Post-IPO Flipping and Turnover: Predictive Factors for Long-Run Returns

Boulat A. Bash
Dartmouth College
boulat@dartmouth.edu
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Abstract

I show that, consistent with Krigman, Shaw, and Womack's (1999) findings on flipping activity, one-year IPO returns are predicted by first-day flipping activity. That is, when block flipping is low, returns are high. I extend their flipping methodology to incorporate the information through the end of the quiet period (25 calendar days after the IPO) and show that flipping during this period is even more informative than the first-day signal. In addition, I find that a higher average relative level of turnover to the end of the quiet period (volume as a percent of shares offered) is significant in predicting higher one-year stock returns beginning after the quiet period. Finally, in examining the time series of flipping from 1993 through 1999, I show that Depository Trust Company's (DTC) IPO tracking system which began in 1997 has had a substantial impact on lowering the amount of subsequent flipping.

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Over the years, a number of market phenomena were identified in financial literature that seem to be potential profit opportunities for savvy investors. Unfortunately, one of the reasons why many of these anomalies are not exploited is the difficulty in replicating the underlying academic studies. Practitioners look not only to identify the incongruities, but also to test their robustness as an investment strategy. However, the needed data may be prohibitively costly to process or even unavailable for practitioners. In this work I examine the short-to-medium term performance of IPOs vis-à-vis observable factors that drive the decision-making process of the investing public. I extend the dataset used for a previous study on the subject by Krigman, Shaw, and Womack (1999). I replicate their original results, showing that the many of the main conclusions hold in a later time series. Furthermore, I extend their examination of "flipping" (10,000 shares or more blocks traded on the bid side of the market) to include flipping in the entire 25 day period up to the end of the quiet period. I also examine "equilibrium turnover" (average volume in days 5 through 25) and find that companies with the highest turnover are most likely to have high future one-year returns.

Krigman, Shaw, and Womack (1999) (KSW) use first-day trading characteristics— first-day return and bid-side block volume in particular — to predict short- and medium-term IPO performance. Their basic premise is that the actions of institutional investors that have obtained new issue allocations are useful for inferring future returns. The academic literature often ascribes such predictive ability to these large entities, citing possibilities of superior information and investment management skill. It is in these investors' best interest, if they are informed, to hold on to the shares that will potentially perform well and immediately sell the stock that is likely to underperform. Their ability to do so will drive the selling pressure on the first day of trading of an overpriced issue. This is called “flipping,” which has been widely publicized in the popular press.

The essential findings of KSW are that IPO first-day performance can be used to predict longer-term stock returns. Firms with relatively high first-day return continue to perform well. They have also shown that institutional investors tend to “flip” the issues with subsequent relatively poor future returns. On the basis of their conclusions, they suggest a profitable trading strategy of buying “IPOs with positive (but not *too* positive) returns *and* with relatively low sell-motivated block trading activity on the first day” (KSW, p. 1043).

My approach is to first replicate KSW results for their testing period from January 1993 through May 1995, and then extend the time series using my more recent sample. I find that the main findings of KSW from 1993 through 1995 hold into 1999.

I extend KSW framework in two ways. First, I collect and analyze the data from the first 25 days of trading in the IPO, or the quiet period. In the first 25 days of an IPO’s life, information is practically non-existent because the SEC requires a “quiet period” where the underwriting investment banks must not comment. Without sell-side research output, information available on these newly-public firms is limited to 1) the financial information in the prospectus and 2) the prices and volume of shares traded.

My second original contribution is to examine the quiet period "normalized" turnover (volume as a percent of shares offered). We know from KSW that large-block sell volume can serve as a proxy for institutional trading and be a powerful predictor of the future returns. However, there is no reason not to ask a more general question of whether overall volume can predict the IPO performance. While the efficient markets hypothesis states that volume cannot be used to infer returns in the future, some research exists which disputes that claim outside of the IPO context[1].

This paper is organized as follows. Section I describes the construction of the dataset. Section II presents the extension and tests of various approaches described in KSW. Section III concludes. Appendix contains details on trade-signing algorithm.

