Market-Wide Impact of the Disposition Effect: Evidence from IPO Trading Volume

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ABSTRACT

I study empirically the market-wide importance of investors' reluctance to realize losses by investigating IPO trading volume. In IPOs all initial investors have a common purchase price, and the disposition effect should thus be at its strongest. Turnover is significantly lower for negative initial return IPOs when the stock trades below the offer price, and increases significantly on the day the price surpasses the offer price for the first time. The increase in volume lasts for two weeks. On a daily level, attaining new maximum and minimum stock prices also produces strong increase in volume. These results suggest that reference price effects play a role in aggregate stock market activity.

JEL Classifications: G10, G30

Key words: IPO, Loss aversion, Disposition effect, Trading volume

I. Introduction

It is well known that investors dislike selling their shares at a loss. This reluctance to realize losses can be motivated by the loss aversion in prospect theory (Kahneman and Tversky 1979), which states that the relation of an asset's price to an investor's reference price affects the investor's utility asymmetrically: The investor will be risk-averse in the domain of gains, but risk-seeking in the domain of losses. An important reference price can be, for example, the price that the investor paid for the asset. Based on loss aversion Shefrin and Statman (1985) present a framework where investors have a disposition to hold on to losing investments and to sell winning investments early. The disposition effect is well documented empirically among futures traders (Heisler 1994; Locke and Mann 2000), individual stock market investors (Odean 1998; Shapira and Venezia 2001; Grinblatt and Keloharju 2001), as well as individual home owners (Genesove and Mayer 2001). Recently prospect theory has also inspired the theoretical asset pricing models of Shumway (1997), Barberis, Huang, and Santos (2001), and Barberis and Huang (2001)[1].

What is not currently known, however, is the extent to which this behavioral bias that many investors share influences aggregate market behavior. This is difficult to resolve since relevant reference prices depend, among other things, on purchase prices that are unique to each investor. Furthermore, knowledge on which reference prices in a given situation are most relevant to investors is far from complete. The present work addresses these questions by studying initial public offerings (IPOs) in which all initial investors have a common purchase price, namely the offer price[2]. In no other situation in the stock market is there as clear a setting to investigate the disposition effect in aggregate. Thus the implications of the disposition effect should be relatively stronger with IPOs than with other stock market investments.

In this paper I investigate the importance of different reference prices for the stock market as an aggregate by examining IPO trading volume. The contribution of the paper is two-fold. First, I

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[1] See also Benartzi and Thaler (1995) for an application of prospect theory in connection with short evaluation horizons in explaining the equity premium puzzle, Jullien and Salanié (2000) for the results of estimating cumulative prospect theory value functions on a large set of British horse racing data, and Loughran and Ritter (2001) for a prospect theory explanation to why IPO issuers do not appear to be particularly disturbed by high initial returns, or 'leaving money on the table'.

[2] This property of IPOs is also utilized by Reese (1998a), who studies capital gains taxation and investor behavior under two different U.S. taxation schemes.

perform a ‘first order’ test for the market implications of the disposition effect: Trading volume should be higher when the stock is trading above the offer price vs. trading below the offer price, if investors are reluctant to trade lossmaking shares. Further, the immediate effect should be seen when the market price of an IPO with a negative initial return exceeds the offer price for the first time. If the disposition effect is significant enough to affect asset pricing, it should show up in trading volume. Conversely, if the disposition effect is not an important determinant of trading volume, its asset pricing implications are probably not significant. Ferris, Haugen, and Makhija (1988) find that the trading volume that occurs when a stock is trading in a particular price range is an important determinant of future trading volume for that stock in the price range in question. Ferris at al. interpret their findings as supporting the disposition effect. Grinblatt and Han (2002) find that stocks with large aggregate unrealized capital gains perform better than those with large unrealized capital losses. This is consistent with their equilibrium model of rational and disposition investors.

My results offer further support for the aggregate impact of the disposition effect. There is a kink at the offer price in the price-volume relation for negative initial return IPOs so that volume is clearly suppressed below the offer price. Turnover increases significantly at the time the stock exceeds the offer price for the first time, and continues to be higher while the stock is trading above the offer price. I control for surpassing other levels, and reaching new record high prices, as well as for stock return, market volume and lagged volume. The impulse to volume from exceeding the offer price lasts for two weeks, incremental to high abnormal volume over the previous week.

The total impact of reaching a new record high stock price while also breaking above the offer price is roughly comparable to that produced by other well-known drivers of trading volume. For example, it corresponds to a 0.8 standard deviation increase in the return, or 2.9 standard deviation increase in market volume.

The second contribution of this paper is that it provides additional evidence on the determination of reference prices. While the prospect theory states that investors evaluate their positions with respect to a reference price, it does not specify what that reference price is. Kahneman and Tversky (1979) consider static settings in which the current asset price is seen as a reference price, but they also recognize other possibilities.

Although it does not follow from prospect theory that selling should necessarily increase exactly at the purchase price, Shefrin and Statman (1985) consider the purchase price to be the benchmark below which investors are reluctant to realize losses[3]. In a laboratory experiment Weber and Camerer (1998) find both the price of the previous period and purchase price to be important reference points. Historical maximum and minimum stock prices are also potential reference points: according to experimental evidence by Gneezy (2000) the maximum stock price is even more significant than the purchase price. Attaining new highs in stock prices is a significant determinant for exercise behavior in employee stock options (Heath, Huddart, and Lang 1999) as well as in standardized exchange traded stock options (Poteshman and Serbin 2003). Moreover, Grinblatt and Keloharju (2001) observe that new highs and lows compared to the past month affect the propensity to sell a stock, but the effect varies with investor type.

The present study provides further evidence on the relative importance of maximum and minimum stock prices as reference points. Attaining new highs and lows over the previous month is found to increase the daily turnover significantly. The effect is very strong for both negative and positive initial return IPOs, it is incremental to the effect of large stock price changes, and robust to various changes in specification. New highs are more important, producing an effect about one and a half times as large as new lows.

The remainder of this paper is organized as follows: Section II describes the data and the samples, Section III develops the hypotheses, discusses the construction of the variables and presents the design for the empirical tests. Section IV presents the results for individual firms and for pooled regressions on subsamples of IPOs with positive and negative initial returns. Section V briefly concludes the study.

II. Data

In this section I describe the data set in more detail. A summary of the sample selection criteria is given in Table 1.

A. Base Sample

The IPO data come from The Securities Data Corporation (SDC) database. All U.S. IPOs between January 1, 1980 and December 31, 1996 where data on offer date, offer price, and gross proceeds are available are matched with Center for Research in Security Prices (CRSP) 1997 daily files. The matching procedure utilizes six-digit CUSIP numbers or ticker symbols to

[3] I henceforth use the term 'reference price' or 'reference point' as a price level that is associated with changes in the willingness to trade.

identify the issuer. This gives 7,138 IPOs, after eliminating 243 cases where the same issuer shows up as having made another IPO later. To exclude observations that are either not true IPOs, or are due to erroneous matching, I excluded firms from the sample whose initial trading date in CRSP does not fall between 0 and 10 days after the IPO date in SDC. This leaves 5,884 IPOs. From this group I excluded IPOs with gross proceeds of $3 million or less (385 firms), and IPOs with an offer price $1 or less per share (another 36 firms). This leaves 5,463 firms. Of this sample, 3,948 firms have an SDC offer date equal to the first trading date in CRSP, whereas 1,325 firms have the day following the SDC offer date as the first trading date. Thus only 190 firms have a lag of two days or more between the first trading date in CRSP and the SDC offer date[4].

For each firm I collected a maximum of two years (508 trading days) of stock return and volume data. This means that for 642 (out of a total of 682) IPOs during 1996, the stock data are truncated at December 31, 1997, leaving 259 daily observations for the last IPO of 1996. I excluded 60 firms that have less than one year (254 trading days) of daily observations available, and further 321 firms that have more than 15 days of missing volume information in CRSP. This leaves a base sample of 5,082 IPOs.

B. Sample Characteristics

The descriptive statistics of the base sample ($N = 5{,}082$) are reported in Table 2. Fifteen percent of the firms (775) have a negative initial return. These firms are labeled 'losers', and, correspondingly, 68% of the firms (3,444) with positive initial return are called 'winners'. The rest of the firms (17%) have exactly zero initial return. The losers are on average smaller. The median market capitalization for losers is $34.7 million, the corresponding figure for all firms being $60 million. Losers also have smaller gross proceeds in approximately the same ratio. The share of losers within firm size deciles increases almost monotonically when moving towards smaller companies. The percentage share of losers is fairly stable over the sample period.

For the study of reference price effects, I selected subsamples from the loser and winner samples. The motivation for this procedure is explained in Section III.A. The subsamples are formed based on the following criteria. I take all loser firms whose stock price crosses the offer price from below for the first time after four weeks (> 20 trading days) of the issue date. A total

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[4] Matching SDC with CRSP based only on time-of-issue CUSIPs gives 5126 firms after further restricting the sample as described above. Thus by utilizing the ticker symbols as well as later CUSIPs I gain 337 firms.

of 342 firms meet this condition and are included in the loser subsample. Correspondingly, for winners, I take all firms whose stock price crosses the offer price from above for the first time after four weeks. This gives 1,712 firms.

