares)x100 across all 304 IPOs, on the IPOs respective *n*th trading days relative to 30 calendar days, which is day 0 in the graph.

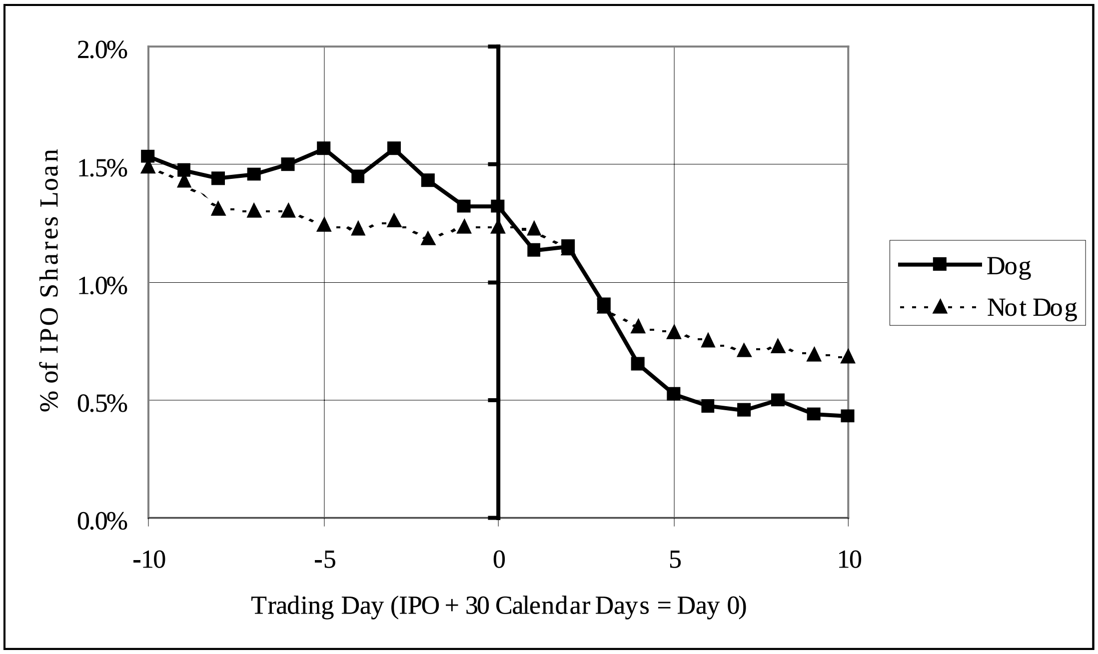

Figure 5. Percentage of IPO Shares Loaned by our Data Provider around 30 Calendar Days, sorted by whether they were trading above their offering prices 13 days before 30 Calendar Days. The IPOs are the 304 IPOs in our sample which were covered by our equity-loan over this period. Event day 0 is the first trading day on or after 30 calendar days after the IPO's first trading date. The figures for Event day *n* are the average of (loaned shares)/(IPO shares)x100 across the 85 IPOs that closed at or below their offering prices on event day -13 ("Dogs," the thick line), and the average across the 219 IPOs that closed above their offering prices on event day -13 ("Not Dogs," the dashed line).