I. Data

I use Securities Data Company's (SDC) database to identify 3,891 IPOs in the period beginning in 1993 and ending in 1999. SDC database contains general descriptive IPO data, including shares offered, underwriters, issuer, etc. Since I examine six-month post-IPO returns, I only use the data from January 1993 though June 1999. I start with data in January 1993 as that is when NYSE Transactions and Quotes (TAQ) intra-day individual trade data (prices and volumes) becomes available.

[1] For example, Lee and Swaminathan (2000) show that low-volume stocks outperform high-volume stocks, controlling for price momentum. Also High-volume losers and low-volume winners show greater persistence of momentum compared to low-volume losers and high-volume winners. Authors claim that high-volume losers and low-volume winners became losers and winners only recently, and thus will remain so for longer period of time. The opposite logic applies to low-volume losers and high-volume winners.

I split my dataset into two parts. First, one corresponding to the period in KSW's study: January 1993 through May 1995. The second subset is the subsequent period, June 1995 through June 1999, so that I can perform out-of-sample tests.

In my analysis, I only use stocks included in Center for Research in Security Prices (CRSP) and TAQ databases. Consistent with prior studies that examined IPO behavior, I eliminate financial corporations. My method of screening out financial firms by their SDC SIC number[2] differs from KSW, but I find little dissimilarity in the results.[3] Furthermore, I restrict the sample by excluding small IPOs. KSW point out that institutions are not likely to invest in the smallest IPOs. Since this study concentrates on the predictive power of observable decisions by institutional investors, smaller stocks with little economic significance only add noise to the model.[4] I use KSW's criteria and delete any security with pro-forma market capitalization less than $50 million and offering share price less than $8.

The TAQ database contains trade and quote data used in inferring trading patterns in IPOs. I was able to collect data on over 95% of the SDC IPOs. The fraction excluded due to missing and erratic data is small, especially considering the complexity of the TAQ database. While KSW collect first 5 days of trading data for their IPOs, I collect 25. This corresponds to the quiet period mandated by SEC.

[2] Financial companies are classified from 6000 to 6999 by SIC. I delete firms in this range.
[3] Laurie Krigman generously provided the dataset and I was able to match my dataset to KSW's. I find that KSW omit 23 of my IPOs, while I miss 30 of theirs.
[4] Trading in block of 10,000 shares or above makes up 43% of first day share volume for 529 smaller IPOs that I exclude, versus 64% for the stocks in my sample. Percentage of block trades as well as flipping ratio is lower as well.

After removing a small number of datapoints due to missing CRSP excess return data, my sample contains 604 IPOs from January 1993 through May 1995, including 159 on the NYSE, 17 on the AMEX, and 428 on NASDAQ.[5] The sample from June 1995 through June 1999 contains 1,341 IPOs, including 274 on the NYSE, 29 on the AMEX, and 1,038 on the NASDAQ.

II. Predicting the performance of IPOs from return and volume data

Krigman, Shaw, and Womack (1999) take a two-factor approach to analyzing the one-year returns of new IPO firms. My first task was to replicate their results; the following summarizes how they obtain their factors and my extensions of their tests.

A. Replicating KSW results over a longer time series

Krigman, Shaw, and Womack (1999) report that various stock market indices including NASDAQ[6] composite and CRSP equal-weighted provide similar results. However, there are four reasons why using CRSP market capitalization (size) decile index is more appropriate. First, it corresponds to the benchmark likely to be used by investment managers. Second, size adjusting mediates bias in the returns, as most IPOs

[5] From January 1993 through May 1995, KSW work with 611 IPOs in the same period, including 114 IPOs on the NYSE, 7 on the AMEX, and 490 on NASDAQ.
[6] 75% of mine and 80% of KSW's IPOs trade on NASDAQ.

are relatively smaller. Third, value weighting reduces bias in compounding. Fourth, this index is commonly used in the academic event-studies.[7]