The last two sections in Table 2 present the descriptive statistics for these subsamples. Firms in the winner subsample are similar to winners overall, with a median market capitalization of $57.7 million. The size of the median firm in the loser subsample corresponds to that of losers overall ($34.6 million), although the average firm is smaller.

III. Hypotheses and Methods

A. Predictions on Trading Volume

The disposition effect postulates that investors tend to hold on to losing investments and to sell winners. If this behavioral bias is strong enough for a large enough group of IPO investors, one should observe depressed trading volume below the offer price, and an increase in volume when the aftermarket price crosses the offer price from below. This is because disposition-effect-prone investors who have not previously sold their shares tend to delay their decision to sell until their investments are 'in the black'. This effect should be strongest for IPOs that have previously not traded above the offer price, i.e. on the day that an issue with negative initial return crosses the offer price from below for the first time.

The timing of the increased volume also depends on the frequency at which investors monitor their investments. Benartzi and Thaler (1995) show that the historical equity market risk premium is consistent with a model of a loss-averse investor who evaluates her portfolio approximately at an annual frequency. IPO investments are perhaps more frequently monitored than, say, mutual funds, but there can still be a lagged response to crossing the offer price, which may materialize days or weeks after the event.

The more time it takes to reach the offer price, the smaller the proportion of initial investors is likely to be. Since in time fewer investors share a common purchase price, the effect may deteriorate to some extent. On the other hand, the disposition of remaining initial investors to sell when they finally 'get out of the red' may increase with time.

Investors in winning IPOs whose price initially rose but subsequently declined close to the offer price might be urged to sell their shares in anticipation and fear of losses. This scenario is a modification of the tendency to sell winners early: conditional on not having sold before, the investor is predicted to sell before losses start to accumulate. This increased selling, as prices fall, should occur slightly above rather than below the offer price. Once the stock falls below the offer price willingness to sell should once again diminish. Thus on the day the stock falls below the offer price, the urge to avoid future losses and the reluctance to realize losses can compete. Their relative strength could depend on the development of market quotes and prices during the day. Discriminating between these effects would require intraday data which is not available for this study. However, if investors use stop-loss orders to help overcome their resistance to realizing losses, as suggested by Shefrin and Statman (1985), and set the trigger level close to the offer price, this would predict increased volume even if the majority of trading during the day is done below the offer price. Overall, the effect on trading volume with winners is probably weaker than the aforementioned effect with losers.

Also potential underwriter price support can increase the volume at levels close to the offer price. This issue is discussed in more detail in Section III.E.

The experimental evidence by Gneezy (2000) and the empirical evidence on stock option exercises (Heath, Huddart, and Lang 1999; Poteshman and Serbin 2003) show that the maximum stock price is an important reference price. Moreover, Grinblatt and Keloharju (2001) provide empirical evidence on determinants of propensity to sell for stock market investors. They find that the likelihood of a sale clearly increases for household investors, financial institutions, and corporations when the asset's price exceeds the maximum price over the past 20 trading days. A corresponding result is also found to apply to the minimum price, but it is significant only for household investors.

Based on the discussion above, I formulate the following hypotheses:

Hypothesis 1: Trading volume is higher on price levels above the offer price for a given IPO stock.

Hypothesis 2: There is an increase in trading volume for negative initial return IPOs as they exceed the offer price for the first time.

Hypothesis 3: There is an increase in trading volume for positive initial return IPOs as they fall below the offer price for the first time.

Hypothesis 4: There is an increase in trading volume for IPOs as their stock prices reach new record highs or lows.

The second and third hypotheses are nested in the fourth one, as the event of exceeding (falling below) the offer price for the first time is also always a new all-time high (low).

B. Measuring Trading Volume

Currently there is no one generally accepted method for measuring abnormal trading volume. Similarly to most recent studies (e.g. Smith Bamber, Barron, and Stober 1999; Chordia and Swaminathan 2000) I use turnover (number of shares traded divided by the number of shares outstanding) as a measure of volume[5]. I obtain the daily number of shares transacted and the number of shares outstanding during that day from CRSP files for each firm.

Tkac (1999) recommends the use of an adjustment for market-wide trading volume when calculating abnormal volume for individual firms. I calculate market volume as follows. The number of shares traded is aggregated daily, leaving out the 30 smallest percent of firms. Small stocks are excluded to reduce the effect that differential bid-ask spreads may have on trading volume (see Tkac 1999). Size ranking is based on the previous year end's market capitalization for each calendar year. The aggregate number of shares outstanding is obtained similarly. The normalized market volume is then the ratio of the aggregate number of shares traded to the aggregate number of shares outstanding[6].

Several studies have documented a contemporaneous relation between trading volume and stock return. Karpoff (1987) reviews earlier literature lending strong support to the existence of a positive correlation between absolute return and volume in daily data. Karpoff further argues that the price-volume relation could be asymmetric, in that a large positive price movement generates more trading than a negative movement of corresponding magnitude. Gallant, Rossi, and Tauchen (1992) find complex nonlinear interactions between prices and volume in their investigation of both lagged and contemporaneous effects. They also document a positive relation

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[5] See Lo and Wang (2000) for a discussion on various measures of trading volume.

[6] Unlike the measure of individual firm trading volume, my measure of market volume is only approximately equal to the corresponding percentage value of shares traded. This is due to the cross-sectional differences in stock price levels. Rather than being a value-weighted average of individual firm turnover ratios, the market volume measure is a number of shares weighted average of individual firm turnover ratios. If unit stock prices were normalized across firms, these two measures would be identical. In reality this measure will probably be biased in favor of smaller firms, since on average small firms tend to have smaller unit stock prices than large firms. In other words, a smaller firm has, on average, a higher number of shares weight than market value weight in the aggregate market. This effect is mitigated by excluding the 30 smallest percent of firms from the aggregate volume calculation.

between volatility and volume. Hiemstra and Jones (1994) find evidence of significant nonlinear Granger causality between daily returns and volume. The causality is bi-directional and robust over all, up to eight, lag lengths considered. Motivated by the results of the above studies I include lagged volume, contemporaneous and lagged returns, as well as squared return as a proxy for volatility in my model of normal volume. I also allow for asymmetry in the effect of contemporaneous return by considering positive and negative returns separately.

Finally, as in Smith Bamber, Barron, and Stober (1999), I apply a log-transformation on all volume variables because of positive skewness of the turnover ratios. Observations with no trading are excluded.

C. Reference Prices

I use the total return since IPO to determine important reference prices. For example, I say that the event of crossing the level 1.10 from below occurs on the first day that the stock closes sufficiently high to yield more than 10% in gross gain to initial investors. In almost all cases this corresponds to the stock price level exceeding the IPO price by 10%. Differences arise if there are dividend payments or stock splits before this event occurs. In some situations it might be more appropriate to use the raw price relative to issue price in determining important reference prices. For example, an investor might place dividend income and capital gains in two separate 'mental accounts' and perceive that he has a paper gain only if the current market price exceeds the offer price, ignoring the dividends received. However, in other situations it might be better to use total returns. For example, when an investor looks at the performance record of a particular IPO investment of hers, she would probably consider the total value of the investment, taking stock splits into account. A third alternative (to using raw prices or return indexes) would be to set up reference prices while correcting for stock splits, but not for dividends.

In selecting the firms I monitor the price change and total return, and exclude firms with more than 5% difference. This allows firms with normal dividends to pass but filters out firms with unusual dividends and stock splits. Because of this screen only about 5% of firms are eliminated from the subsamples that I study: dividends are not very large for many of the Nasdaq-listed firms in their first two years of trading, and regular stock splits are rare while the stock is still trading relatively close to the offer price.

Henceforth, for ease of exposition, I refer to *stock price* in the context of stock price passing reference levels or trading in a particular range when in fact I talk about the *return index*. The return index is calculated by CRSP from daily closing prices. It is thus possible that a stock price can cross a price level intraday, and then return back below (or above) the level at market closing. Obviously, then, using closing prices to determine crossings is biased towards later passage times. Although not formally reported in the paper, I checked for the effect of intraday prices by comparing the results of intraday high and low prices to closing prices in an analysis of trading volume around a date of crossing reference levels. Hardly any differences in the results were detected. In most cases the passage times were the same with both methods.

For a crossing event to occur, I require that the price exceed the reference level. However, I checked the effect of loosening this constraint by allowing also prices equal to the reference level to qualify as a crossing event. Both definitions give essentially the same results.

D. Regression Analysis of Daily Turnover

I use a two-step procedure for estimating the behavior of turnover for two subsamples, losers and winners. First I estimate a model of normal turnover for each firm separately. I then run a pooled OLS regression on the first step residuals to determine the magnitude of behavioral effects. Since IPOs are known to cluster in time, the observation periods of many firms can overlap significantly, causing cross-correlations in the residuals. I return to this issue at the end of the section, but first I describe the regressions in more detail.