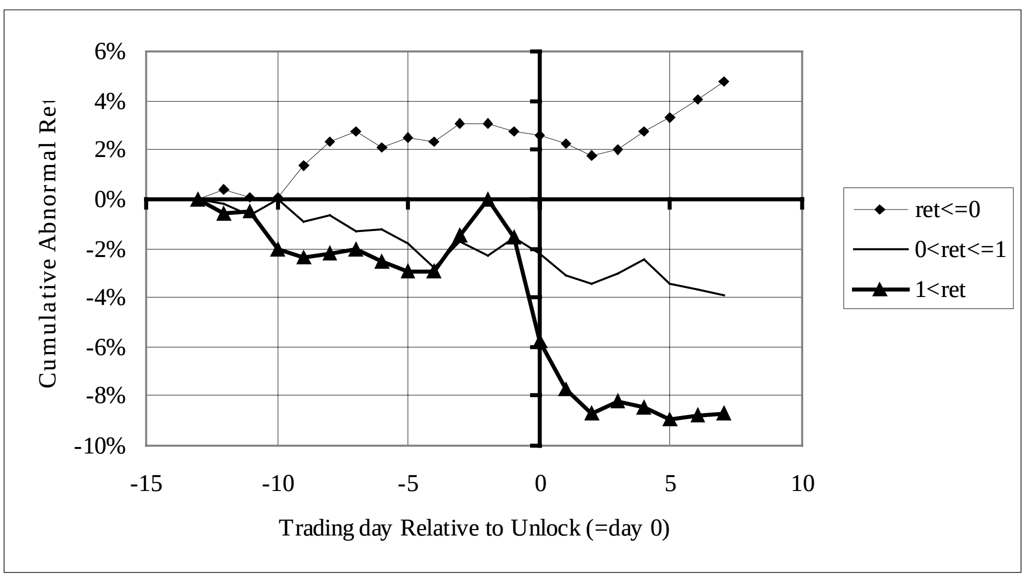

Figure 6. Cumulative Abnormal Returns of IPOs from 13 trading days before the unlock day to seven trading days after, sorted by previous return. The IPOs are the 198 IPOs in our sample which were covered by our equity-loan data over this period plus 3 days (days –10 through +10). For each IPO we calculate the abnormal return (i.e. $(1+r)/(1+r_{VW})-1$) on each event day, then average by event day across IPOs and finally calculate the cumulative return. The thin line with diamonds represents the 85 IPOs that closed at or below their offering prices on event day –13, the thick represents the 44 that closed at more than twice their offering prices on event day –13, and the other line represents the 69 IPOs in between.

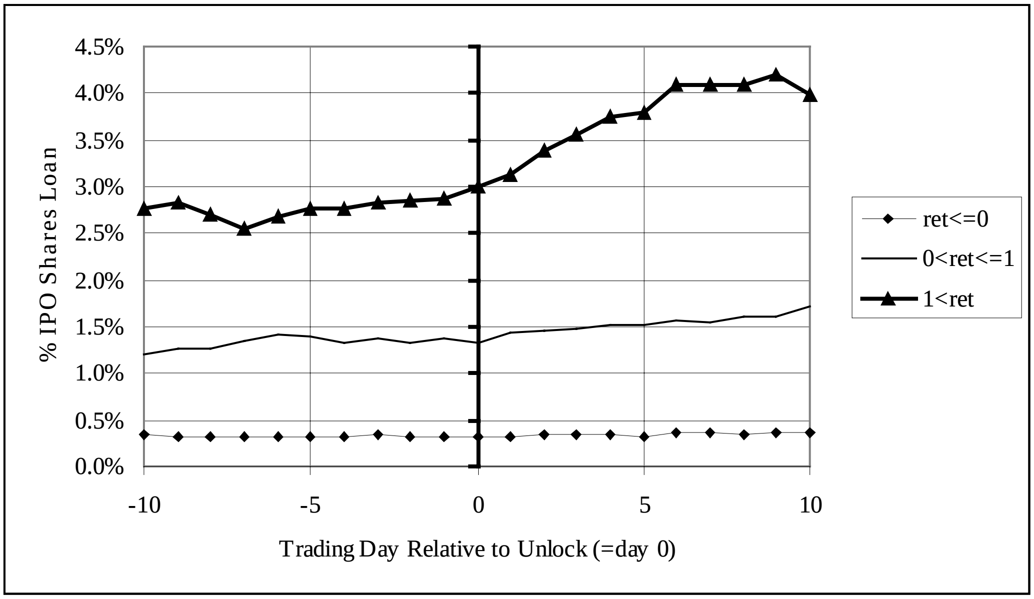

Figure 7. Percentage of IPO Shares Loaned by our Data Provider around the unlock day, Event day 0, sorted by lifetime return to Event day –13. The IPOs are the 198 IPOs in our sample which were covered by our equity-loan data over this period. The figures for Trading day *n* are the average of (loaned shares)/(IPO shares)x100 across the 85 IPOs that closed at or below their offering prices on Event day -13 (the thin line, with diamonds), the average across the 44 IPOs that closed above twice their offering prices on Event day –13 (the thick line), and across the 69 IPOs in between (the other line).