The size adjusting is made by subtracting the compounded return on the appropriate CRSP market capitalization decile portfolio from the total return:

$$ER^{i}_{3toM} = \left[\prod_{t=3}^{M} \left(1 + r_t^i\right) - \prod_{t=3}^{M} \left(1 + r_t^{size}\right) \right], \tag{1}$$

where r_t^i is the raw return on stock *i* on day *t*, and r_t^{size} is the return on the CRSP size decile that stock *i* on day *t*. Monthly (21 trading days) returns are compounded starting on the 3rd trading day of the IPO. The excess returns for individual stocks are averaged into PER (Portfolio Excess Returns) for each sub-partition of the sample in the study as follows:

$$PER = \frac{1}{n_M} \left(\sum_{i=1}^{n} ER^i \right) \tag{2}$$

where n_M is the number of firms in portfolio.[8]

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[7] Canina, Michaely, Thaler, and Womack (1998) provide excellent background on using various kinds of stock returns time-series.

[8] Some prior academic studies of IPO performance used value-weighted PER. I believe that value-weighting will create unnecessary and potentially harmful bias towards larger firms. Portfolios in this model are constructed with greater emphasis on testing the information content of the factors based on the investor decision-making at the IPO events. As Loughran and Ritter (2000) point out, this "traditional event study approach in which all observations are weighted equally will produce point estimates that are relevant from the point of view of a manager, investor, or researcher attempting to predict the abnormal returns associated with a random event." (see footnote 2, Loughran and Ritter (2000))

I follow KSW and partition my sample into 4 portfolios of IPOs sorted by first day return, defined as return from IPO offer price to first day closing trade. First day return is zero percent or less on IPOs classified as "cold," between zero and 10% for "cool", between 10% and 60% for "hot," and above 60% for "extra-hot." I report summary statistics for both the replicated and extended period in Table I. The results generally hold for both the descriptive figures and the statistical tests. However, I find that KSW's findings on extra-hot IPOs, while underperforming in their study, do not underperform in the later sample. However, much lower medians in this subset indicate a right-skewed return distribution. I report excess returns in Figure I.

[Figure I about here]

I also obtain first-day *volume* results similar to KSW for cold, cool, and hot IPOs. Volume looks noticeably higher for extra-hot issues, however, Atkins and Dyl (1997) point out that the measure of volume reported by the dealer-driven NASDAQ market is not consistent with NYSE, and other auction markets.[9] They suggest halving NASDAQ volume to account for transactions with the dealers. When this adjustment is performed, the large difference disappears.

[9] Atkins and Dyl (1997) describe the case of Dealer X reporting as a transaction the sale of 1,000 shares by Investor A. Afterward, Investor B's acquisition of these 1,000 shares from Dealer X is recorded as another transaction. This results in the reported trading volume of 2,000 shares. In case Dealer X sells the stock to Dealer Y and Investor B buys from Dealer Y thereafter, the volume increases to 3,000 shares and so on. From examining a sample of NASDAQ stocks that switched to trading on NYSE, Atkins and Dyl (1997) suggest a factor of one-half to mitigate this upward bias.

Flipping is a measure of the selling pressure on the IPO by institutional traders. It is defined by KSW as the ratio of daily sell-motivated block volume to total daily volume. A block is defined as 10,000 shares or more. The sum of block trades is used as a proxy for the daily trading activity of large traders. KSW report that the results are very similar when 5,000 share block cutoff is used. I follow KSW in using Lee and Ready (1991) tick-test algorithm to sign each trade as either sell- or buy- motivated. Lee and Radhakrishna (1996) report that while only 60% of the trades can be unambiguously signed, the success rate for those that can be is 93%[10].