In step one I estimate a model of turnover for each firm i with T_i days (254 to 508) of data and m_1 explanatory variables common to all firms, but taking firm-specific values:

$$\mathbf{v}_i = \alpha_i \mathbf{1} + \mathbf{X}_i \boldsymbol{\beta}_i + \mathbf{e}_i \qquad (1)$$

where

$\mathbf{v}_i$ = $T_i \times 1$ vector of log of firm i daily turnover (number of shares traded / number of shares outstanding)

α_i = regression constant for firm i

$\mathbf{1}$ = $T_i \times 1$ vector of ones

$\mathbf{X}_i$ = $T_i \times m_1$ matrix of first step explanatory variables for firm i

$\boldsymbol{\beta}_i$ = $m_1 \times 1$ vector of regression coefficients for firm i

$\mathbf{e}_i$ = $T_i \times 1$ vector of error terms for firm i

In step two I run a pooled OLS regression with m_2 explanatory variables. The individual error terms $\mathbf{e}_i$ from equation (1) for N firms are stacked to form the dependent variable $\mathbf{Y}$:

$$\mathbf{Y} = \mathbf{Z}\boldsymbol{\beta} + \boldsymbol{\varepsilon}, \qquad (2)$$

$$\mathbf{Y} = \begin{bmatrix} \mathbf{e}_1 \\ \mathbf{e}_2 \\ \vdots \\ \mathbf{e}_N \end{bmatrix}, \quad \mathbf{Z} = \begin{bmatrix} \mathbf{Z}_1 \\ \mathbf{Z}_2 \\ \vdots \\ \mathbf{Z}_N \end{bmatrix}$$

$\mathbf{Y} = \left(\sum_{i=1}^{N} T_i\right) \times 1$ vector of stacked error terms $\mathbf{e}_i$ from (1)

$\mathbf{Z} = \left(\sum_{i=1}^{N} T_i\right) \times m_2$ matrix of second step explanatory variables

where $\mathbf{Z}_i = T_i \times m_2$ matrix of second step explanatory variables, with values specific to firm i

$\boldsymbol{\beta} = m_2 \times 1$ vector of regression coefficients

$\boldsymbol{\varepsilon} = m_2 \times 1$ vector of error terms

In step one I control for market turnover, previous days' turnover, contemporaneous and lagged returns, and seasoning effects to determine the abnormal turnover for each firm. In step two I use a set of dummy variables that indicate crossings of specific stock price levels, new high and low prices, and trading within specific price ranges. The variables used in the regressions are listed and described in Table 3.

A variable of special interest is the dummy indicating the first crossing of the offer price level. For loser firms this dummy receives the value of one on the day that the stock price first crosses the offer price from below. For winners, correspondingly, the dummy receives the value of one on the day that the stock price first crosses the offer price from above. As control variables I form similar first-cross dummies for various other price levels. These levels are 0.95, 1.00, 1.05, …, 1.55 for losers and 1.20, 1.15, 1.10, …, 0.80 for winners[7].

Dummies for new maximum and minimum stock prices over the previous month (21 trading days) are also included.

The disposition effect should be at its strongest when the stock price crosses the offer price for the first time. However, increased trading close to the offer price may lead to a sustained increase in volume at that price level. This is because new investors who buy the initial investors' increased supply of shares at offer price may, in turn, be dispositioned to sell the shares only at or above the offer price. Hence, corresponding to the aforementioned price levels, I include dummy variables for crossing the offer price not for the first time, but for any time after the first time. I also include a few additional price levels not included for the first-cross dummies to increase the range that I cover for loser firms: These levels are 0.70, 0.75, …, and 0.90. These additional control dummies take the value of one also on the first crossing, as in these cases there are no separate first-cross dummies for that event.

In addition to dummies for crossing price levels I include dummies for the stock price residing in a particular range, such as [1.05, 1.10[, relative to offer price. These dummies capture any abnormal volume directly related to the stock's trading range without considering crossing any price levels. The price range of [1.00, 1.05[serves as a benchmark, and the dummy is omitted.

As mentioned in the beginning of the section, the estimation periods of individual firms can overlap. However, my research design should mitigate the harmful impact of cross correlations. Since volume is correlated with contemporaneous and lagged returns, my model of abnormal trading volume, which includes return based variables in addition to market volume, should clean out most systematic effects. For example, suppose such new information comes to the market that is prone to affect IPO firms distinctively from the rest of the market. To the extent that this information has relevance for prices, its effect is picked up by the return variables. Thus the cross-sectional effect on residuals should be diminished as long as shocks to IPO market specific or industry specific trading volume are correlated with contemporaneous or lagged stock returns, or with market volume.

[7] Only one first-crossing level below offer price, namely 0.95, is included as an explanatory variable for loser firms. Lower first crossing levels are not included due to the fact that only 67 firms in the sample start trading below the level 0.90.

I examined the ability of the abnormal volume model to produce well behaved residuals in the sample of 342 negative initial return IPOs[8]. The mean length of sample overlap is 57 days, but conditional on having overlap, the mean is 221 days. I calculated a pairwise correlation coefficient for all firm pairs, where the overlap was 30 days or longer (24.2% of firm pairs). The mean correlation conditional on overlap of ≥ 30 days is 0.0084 (median 0.0083). The distribution of the pairwise correlations is very symmetric and close to normal, with a standard deviation of 0.0833. The correlation coefficient is statistically significant at the 5% level in 1,607 firm pairs, which is 2.8% of all possible firm pairs. However, under the null hypothesis of zero correlation across all pairs, one would expect under half of that figure to turn out significant (5% × 24.2% = 1.2%). Of those cases where correlation is significant it is positive in 61.4% of the cases. Consequently, statistically significant positive correlations appear in 1.7% of firm pairs. Autocorrelation of the residuals is 0.0012. Although slightly more positive correlations appear than expected by chance the residuals appear well behaved overall.

E. Underwriter Price Support

It is well known that underwriting investment banks engage in price-supporting activities for many IPOs. This section briefly describes these activities, their consequences, and the measures taken to ensure that they would not distort the results of this paper.

Direct evidence of price support is limited because of scarcity of data. Some recent studies have, however, analyzed actual underwriter transactions (Aggarwal 2000; Boehmer and Fishe 2002; Puri and Prabhala 1999; and Ellis, Michaely, and O'Hara 2000)[9]. The principal form of price support involves the underwriter buying shares from the aftermarket in order to cover a short position established when allocating the shares. Aggarwal (2000) contains a thorough description of underwriters' support activities. She observes that underwriters frequently oversell the issue resulting in a short position. This overselling can be covered by exercising the overallotment option[10], or by making aftermarket purchases, or a combination of both.

[8] The results are reported for the second-stage pooled residuals, but first-stage residuals give almost identical answers.

[9] Since April 1997 underwriters have been required to keep records of short covering transactions.

[10] The overallotment option gives the underwriter the right to purchase additional shares from the issuing firm, usually up to a maximum of 15% of the offering, at a cost of offer price minus the gross underwriting fee. Typically the underwriter must exercise this option within 30 calendar days from the offering.

As mentioned, price support is a common practice, e.g., half of all IPOs in Aggarwal's sample are supported. There are, however, systematic differences between IPOs. IPOs with initial returns exactly equal to zero are the most likely candidates for price support[11]. The likelihood for price support is lower for firms with higher initial returns. The limited evidence from negative initial return IPOs is that they are supported in half of the cases. In general, supported IPOs tend to be larger issues, and have higher offer prices (Aggarwal 2000; Boehmer and Fishe 2002; Puri and Prabhala 1999).

There is a consensus in the literature that the vast majority of price support trades are executed during the first few days. Aggarwal (2000) finds that most price support activities end within 10 to 15 trading days, but 16% of IPOs are still supported at day 20, and 6% are supported at day 30 and beyond. For those issues that are supported, the amount of support declines fast. Boehmer and Fishe (2002) report that only about 5% of total short covering is executed after 11 or more days. Ellis, Michaely, and O'Hara (2000) find that underwriters accumulate inventory on average up to 15 days. For a group of 14 IPOs that trade at or below offer price for the first 20 trading days, the inventory accumulation lasts for 21 days, after which the underwriter reduces the inventory for a few days.

In addition to observing the number of days since offer, there are some additional clues about the timing of the activity. Aggarwal (2000, p. 1090) comments: "Underwriters generally engage in aftermarket short covering either when the stock initially starts trading or when they see the stock price weakening the most". Boehmer and Fishe (2002) find that short covering is executed on days with more selling pressure. Short covering is also more likely when prices are below the offer price[12].

Price support has a temporary impact on liquidity and returns. Hanley, Kumar, and Seguin (1993) show that support activities influence the bid-ask spread for 10 to 15 days after the offer, and that prices decline after day 10 for negative initial return IPOs[13]. Cross-sectional return distributions show a peak just above zero return, persisting even after 20 days from the offering

[11] For direct evidence see Aggarwal (2000) and Puri and Prabhala (1999); for indirect evidence see Ruud (1993) and Asquith, Jones, and Kieschnick (1998).

[12] Assuming a typical gross spread of 7% (see Chen and Ritter 2000), and ignoring other costs and benefits, aftermarket short covering would be more profitable than exercising the overallotment option only when the price is below a level corresponding to 93% of the offer price.

[13] Boehmer and Fishe (2002) find a similar effect on the bid-ask spread with actual underwriter short covering data, corroborating the validity of the bid-ask spread as an indirect measure of price support activity.