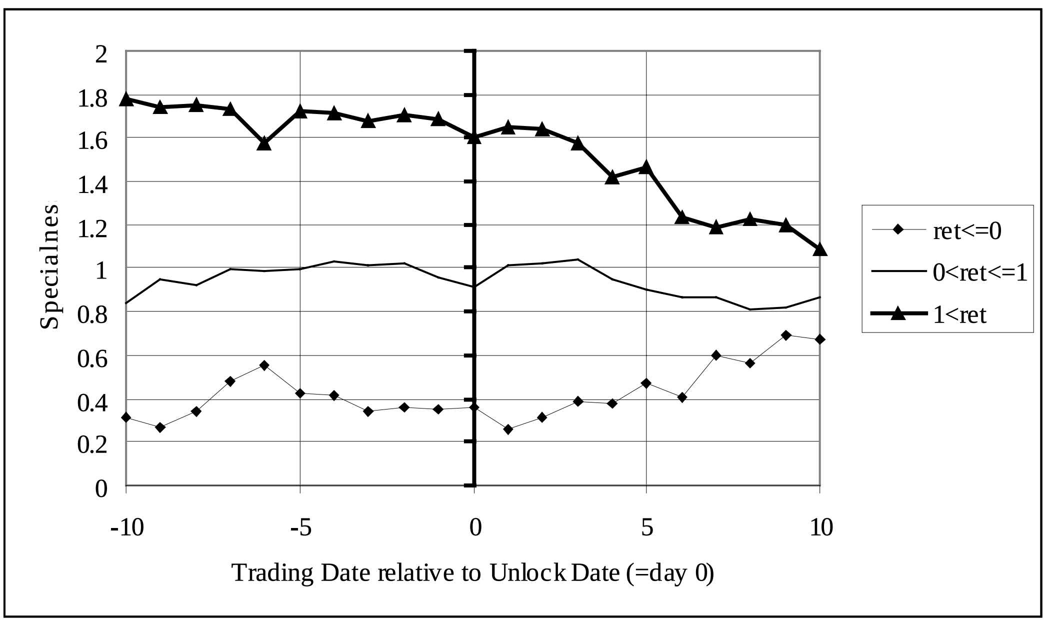

Figure 8. Average specialness of IPOs Loaned by our Data Provider around the unlock day, Event day 0, sorted by lifetime return to Event day –13. The IPOs are the 198 IPOs in our sample which were covered by our equity-loan data over this period. The figures for Trading day *n* are the average specialness across the loaned IPOs among the 85 that closed at or below their offering prices on Event day -13 (the thin line, with diamonds), the 44 that closed above twice their offering prices on Event day !13 (the thick line), and across the 69 in between (the other line).

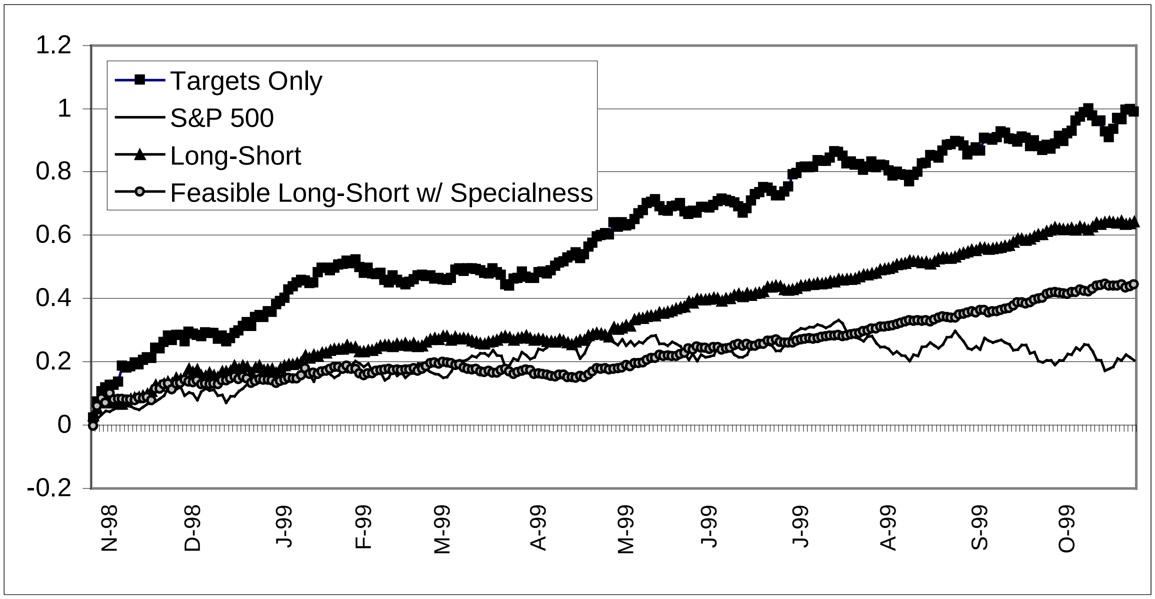

Figure 9. Cumulative Merger Portfolio Returns. We compute returns on a portfolio comprising a long position in the target and a short position in the acquiring firm. For the *"Long-Short"* portfolio, day t returns for merger position i are $r_{i,t} = r_{T,t} - r_{A,t}$ where $r_{A,t}$ and $r_{T,t}$ are day-t returns on the acquiring and target firms' stocks, respectively. For the *"Feasible Long-Short w/Specialness"* portfolio, day t returns for merger position i are $r_{i,t} = r_{T,t} - r_{A,t} - S_{A,t+3}$ where $S_{A,t+3}$ is the specialness of the acquiring stock on day t+3 (as defined in the text). A merger pair is only included in the feasible portfolio if our database indicates the existence of a loan in the acquirer's stock on day *t+3*. Portfolio returns do not include mergers until two trading days after the announcement. Day t returns for merger position i are $r_{i,t} = r_{T,t}$ in for the "Targets Only" portfolio. We compute the cumulative return over the 251 trading days between October 28, 1998 and October 26, 1999.