Flipping can be approached as a result of a decision-making process of large investors. KSW propose that the return from the offer price to the *first* trade is a significant factor driving the investment manager's motivation to flip an IPO. I estimate a model of the institutional manager's decision to flip.[11] For the period from January 1993 through May 1995, the regression is:

$$\begin{aligned} &Flipping = \underset{(5.25)}{0.222} + \underset{(2.59)}{0.022}\ln(Mktcap) - \underset{(-7.869)}{0.293}Return \\ &N = 604 \quad Adj.R^2 = 0.111 \quad F-value = 32.69 \quad p\text{-}value < 0.0001, \end{aligned} \tag{3}$$

and for the period from June 1995 through June 1999:

[10] Please see the Appendix for description of the signing algorithm and the tick-test.

[11] KSW include underwriter rank based on equity capital as an additional explanatory variable. I omit the variable due to the lack of data. KSW report a coefficient of 0.0001 with the White's heteroskedasticity-adjusted *t*-statistic of 1.46; I do not believe omitting this variable introduces substantial bias to the model.

$$Flipping = 0.267 + 0.008\ln(Mktcap) - 0.117 Return$$
$$(10.17) \quad (1.45) \qquad\qquad (-4.35) \tag{4}$$
$$N = 1341 \quad Adj.R^2 = 0.099 \quad F-value = 9.5 \quad p\text{-}value = 0.0001,$$

where *Mktcap* is the total market capitalization of the firm at the IPO, and *Return* is calculated from the offer price to the first trade. (White's heteroskedasticity-adjusted *t*-statistics are reported in parenthesis.) The regression shows that when large investors notice negative first-trade returns, they are more likely to flip the IPO. It is evident from the regression results that the model is robust overtime.

KSW report that partitioning *both* on first-day return (the measure of the "temperature" of the IPO) and on the level of first-day flipping has a substantial predictive power for the future returns. I report similar results (see Table II and Figure III), however I find high mean return for lesser-flipped extra-hot IPOs. As stated above, a low median for extra-hot IPOs demonstrates right-skewness of the distribution.

[Table II and Figure III about here]

B. Effect of the Depository Trust Company's "flipper killer" initiative

As of June 2nd, 1997, Depository Trust Company (DTC) put in place Initial Public Offering Tracking System, which monitors flipping of the IPOs.[12] Underwriters are

[12] Aggarwal (2000) summarizes the operation of the "flipper killer". Two reports are generated. Lead underwriter is sent a list of syndicate members whose shares get flipped, including the sale price, trade date, number of shares, and the clearing agent's participant number. This report omits details on other

interested in price stability at the time of an IPO. Flipping can drive the stock price downwards and may force the underwriter to exercise costly price support, which substantially decreases profits from the deal. Thus, it is in the underwriter's best interest to identify and punish the investors who flip the issue. One should see a decrease in the flipping activity following the implementation of DTC's system. I find that the significant praise that the "flipper killer" changes received in the financial press is not without merit. As shown on Figure II, the level of flipping drops substantially in the period after June 1997.

[Figure II about here]

The response to DTC's system is especially notable considering Aggarwal's (2000) finding that flipping accounts for roughly 19% of volume in the first two days using data obtained directly from the various investment banks. Using KSW's method, I find that flipping accounts for 26% of volume in the same period. This corresponds to Aggarwal's (2000) result, since my estimator may be biased upwards in predicting the true level of flipping due to shares being traded several times after they are flipped.[13] However, if this is true, I believe that capturing these "ripple trades" actually produces a better estimator of the true effect of flipping on IPO performance.[14] Though crude, the

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syndicate members' customers. The second report sent to all syndicate members including the lead underwriter accounts actual trades by institutional and retail customers. The system allows for up to 120 days of monitoring, but, while its costs are insignificant, usually lead underwriter stops tracking after 30 days. For more details, please see SEC Release No. 34-37208, May 13, 1996.

[13] Aggarwal points to this "percolation" as a possible explanation of high first-day volume.

[14] Aggarway collects the flipping data from 9 investment banks for 193 companies out of 627 IPOs identified in her sample period. The small sample may result in larger estimator error. Also, since she includes small companies (while I exclude them) for which the level of flipping is characteristically low Aggarwal's aggregate flipping values may be biased down. Please note as well that while Aggarwal reports flipping for the first two days, I look only at the first day. In an unreported test I find negligible difference between one- and two-day flipping coefficients.

ratio of the inferred sell-motivated block volume to total volume serves as an effective proxy for the level of flipping actually taking place. The practitioners, having little or no ready access to actual underwriter data may find this inexpensive measure very useful.