(Asquith, Jones, and Kieschnick 1998). However, other factors besides price support may also explain the result, and Asquith et al. interpret their evidence as consistent with price support ending by the second week. Aggarwal (2000) shows that IPOs with aftermarket short covering first experience negative returns, but the cumulative returns start to drift upward after about 15 days, after which their behavior is similar to IPOs with no aftermarket short covering. Boehmer and Fishe (2002) observe that underwriters follow a passive policy of price support, i.e., they provide liquidity but do not attempt to bid up prices.

Based on the evidence presented above, I now assess the relevance of price support for the tests conducted in this paper. Support activity can result in increased trading volume on a day with high seller-initiated volume. Most support activity would be expected slightly below the offer price, i.e., at a price range of 95-100%. Hence price support may well increase volume on a day when a winner IPO falls below the offer price for the first time. Conversely, volume on a day when a loser IPO exceeds the offer price is unlikely to be influenced by underwriter support. For both groups of firms price support can work against the disposition effect hypothesis in the price range of 95-100%, by causing increased volume in that range.

To alleviate the possibly distorting effects of price support, I only study firms whose stock price crosses the offer price for the first time after 20 trading days since issue date, and exclude the first 20 trading days when estimating (1) and (2). Moreover, firms with initial return exactly equal to zero are excluded. I believe that these remedies are effective against the impact of price support, but I nevertheless perform robustness checks by extending the number of excluded trading days beyond 20.

IV. Results

This section presents the results of abnormal volume regressions. There are two subsamples:

Losers – firms with a negative initial return whose stock price crosses the offer price from below for the first time between 21 and 508 days after the issue date. A total of 342 firms meet this condition.

Winners – firms with an initial return greater than zero whose stock price crosses the offer price from above for the first time between 21 and 508 days after the issue date. A total of 1,712 firms meet this condition.

Summary statistics of the basic turnover and return variables for these subsamples are presented in Table 4.

A. Trading Volume and Initial Return

As an introductory analysis, I examine the relation between initial return and first-day trading volume of IPOs. If investors were strongly dispositioned to sell winners and hold on to losers even on the first trading day, one would expect a kink at zero return in the volume-initial return relation, such that losers would have smaller volume. However, this pattern is not observed. Figure 1 depicts the median share turnover by initial return category in 2.5% intervals. It seems that IPOs with negative initial return, down to –7.5%, are not any less traded on the first day than are IPOs with a commensurate positive initial return. IPOs with zero initial return, on the other hand, seem to be less traded. As discussed in Section III.E potential underwriter price support can affect trading volume particularly on the first day of trading.

Reese (1998b) finds a positive relation between an IPOs initial return and its trading volume for up to three years after issuance. However, my results on first-day turnover offer support for the existence of a positive initial-return / volume relation only for winner firms. I ran first-day turnover regressions on initial returns in a sample of 5,007 IPOs estimating separate coefficients for negative and positive initial return, as well as a dummy variable for zero initial return[14]. The firms are divided into five groups based on time of issue market capitalization. Free float percentage and offer price are used as control variables, and yearly dummies are added for correcting market cycle effects. The results (not reported) show that the coefficient for positive initial return is significantly positive in all size groups with *t*-values ranging from 5.61 to 15.31. The coefficients for negative initial return are also all positive, but insignificant. In addition, the coefficient for the zero initial return dummy is strongly negative for the three largest size groups (*t*-values from –7.05 to –8.90). It is insignificant for the two smallest size groups, as there are not many observations with zero initial return in these size groups. Based on these results there does not appear to be any asymmetry around zero return that would support a market-wide disposition effect during the first day of trading.

[14] This sample corresponds to the base sample of 5,082 IPOs less IPOs where free float is greater than 100% of outstanding shares, i.e., where there is an error in either SDC on offer amount or in CRSP on the number of shares outstanding.

B. Individual Firms

Table 5 shows the results for individual firm turnover regressions for losers and winners. The parameter estimates and *t*-statistics are in most cases similar for both groups, suggesting a fairly well specified model. In line with previous research, previous days' turnover is positively correlated with current turnover. The coefficient for market turnover is also significant for over 50% of the firms. The relation between contemporaneous turnover and stock return is quite strong, which is also in line with previous studies. Lagged returns do not appear significant for most firms. Three lagged return variables are retained, after experimenting with more lags, as a compromise between parsimony and earlier research suggesting a longer pattern of lags (see Hiemstra and Jones 1994).

The effect of volatility (proxied by the square of the contemporaneous return) seems inconsistent, since coefficients are negative for losers, and the average and median estimates are far apart for winners, 9.68 and –0.69 for winners, respectively. Actually volatility is not significant for approximately 95% of the firms in the loser sample. From a statistical point of view, it should be excluded from the model. However, I retain it in light of earlier strong evidence on the interaction of volume and volatility (see Gallant, Rossi, and Tauchen 1992). The variables proxying seasoning effects (time since offer date in months and time squared) do not seem to have a major role. They are, however, included as a means of detrending the turnover series to ensure stationarity. The residuals from these regressions are used as the dependent variable for the pooled regressions in Tables 6 and 7.

C. Pooled Regressions

In this section I analyze the ability of reference prices to explain abnormal turnover. I find evidence supporting the influence of disposition effect. The results of the pooled regression for losers in Table 6 show that volume is clearly lower when the stock is trading below the offer price. The price range dummies are almost all negative below the offer price, and highly significant through the range 0.75 to 1.00. Crossing the levels 1.00 and 1.05 from below for the first time results in a statistically significantly higher turnover (with *t*-values of 2.8 and 3.4). Dummies for one-month maximum and minimum stock prices are included in the same regression, so the effect of crossing the levels is incremental to attaining new price records. The increase in turnover is slightly stronger with level 1.05. There are 339 cases of first-crossing the level 1.00, and correspondingly, 316 for the level 1.05, of which 67 are joint, i.e, occur on the same day. The correlation coefficient between these dummy-variables is 0.20. Thus the result for the level 1.05 is not driven primarily by the concurrent crossing of the offer price. However, a further 116 crossings of the level 1.05 occur within five trading days since crossing the level 1.00. Hence for over half of the firms the level 1.05 is crossed shortly after the offer price. Therefore a portion of the turnover increase associated with the level 1.05 may be influenced by the earlier infiltration of the offer price. This may be due to the investors' lagged reaction, or, simply, to the persistence of higher trading activity. This hypothesis is investigated at the end of this section.

The fact that level 1.05 is stronger than level 1.00 could suggest that investors use a 'break-even' price as more important a reference price than the nominal purchase price: An investor might break even in his mental account after allowing for transaction costs and a minimum return requirement, perhaps benchmarked against some fixed income investment. However, since this conjecture is not derived from a formal model it should be considered speculative[15]. Other price levels are mostly insignificant, as expected.

The maximum and minimum stock prices appear to be important reference prices by themselves. The coefficients for both one-month-high and one-month-low dummies are highly significant (*t*-values of 26.9 and 18.3). In addition to one month, I considered various alternative time windows for calculating price records. I ran a regression repeatedly and changed the time period for price records with each round, holding the set of other variables constant. The considered periods, in addition to one month, were one week, two weeks, three months, six months, and, finally, the complete history since the IPO. The one-month time window was selected based on a superior *F*-statistic and on earlier evidence by Grinblatt and Keloharju (2001), who find it to be the best choice for explaining selling behavior. Nevertheless, all time windows for calculating price records produce highly significant results.

The results for winners are presented in Table 7. Crossing the level 1.00 from above for the first time produces a stronger effect than the neighboring levels, with a *t*-value of 3.3. The effect of level 1.05 is indistinguishable from zero, suggesting that trading does not increase until the offer price level is infiltrated. As with the loser subsample, attaining new one-month-high or -low prices increases turnover significantly and new highs produce stronger effects than new lows (*t*-

[15] The level 1.00 becomes stronger than level 1.05 if outliers are removed as follows: Exclude the five largest and smallest values for the dependent variable (abnormal volume) on days when first crossing levels 0.95, 1.00, 1.05, and 1.10.

values 68.8 and 48.9). The price range dummies below the offer price are negative, but insignificant. These results do not unambiguously support the disposition effect. Trading volume does decrease when the stock falls below the offer price after the first time. A similar effect occurs with other levels below the offer price (from 0.95 to 0.80). However, if this is due to the disposition effect it is unclear why the effect is not picked up by the price range dummies.

An alternative explanation for the increase in volume at offer price could be that investors who missed out on the stock at the time of the IPO are now willing to buy once the stock is back to offer price[16]. I investigated this possibility as follows. First, this tendency should be particularly strong in hot IPOs, because there are many investors who were prepared to buy much more than what they were allocated. Secondly, if investors think that the fair value for an IPO is the offer price and are happy to buy at that price level also on the aftermarket, then their demand should increase the lower the stock falls. The results for price range dummies do not support this prediction, however. Some support for this interpretation is provided by the results on hot IPOs (initial return $\geq$ 20%, results not reported). There the significant level is not the offer price, but rather the level 0.95, thus showing an increase after falling below the offer price.