C. Turnover in the quiet period as potential predictor of returns

Krigman, Shaw, and Womack (1999) use large-block sell volume on the first day of trading in an IPO to predict its future performance. I extend their methodology by examining the predictive power of the turnover ratio (volume as a percent of shares offered) in the quiet period (defined as the first 25 days of trading in an IPO) for long-term returns.

As Figure IV illustrates, turnover is high on the first day of trading, but falls substantially in the next few days to the "equilibrium" level. The initial turnover and the magnitude of the drop depends on the first-day return, which is KSW's proxy for underpricing. I therefore attempted to fit this pattern of decline using an exponential decay model:

$$TURNOVER = \beta_1 + \beta_2 e^{-\beta_3 t} \tag{3}$$

where β_1 is the equilibrium turnover; β_2 and β_3 are parameters of the exponential function, specifying in our case the highest point of the curve on the first day, and the speed of the decline respectively; t is time as days 1 through 25.

[Figure IV about here]

Non-linear regression was used to fit the turnover data for each of the 1945 stocks in the sample. [15] Unfortunately, β_2 and β_3 were not found to be useful parameters in predicting the IPO performance. The variable, equilibrium turnover (β_1), was found to be very significant in predicting future returns. I found the equilibrium turnover coefficient (β_1) to be nearly identical to the mean turnover calculated from day 5 though 25 of each IPO. Thus the exponential model was scrapped in favor of the simpler representation of the mean day-5 through day 25 turnover[16].

IPOs with higher quiet-period equilibrium turnover perform better in the months following the quiet-period. The effect of equilibrium turnover is demonstrated in Figure V. One year after the end of the 25-day quiet-period, the top decile outperforms the bottom decile by 65%.

[Figure V about here]

It seems that a significant difference exists between the first few days of trading in an IPO and the rest of the quiet period. While KSW document the predictive ability of the proxy for flipping in the first day, I test the power of the aggregate institutional

[15] Gauss-Newton method used to fit the data failed to converge on 325 (17%) datapoints. However, I believe that conclusions drawn from this experiment are relevant notwithstanding this constraint.
[16] Naturally, the average turnover can be found for all 1945 datapoints in the sample and is not limited to the stocks for which the exponential model converged.

selling pressure during the "equilibrium" phase of the quiet period. I construct a cumulative flipping variable as the fraction of block (10,000 shares or more) sell-signed volume from days 3 through 25 to total volume in that period.

The cumulative flipping variable is tested in a regression reported in Table III. Other independent variables include combined first and second day flipping[17]; first day raw return (a proxy for underpricing in KSW); and equilibrium quiet-period turnover. All independent variables except one demonstrate diminishing power for explaining returns as the duration increases; the aggregate quiet-period flipping is the exception. The model shows substantial explanatory capability, especially for 3- and 6-month size-adjusted returns.

[Table III about here]

The final table, Table IV, and corresponding Figure VI shows the results of a partition of IPOs, first sorted by low, medium and high turnover, and then those subgroups sorted by low, medium, and high flipping. As the reader can see, the intersection of high equilibrium turnover and low flipping produces the highest future returns in all three time periods (3-month, 6-month, and 1 year).

[Table IV and Figure VI about here]

[17] I chose to combine first and second day flipping (instead of using a simple first-day measure) in order to complement the quiet-period flipping measure calculated from days 3 through 25. In an unreported test I find negligible difference between one- and two-day flipping coefficients.

III. Conclusion

My research supports the conclusion that institutional investors appear to be informed investors in IPOs. They are able to execute prudent (and profitable) investment strategy and respond to expected low returns in the future by selling the shares of subsequently poor issues as soon as they can. KSW point out that flipping is thus a fully rational response to mispricing of the IPOs by the investment banks.