As a second specification, I also include interactions between the high and low dummies and a dummy for absolute stock return being greater or equal to 5% to reinforce the design by which I control for stock return effects. By construction, the expected return on days when a new high (low) is attained, is greater (smaller) than the expected return conditional on return being positive (negative). The interaction variables are significant for winners, but only LO1M $\times$ $R \geq 5\%$ is significant for losers. The signs of the coefficients are all positive. Almost all crossing variables are slightly reduced when these interactions are included, but the results are qualitatively similar overall.

The more time it takes for the crossing to occur, the more turnover there is in the original investor base, and the offer price may not carry any special meaning to new investors. However, the rate at which the status of the offer price weakens is not very high. When observations only after 40 days since the offer are included the status of the offer price actually strengthens for both losers and winners. The next level, i.e., 0.95 for losers and 1.05 for winners, gets weaker. The offer price is stronger for losers also after 60 days (it was not tested for winners).

If surpassing the offer price is really a significant determinant of turnover then the effect should persist for more than just one day. To find this out I construct weekly dummies for first-

[16] A similar argument could also be used to explain increased volume at new record low prices.

crossing various price levels. A dummy for the first week takes the value of one during the five trading days following the crossing day, dummy for the second week for the next five days, and so on, up to week number 4. I include levels from 0.95 to 1.45, as well as all new record high prices. As control variables I use the cumulative abnormal volume over the previous week (WABVOL) for each day, daily all-time highs and lows, and the price range dummies. The results of estimating this regression for the loser sample are presented in Table 8. The results show an increase in trading volume up to two weeks after a new all-time high. Incremental to that, the results show a highly significant increase after crossing the offer price for two weeks. The t-value for the first week is 6.5 and the coefficient is nine times larger than the coefficient for the all-time high. Some coefficients for the first week are also significant with other levels (1.05, 1.20, 1.35), but they are much less impressive. In sum, these results show strong persistence in higher volume associated with surpassing the offer price.

Overall, the adjusted R^2:s of all the regressions are low, in the order of one percent. This is partly a result of the two step method, where the pooled regressions are used for explaining the residuals from first step individual firm regressions. Nevertheless, it also shows that daily volume is mostly unpredictable.

D. The Magnitude of the Effect

This section discusses the impact of the reference price effects on turnover. Every first-time crossing event from below is also a one-month high. Crossing the offer price also causes the price range to change. Thus the total effect of crossing the level 1.00 from below for the first time is the sum of the estimated coefficients for HI1M, 1st CROSS 1.00 B, and the change in the price range dummies. Assuming that the price moves from the range [0.95, 1.00[to [1.00, 1.05[, there is a total increase of 0.52 in log turnover. This translates to a 68% increase in turnover. About half of the increase in log turnover is attributed to attaining a new monthly high price. About a third is explained by the event of crossing the offer price and the remaining one tenth of the increase comes from switching from price range [0.95, 1.00[to [1.00, 1.05[.

This compares to other key determinants of turnover as follows. Using the mean coefficient estimated from the individual firm regressions, a one standard deviation increase in positive stock return leads to a 90% increase in turnover. This is roughly comparable to the effect of crossing the offer price. Other well-known drivers of trading volume, namely the previous day's volume and market volume, cause increases of 36% and 20%, respectively. In other words, it would take a three standard deviation increase in market volume to produce an effect on an individual IPO's volume similar to crossing the offer price.

The first-cross dummies for the levels 1.00 and 1.05 have higher standard errors than the high and low dummies. This would suggest that the high/low effect is more robust across firms. However, the difference in standard errors is largely explained by the greater number of one-month-highs / lows: the first crossing of a level is a one-time event for a firm, whereas new price records can be attained on any given day. For example, for losers there are about 36 times more one-month highs (12,266 cases) than there are first-crossings of the level 1.00 (339 cases).

In dollar terms, the impact on trading volume is as follows. The average dollar trading volume for a loser firm is $403,000 (Table 4) and mean volume conditional on positive stock return is $580,000. A 68% increase from this level caused by crossing the offer price for the first time thus implies an increase of $396,000 in dollar volume. The median figures are much lower: the median dollar trading volume given positive return is $117,000 of which 68% is $79,000. The contribution of first crossing the level 1.00 and switching from price range [0.95, 1.00[to [1.00, 1.05[, incremental to the one-month-high effect, is 26% (an increase of 0.23 in log turnover). Using these figures the marginal increase in dollar volume, on top of the 49% increase caused by the one-month-high, is $150,000 in the average case and $30,000 in the median case. Thus although there is a substantial impact in relative terms, the absolute dollar amounts are not very large in IPOs with negative initial return.

V. Conclusion

This paper has examined the importance of different reference levels in stock prices for the market as an aggregate. I utilize a unique laboratory for testing the disposition effect, namely the aftermarket trading volume of initial public offerings. I find support for the influence of disposition effect in negative initial return IPOs: trading below the offer price is suppressed compared to trading at prices above the offer price. There is also an increase in turnover at the time the stock exceeds the offer price for the first time. The effect is slightly stronger when the stock price passes the level 1.05 times offer price. The increase in volume lasts for two weeks. Trading volume also increases for positive initial return IPOs on the day the stock price first falls below the offer price. While this finding can be consistent with loss aversion, it is also consistent with other explanations. Overall the results for winner IPOs do not offer clear support for the disposition effect.

Attaining a new maximum or minimum price compared to the past month is associated with a significant increase in turnover in all the IPOs studied. On a daily horizon this effect is more consistent than the one produced by crossing the offer price. It is also significant for the following two weeks, but the longer-term effect is not nearly as strong as that produced by exceeding the offer price. New highs are more important, producing an effect about one and a half times as large as new lows.

In percentage terms, turnover is found to increase 68% as the stock price exceeds the offer price for the first time. More than half of the increase is explained by attaining a new monthly high price. The marginal effect of first-crossing the offer price, or, attaining a new record price, are both associated with turnover changes of similar magnitude as the following well known drivers of a stock's turnover: a one standard deviation increase in previous day's turnover or current day market turnover, or half a standard deviation increase in current day return.

One must be careful when assessing the implications of the above results on trading volume in general. This setting was designed to maximize the impact of the disposition effect: The issue price, common to all investors, forms a natural anchoring point. Furthermore, IPOs generally, and the ones in the loser subsample in particular, are relatively small firms, and almost all known stock market patterns are stronger for small firms than for large firms (Loughran and Ritter 2000). It is thus likely that this study provides an upper bound estimate for the aggregate influence of the disposition effect. Generally the effect is probably weaker.

Further empirical research is needed for uncovering the potential effects of reference points on asset returns, in addition to volume studied here. These studies can shed more light on whether asset pricing models that incorporate loss aversion and reference prices are likely to be successful.

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Table 1

Sample Selection Criteria

# Firms left	# Excluded	Reason for exclusion
7,138		All U.S. IPOs January 1, 1980 - December 31, 1996 in SDC where data available matched with CRSP daily files.
5,884	1,254	Initial trading date in CRSP more than 10 days after the IPO date in SDC
5,463	421	Gross proceeds $3 million or less or offer price $1 or less per share
5,403	60	Less than one year (254 trading days) of data
5,082	321	More than 15 days of missing volume

Table 2

Descriptive Statistics of IPOs by Initial Return Type and for the Subsamples

Descriptive statistics by initial return type and for the winner- and loser subsamples used in the regression analyses of trading volume. A firm is classified as a winner, loser, or neutral based on its first day return so that the return is positive for winners, negative for losers and zero for neutrals. The offer dates are between January 1, 1980 and December 31, 1996.

	Offer year	Initial return	Gross proceeds, millions	Offer price	Market capitalization, millions	% of shares offered
All firms, *N* = 5,082 (100%)						
Mean	1990.4	10.54 %	50.65	11.31	134.42	42.2 %
Median	1992	3.57 %	21.20	11.00	60.03	34.7 %
St. Deviation	4.35	20.05 %	118.26	5.37	426.30	24.3 %
Winners, *N* = 3,444 (68%)						
Mean	1990.5	16.93 %	43.18	11.48	136.43	38.1 %
Median	1992	9.56 %	20.80	11.00	60.39	33.1 %
St. Deviation	4.3	21.18 %	103.55	5.33	467.79	20.6 %
Losers, *N* = 775 (15%)						
Mean	1990.4	-6.14 %	35.34	9.88	91.63	44.0 %
Median	1992	-3.56 %	13.80	9.50	34.70	37.3 %
St. Deviation	4.4	7.81 %	120.89	6.24	342.21	25.5 %
Neutrals, *N* = 863 (17%)						
Mean	1990.2	0.00 %	94.25	11.92	155.93	54.3 %
Median	1991	0.00 %	37.50	11.50	79.92	41.7 %
St. Deviation	4.4	0.00 %	155.41	4.37	281.11	32.9 %
Winner subsample, firms with initial return >0 that cross the offer price from above for the first time between days 21 and 508, *N* = 1,712						
Mean	1990.8	20.6 %	42.10	11.07	133.09	38.7 %
Median	1992	13.4 %	19.75	10.50	57.67	33.3 %
St. Deviation	4.4	22.7 %	107.43	5.39	444.75	25.5 %
Loser subsample, firms with initial return <0 that cross the offer price from below for the first time between days 21 and 508, *N* = 342						
Mean	1989.2	-6.4 %	25.64	9.31	65.09	46.4 %
Median	1989	-4.2 %	13.15	9.00	34.45	37.9 %
St. Deviation	4.29	6.6 %	49.19	4.97	101.84	32.7 %

Table 3

Variables Used in the Regressions and Their Descriptions.

Panel A. Explanatory variables in individual firm (step one) regression, [X_i in (1)].
A model of normal volume is estimated for each firm separately. Dependent variable: logarithm of daily turnover (number of shares traded / number of shares outstanding).

Variable	Description
Volume variables	
Market Turnover	(logarithm of) Aggregate number of shares traded divided by the aggregate number of shares outstanding. Three smallest deciles of firms by market capitalization are excluded.
Turnover	(logarithm of) Number of firm *i* shares traded divided by the number of shares outstanding.
Turnover (–*n*)	(logarithm of) Turnover at day –*n* relative to observation day, i.e. lagged *n* trading days.
Seasoning variables	
Time	Time in months relative to offer date.
Time^2	Time in months squared.
Stock return variables	
R	Daily logarithmic stock return.
MAX[*R*, 0]	Return, if it is positive. Zero if return is negative.
–MIN[*R*, 0]	Absolute value of return, if return is negative. Zero if return is positive.
Volatility	The daily stock return squared.
R (–*n*)	Stock return at day –*n* relative to observation day, i.e. lagged *n* trading days.
R[–5, –3]	Stock return over days –5 to day –3 relative to observation day, i.e. calculated from the closing price of day –6 to the closing price of day –3.

Table continues on next page.

Table 3 Continued

Panel B. Explanatory variables in pooled (step two) regression [Z in (2)].
A pooled regression with step one residuals as the dependent variable is estimated for determining the magnitude of behavioral effects.

Variable	Description
HI1M	Previous-month-high dummy: 1 if the return index indicates the highest value during the previous month (21 trading days), 0 otherwise.
LO1M	Previous-month-low dummy: 1 if the return index indicates the lowest value during the previous month (21 trading days), 0 otherwise.
1st CROSS *X* B	Dummy variable: 1 if the stock return index crossed the level *x* relative to offer price *from below* for the first time, 0 otherwise. E.g. 1st CROSS 1.05 B gets the value of 1 on the day that the stock price for the first time closes above the level of 1.05 times offer price, coming *from below* the level (Return index is used so stock price is adjusted for dividends and splits).
1st CROSS *X* A	Dummy variable: 1 if the stock return index crossed the level *x* relative to offer price *from above* for the first time, 0 otherwise. E.g. 1st CROSS 1.05 A gets the value of 1 on the day that the stock price for the first time closes below the level of 1.05 times offer price, coming *from above* the level. (Return index is used so stock price is adjusted for dividends and splits).
CROSS 1st,…,*N*th *x* B (or A)	Dummy variable: 1 if the stock return index crossed the level *x* relative to offer price *from below* (B), or *from above* (A), 0 otherwise. Compared to 1st CROSS this variable ignores the order of the crossing (it does not make a distinction between the first, second, or the *n*th time). It gets the value 1 every time the stock goes over (CROSS 1st,...,Nth *X* B) or under (CROSS 1st,...,Nth *X* A) the level *X*, such that it comes from the other side of the level *x*. E.g. CROSS 1st,...,Nth 1.05 B gets the value of 1 on all the days that the stock price closes above the level of 1.05 times offer price, such that the previous day's close lies below the level of 1.05 times offer price. (Return index is used so stock price is adjusted for dividends and splits).
CROSS 2nd,...,*N*th *x* B (or A)	Same as CROSS 1st,…,*N*th *X* B (or A), except that the first crossing is ignored. That is, CROSS 2nd,...,*N*th *X* B (or A) = CROSS 1st,…,*N*th *X* B (or A) – 1st CROSS *X* B(or A).
RANGE [X_1, X_2[	Dummy variable: 1 if the stock price (using a return index) is inside the price range [X_1, X_2[, 0 otherwise. E.g. RANGE [1.05, 1.10[gets the value of 1 on all days that the return index indicates a gain of greater than or equal to 5% but less than 10% from the offer price, 0 otherwise.
HI1M × I($R \geq 5\%$)	Interaction dummy between HI1M and I(R ≥ 5%), where I(R ≥ 5%) is 1 whenever the return is greater or equal to 5%.
LO1M × I($R \leq -5\%$)	Interaction dummy between LO1M and I($R \leq -5\%$), where I($R \leq -5\%$) is 1 whenever the return is smaller or equal to –5%.

Table 4

Summary Statistics of Daily Return and Turnover Variables for the Loser and Winner Subsamples

These statistics are calculated from pooled firm days of 342 initial loser IPOs and 1,712 initial winner IPOs. The data period for each firm covers the first two years of trading with the first four weeks excluded (trading days from 21 to 508 with respect to the IPO date). The losers and winner subsamples are as used in the regressions: Only losers (winners) that cross the level 1.00 from below (above) for the first time between days 21 and 508 are included. Days with no trading are excluded. The sample period is Jan. 1, 1980 to Dec. 31, 1997.

	Losers 342 firms and 146,090 firm-days			Winners 1,712 firms and 749,223 firm-days		
Variable	Mean	Median	Standard deviation	Mean	Median	Standard deviation
Turnover	0.50%	0.20%	1.16%	0.58%	0.24%	1.25%
Turnover | $R > 0$	0.66%	0.27%	1.53%	0.72%	0.32%	1.37%
Market turnover	0.33%	0.32%	0.09%	0.34%	0.33%	0.09%
Dollar trading volume	403,270	71,000	2,055,248	865,563	138,225	3,494,059
Dollar trading volume | $R > 0$	580,166	116,550	2,644,614	1,171,738	220,106	4,361,474
R	0.1%	0	4.96%	0.03%	0	5.12%
R | $R > 0$	4.21%	2.86%	5.02%	4.18%	2.85%	4.90%
R | $R < 0$	–3.78%	–2.70%	3.73%	–3.87%	–2.75%	–3.91%
Volatility	0.28%	0.07%	0.98%	0.26%	0.03%	2.51%

Table 5

Average and Median Results of the Individual Firm Daily Turnover Regressions

Dependent variable: logarithm of daily turnover. Average and median coefficients, *t*-values below in parentheses, and adjusted R^2:s of individual firm regressions for initial loser and initial winner firms. Only losers (winners) that cross the level 1.00 from below (above) for the first time between days 21 and 508 are included (a total of 342 losers, and 1,712 winners). Each firm has a maximum of 487 daily observations. The residuals of these regressions are used as the dependent variable with the pooled regressions. The sample period is Jan. 1, 1980 to Dec. 31, 1997.

	Losers		Winners	
	Averages	Medians	Averages	Medians
Constant	-0.77	-0.78	0.18	0.39
	(-0.32)	(-0.45)	(0.19)	(0.23)
Market Volume	0.68	0.66	0.79	0.79
	(2.31)	(2.28)	(2.71)	(2.61)
Volume(–1)	0.20	0.20	0.21	0.20
	(4.40)	(4.39)	(4.61)	(4.47)
Volume(–2)	0.09	0.09	0.09	0.09
	(2.16)	(2.07)	(2.13)	(2.09)
Time	-0.02	-0.03	-0.05	-0.05
	(-0.34)	(-0.69)	(-1.00)	(-1.25)
$Time^2$	0.00	0.00	0.00	0.00
	(0.25)	(0.46)	(0.72)	(0.92)
MAX[*R*, 0]	12.76	11.01	10.98	10.04
	(3.00)	(2.72)	(2.87)	(2.63)
–MIN[*R*, 0]	8.83	7.48	8.27	7.31
	(2.04)	(1.81)	(2.12)	(1.95)
Volatility	-3.91	-3.16	9.68	-0.69
	(-0.40)	(-0.15)	(-0.18)	(-0.05)
R (–1)	1.74	1.62	0.70	0.55
	(1.15)	(1.11)	(0.46)	(0.43)
R(–2)	1.15	0.93	0.43	0.32
	(0.75)	(0.72)	(0.29)	(0.27)
R[–5, –3]	0.88	0.85	0.37	0.24
	(0.76)	(0.77)	(0.31)	(0.25)
Adjusted R^2	27.6 %	25.7 %	25.5 %	23.0 %
Number of firms	342		1,712	
Maximum number of observations per firm: 487				

Table 6

Results of the Daily Pooled Turnover Regression for Loser –Type Firms

Sample: Losers (initial return < 0) that cross the level 1.00 (offer price) from below for the first time between days 21 and 508 (342 firms). Dependent variable: residuals from equation (1), [Results of estimating (1) are reported in Table 5]. HI1M and LO1M are dummies for new record high and low stock prices attained during the past 21 trading days. 1st CROSS *X* B is a dummy variable for crossing a stock price level (using a return index) from below for the 1st time, where *X* is in units of offer price. CROSS 1st,…,*N*th *X* B is a dummy for generally crossing a stock price level from below, where *X* is in units of offer price. CROSS 2nd,…,*N*th *X* B is a dummy for crossing a stock price level from below generally, except for the first time, where *X* is in units of offer price. RANGE [X_1, X_2[is a dummy for the stock trading in a particular range in relation to offer price: at or above X_1, and strictly below X_2. First specification is the base case. Second specification adds interaction dummies between HI1M and I(R ≥ 5%), and LO1M and I(R ≤ –5%), where I(*E*) is indicator function for event *E*, and *R* is the daily stock return. *t*-values are calculated using a heteroskedasticity consistent covariance matrix. The sample period is Jan. 1, 1980 to Dec. 31, 1997.