In the first 25 days of an IPO's life, new information is practically non-existent because the SEC requires a quiet period where the underwriting investment banks must not comment. Without sell-side research output, information available on newly-public firms is limited to 1) the financial information in the prospectus and 2) the prices and volume of shares traded. I collected transactions-level data for this entire 25-day period for all IPOs in my sample.[18] The empirical results on this study, especially the confirmation of Aggarwal's (2000) result, reassure me that early trading patterns of IPOs are predictive of future new issue returns and, thus, the analysis of these microstructure characteristics of the IPO quiet period produces significant predictive power for IPO returns.

[18] KSW collect first 5 days of transactions data.

Appendix: Trade-signing algorithm

The flipping ratio in Section II.C is computed as the sum of volume resulting from sell-motivated transactions of 10,000 shares or higher during the relevant day divided by the total volume for that day. Since TAQ dataset does not include the specific order data, I assign the side of the trade using the tick test algorithm proposed by Lee and Ready (1991) (LR).

The most basic tick only uses the price data and classifies the trades into four categories: uptick (downtick) when the price is higher (lower) then the previous trade, and zero-uptick (zero-downtick) when the price remains the same, but the last price change was an uptick (downtick). Uptick (downtick) and zero-uptick (zero-downtick) correspond to buy (sell) trades.

A more effective method is to compare the trade price to the midpoint of the prevailing quote at the time of the transaction. This accounts for order-flow induced quote changes between trades. However, finding the prevailing quote, relevant to the parties at the transaction, is tricky, as quotes are often revised at the trade. As suggested by LR, I compare the price to a the best quote for the stocks across all exchanges five seconds before the each trade, except for NASDAQ issues, where I use no delay. Classification remains the same: uptick (downtick) when the price is higher (lower) then the midpoint of the spread at the prevailing quote.

Lee and Radhakrishna (1996) test LR's approach using NYSE TORQ dataset. In addition to quotes and trades, TORQ contains data on individual orders, including the parties on each side of the trade, the specifics on execution of their orders, identities of the traders (individuals versus institutions), and order characteristics (buy- or sell-initiated trade.) Though this unique database is limited in scope, covering a sample of only 144 NYSE firms over a three-month period, it is a useful check on the correctness of the crude inference techniques.

By comparing the actual recorded details on the orders Lee and Radhakrishna (1996) find that while 40% of the trades are "non-directional." But for the 60% that can be signed using the tick test described above, 93% of the trades are signed correctly.[19] Thus LR algorithm is crude yet powerful.

[19] Lee and Radhakrishna (1996) also find that only 6% of the orders are split up at the execution. This supports my share-size proxy for block trades.

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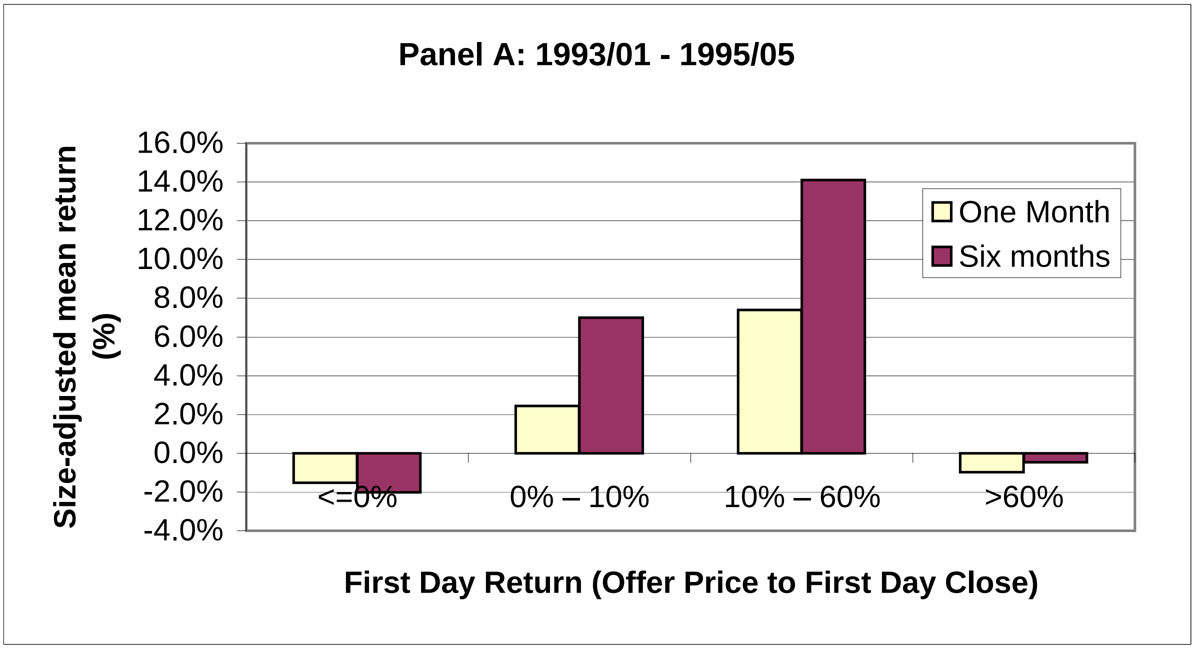
Figure I: Performance of IPOs categorized by first day return