	Base case - no interactions		Including return - HI/LO interactions	
	Coefficient	t-statistic	Coefficient	t-statistic
Constant	-0.01	-0.43	0.00	-0.34
HI1M	0.29	26.87	0.28	23.26
LO1M	0.20	18.35	0.17	12.18
HI1M × I(R ≥ 5%)			0.03	1.31
LO1M × I(R ≤ –5%)			0.08	3.95
1st CROSS 0.95 B	0.08	0.75	0.07	0.65
1st CROSS 1.00 B	0.17	2.77	0.17	2.70
1st CROSS 1.05 B	0.18	3.35	0.17	3.22
1st CROSS 1.10 B	0.08	1.43	0.07	1.33
1st CROSS 1.15 B	0.08	1.27	0.07	1.21
1st CROSS 1.20 B	0.15	2.39	0.15	2.32
1st CROSS 1.25 B	0.05	0.70	0.04	0.63
1st CROSS 1.30 B	0.13	2.04	0.13	1.98
1st CROSS 1.35 B	-0.10	-1.51	-0.10	-1.58
1st CROSS 1.40 B	0.10	1.42	0.09	1.36
1st CROSS 1.45 B	-0.03	-0.50	-0.04	-0.56
1st CROSS 1.50 B	0.12	1.77	0.11	1.69
1st CROSS 1.55 B	-0.06	-0.86	-0.06	-0.95
CROSS 1st,…,Nth 0.70 B	-0.11	-3.05	-0.11	-3.11
CROSS 1st,…,Nth 0.75 B	-0.05	-1.56	-0.05	-1.63
CROSS 1st,…,Nth 0.80 B	-0.04	-1.22	-0.04	-1.30
CROSS 1st,…,Nth 0.85 B	-0.02	-0.72	-0.02	-0.82
CROSS 1st,…,Nth 0.90 B	0.03	1.18	0.03	1.07
CROSS 2nd,…,Nth 0.95 B	-0.07	-2.48	-0.08	-2.57
CROSS 2nd,…,Nth 1.00 B	-0.01	-0.38	-0.01	-0.44
CROSS 2nd,…,Nth 1.05 B	-0.08	-2.49	-0.08	-2.55
CROSS 2nd,…,Nth 1.10 B	-0.06	-1.78	-0.06	-1.84
CROSS 2nd,…,Nth 1.15 B	-0.04	-0.99	-0.04	-1.05
CROSS 2nd,…,Nth 1.20 B	0.01	0.18	0.01	0.13
CROSS 2nd,…,Nth 1.25 B	-0.09	-2.22	-0.09	-2.26
CROSS 2nd,…,Nth 1.30 B	0.02	0.42	0.02	0.38

CROSS 2nd,…,Nth 1.35 B	0.00	-0.02	0.00	-0.07
CROSS 2nd,…,Nth 1.40 B	0.07	1.69	0.07	1.65
CROSS 2nd,…,Nth 1.45 B	-0.08	-1.89	-0.09	-1.93
CROSS 2nd,…,Nth 1.50 B	0.00	0.10	0.00	0.05
CROSS 2nd,…,Nth 1.55 B	0.00	-0.03	0.00	-0.07
RANGE [0.00, 0.10[	-0.05	-0.89	-0.05	-1.01
RANGE [0.10, 0.20[	0.03	0.61	0.02	0.46
RANGE [0.20, 0.30[	-0.06	-1.74	-0.07	-1.91
RANGE [0.30, 0.40[	0.01	0.32	0.00	0.13
RANGE [0.40, 0.50[	-0.04	-1.69	-0.04	-1.86
RANGE [0.50, 0.60[	-0.03	-1.68	-0.03	-1.86
RANGE [0.60, 0.70[	-0.09	-5.23	-0.09	-5.35
RANGE [0.70, 0.75[	-0.05	-2.52	-0.05	-2.57
RANGE [0.75, 0.80[	-0.08	-4.60	-0.08	-4.63
RANGE [0.80, 0.85[	-0.06	-3.17	-0.06	-3.19
RANGE [0.85, 0.90[	-0.08	-4.30	-0.08	-4.29
RANGE [0.90, 0.95[	-0.07	-3.87	-0.07	-3.84
RANGE [0.95, 1.00[	-0.06	-3.29	-0.06	-3.26
RANGE [1.05, 1.10[	0.04	1.90	0.04	1.91
RANGE [1.10, 1.15[	0.05	2.22	0.05	2.23
RANGE [1.15, 1.20[	0.00	0.18	0.00	0.19
RANGE [1.20, 1.25[	-0.05	-1.88	-0.05	-1.87
RANGE [1.25, 1.30[	0.01	0.44	0.01	0.46
RANGE [1.30, 1.40[	0.00	0.21	0.00	0.24
RANGE [1.40, 1.50[	0.02	0.81	0.02	0.82
RANGE [1.50, 1.60[	0.01	0.48	0.01	0.51
RANGE [1.60, 1.70[	-0.02	-0.92	-0.02	-0.94
RANGE [1.70, 1.80[	0.00	0.07	0.00	0.04
RANGE [1.80, 1.90[	-0.02	-0.73	-0.02	-0.76
RANGE [1.90, 2.00[	-0.02	-0.83	-0.02	-0.86
RANGE ≥ 2.00	0.01	0.70	0.01	0.64
Adjusted R^2	0.9%		0.9%	
# of observations	146,051		146,051	
# of variables	59		61	

Table 7

Results of the Daily Pooled Turnover Regression for Winner –Type Firms

Sample: Winners (initial return > 0) that cross the level 1.00 (offer price) from above for the first time between days 21 and 508 (1,712 firms). Dependent variable: residuals from equation (1), [Results of estimating (1) are reported in Table 5]. HI1M and LO1M are dummies for new record high and low stock prices attained during the past 21 trading days. 1^{st} CROSS *X* A is a dummy variable for crossing a stock price level (using a return index) from above for the 1^{st} time, where *X* is in units of offer price. CROSS 1^{st},…,*N*th *X* A is a dummy for generally crossing a stock price level from above, where *X* is in units of offer price. CROSS 2^{nd},…,*N*th *X* A is a dummy for crossing a stock price level from above generally, except for the first time, where *X* is in units of offer price. RANGE [X_1, X_2[is a dummy for the stock trading in a particular range in relation to offer price: at or above X_1, and strictly below X_2. First specification is the base case. Second specification adds interaction dummies between HI1M and I(R ≥ 5%), and LO1M and I(R ≤ –5%), where I(*E*) is indicator function for event *E*, and *R* is the daily stock return. *t*-values are calculated using a heteroskedasticity consistent covariance matrix. The sample period is Jan. 1, 1980 to Dec. 31, 1997.

	Base case - no interactions		Including return - HI/LO interactions	
	Coefficient	t-statistic	Coefficient	t-statistic
Constant	-0.05	-8.01	-0.05	-7.69
HI1M	0.31	68.84	0.29	52.11
LO1M	0.22	48.88	0.19	34.51
HI1M × I(R ≥ 5%)			0.06	6.93
LO1M × I(R ≤ –5%)			0.08	9.48
1st CROSS 1.20 A	0.07	1.47	0.05	1.01
1st CROSS 1.15 A	0.02	0.33	0.01	0.11
1st CROSS 1.10 A	0.06	1.49	0.05	1.19
1st CROSS 1.05 A	0.03	0.77	0.01	0.36
1st CROSS 1.00 A	0.09	3.26	0.08	2.91
1st CROSS 0.95 A	0.06	2.10	0.05	1.61
1st CROSS 0.90 A	0.03	0.99	0.01	0.43
1st CROSS 0.85 A	0.00	0.13	-0.01	-0.31
1st CROSS 0.80 A	0.07	2.28	0.05	1.57
CROSS 2nd,…,Nth 1.20 B	-0.02	-1.67	-0.03	-2.09
CROSS 2nd,…,Nth 1.15 B	-0.02	-1.10	-0.02	-1.45
CROSS 2nd,…,Nth 1.10 B	-0.01	-0.65	-0.01	-0.98
CROSS 2nd,…,Nth 1.05 B	-0.02	-1.82	-0.03	-2.18
CROSS 2nd,…,Nth 1.00 B	-0.05	-3.60	-0.06	-3.89
CROSS 2nd,…,Nth 0.95 B	-0.04	-2.73	-0.05	-3.03
CROSS 2nd,…,Nth 0.90 B	-0.04	-2.74	-0.05	-3.06
CROSS 2nd,…,Nth 0.85 B	-0.07	-4.51	-0.08	-4.79
CROSS 2nd,…,Nth 0.80 B	-0.09	-5.09	-0.09	-5.48
RANGE [0.00, 0.70[	0.01	1.50	0.01	0.80
RANGE [0.70, 0.75[	0.00	-0.08	0.00	-0.33
RANGE [0.75, 0.80[	0.00	0.41	0.00	0.38
RANGE [0.80, 0.85[	0.00	0.49	0.00	0.43
RANGE [0.85, 0.90[	0.00	0.30	0.00	0.28
RANGE [0.90, 0.95[	-0.01	-1.31	-0.01	-1.32
RANGE [0.95, 1.00[	-0.01	-0.84	-0.01	-0.80

RANGE [1.05, 1.10[	0.01	0.97	0.01	1.00
RANGE [1.10, 1.15[	0.00	-0.26	0.00	-0.22
RANGE [1.15, 1.20[	0.00	-0.09	0.00	-0.05
RANGE [1.20, 1.25[	0.01	1.51	0.01	1.40
RANGE [1.25, 1.30[	0.01	0.61	0.00	0.49
RANGE ≥ 1.30	0.02	2.91	0.02	2.75
Adjusted R^2	0.8%		0.8%	
# of observations	764,919		764,919	
# of variables	34		36	

Table 8

Impact of All-Time-Highs and Crossing Price Levels over the Following Weeks

Sample: Losers (initial return < 0) that cross the level 1.00 (offer price) from below for the first time between days 21 and 508 (342 firms). Dependent variable: residuals from equation (1), [Results of estimating (1) are reported in Table 5]. The table presents a grid of weekly dummies and price levels (in units of offer price). Each dummy for week 1 receives the value 1 on the five days following the first crossing of ‘Level’, dummy for week 2 receives the value 1 on days 6 to 10, week 3 on days 11 to 15, and week 4 on days 16 to 20. ALL-TIME HIGH and ALL-TIME LOW are dummies for new record high and low stock prices. WABVOL is a cumulative sum of the prior five-day abnormal volume. Price range dummies (results not reported) are also included as explanatory variables. *t*-values (in parentheses) are calculated using a heteroskedasticity consistent covariance matrix. The sample period is Jan. 1, 1980 to Dec. 31, 1997.

	Week after exceeding Level			
Level	1	2	3	4
ALL-TIME HIGH	0.02	0.02	0.00	-0.02
	(3.58)	(3.45)	(-0.43)	(-2.87)
0.95	0.04	-0.01	-0.11	0.01
	(0.86)	(-0.13)	(-2.08)	(0.25)
1.00	0.18	0.11	0.04	0.07
	(6.50)	(3.58)	(1.28)	(2.35)
1.05	0.08	0.03	0.04	0.01
	(2.62)	(0.98)	(1.04)	(0.24)
1.10	0.00	-0.02	-0.05	-0.04
	(-0.08)	(-0.60)	(-1.35)	(-1.00)
1.15	0.06	0.09	0.11	0.09
	(1.66)	(2.32)	(2.74)	(2.32)
1.20	0.08	0.05	0.03	0.04
	(2.28)	(1.23)	(0.75)	(1.05)
1.25	0.02	-0.05	0.01	-0.02
	(0.55)	(-1.27)	(0.13)	(-0.45)
1.30	-0.01	0.07	0.08	0.00
	(-0.30)	(1.54)	(1.59)	(-0.02)
1.35	0.10	0.06	0.05	0.09
	(2.13)	(1.23)	(1.03)	(1.90)
1.40	-0.02	-0.02	0.01	-0.03
	(-0.37)	(-0.45)	(0.11)	(-0.64)
1.45	0.02	0.02	0.06	0.09
	(0.52)	(0.39)	(1.41)	(2.00)
WABVOL	0.02	(16.83)		
ALL-TIME HIGH	0.26	(18.46)		
ALL-TIME LOW	0.23	(10.73)		
Adjusted R^2	1.0%			
# of observations	146,051			
# of variables	69			

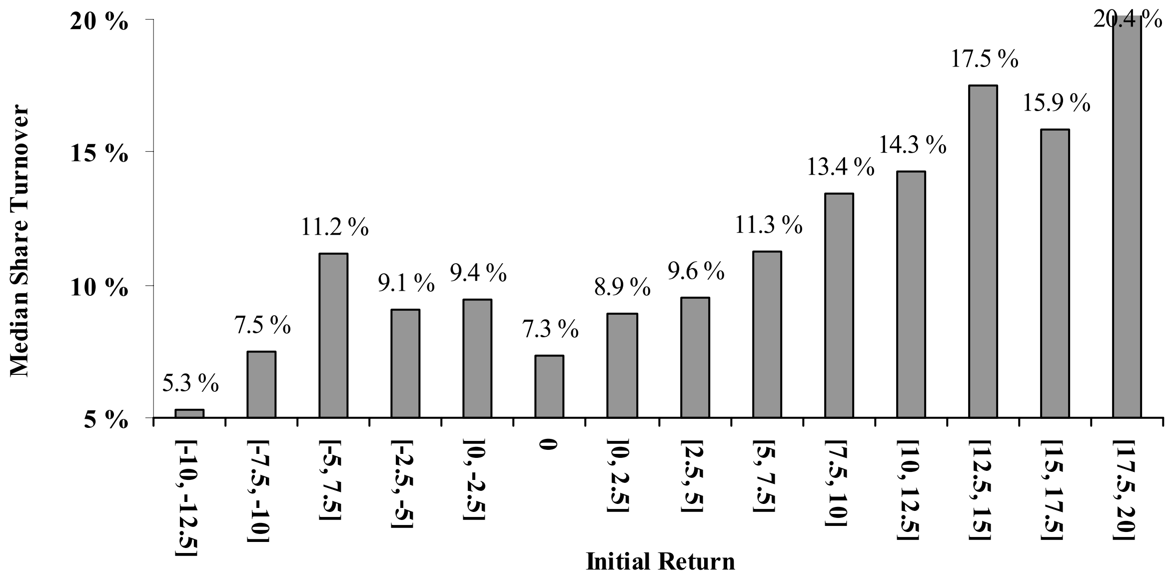

Figure 1. First day turnover and initial return. The bars represent the median first-day share turnover in initial return category. From the firms in the base sample with volume data available on the first day of trading (5,108 firms) ones with initial return between –12.5% and 20% are selected (4,487 firms, or 88%) and divided into categories based on initial return, with 2.5% increments. A separate category is added for firms with exactly zero initial return. The lowest return category, [–10, –12.5], contains the smallest number of firms (35). The next 2.5% interval, [–12.5, –15] has only 18 firms and a cutoff is therefore placed at –12.5%. Share turnover is calculated as the number of shares traded divided by the number of shares outstanding. The offer dates are between Jan. 1, 1980 and Dec. 31, 1996.

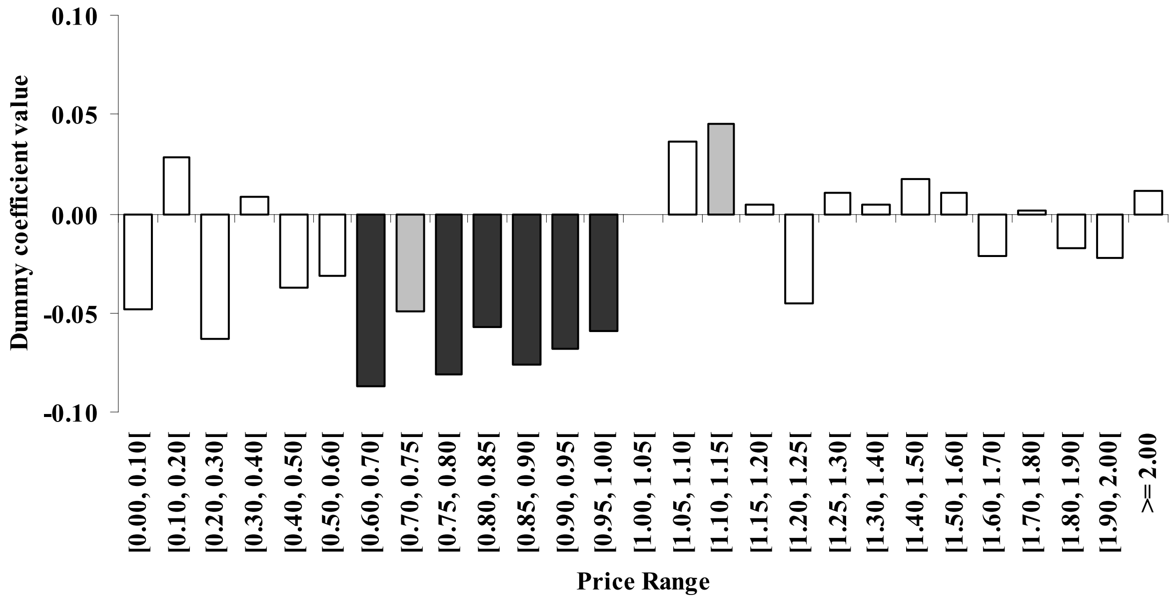

Figure 2. Abnormal turnover and the price range relative to offer price. The bars represent the estimated regression coefficient values taken from Table 6 for price range dummies, where the dependent variable is abnormal volume (residuals from equation 1). The dark bars indicate statistical significance at the 1% level, gray bars at the 5% level. Sample: Losers (initial return < 0) that cross the level 1.00 (offer price) from below for the first time between days 21 and 508 (342 firms). The sample period is Jan. 1, 1980 to Dec. 31, 1997.