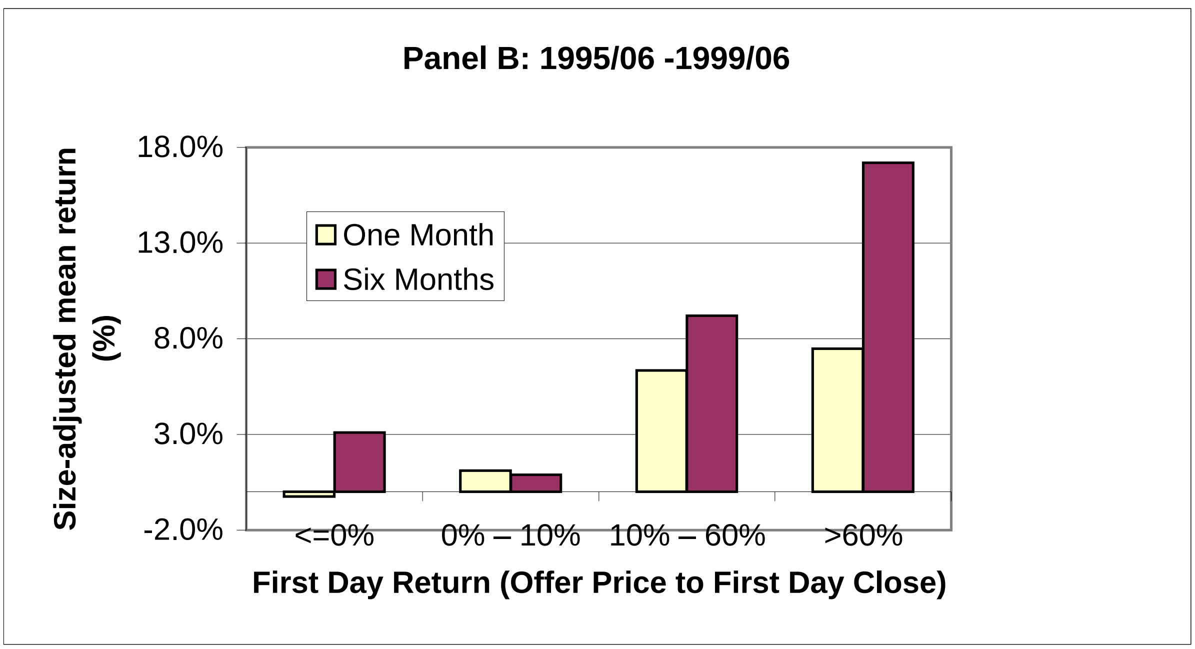


Figure II: Decline of flipping overtime
The flipping ratio is defined as daily sell-motivated block volume to total daily volume.

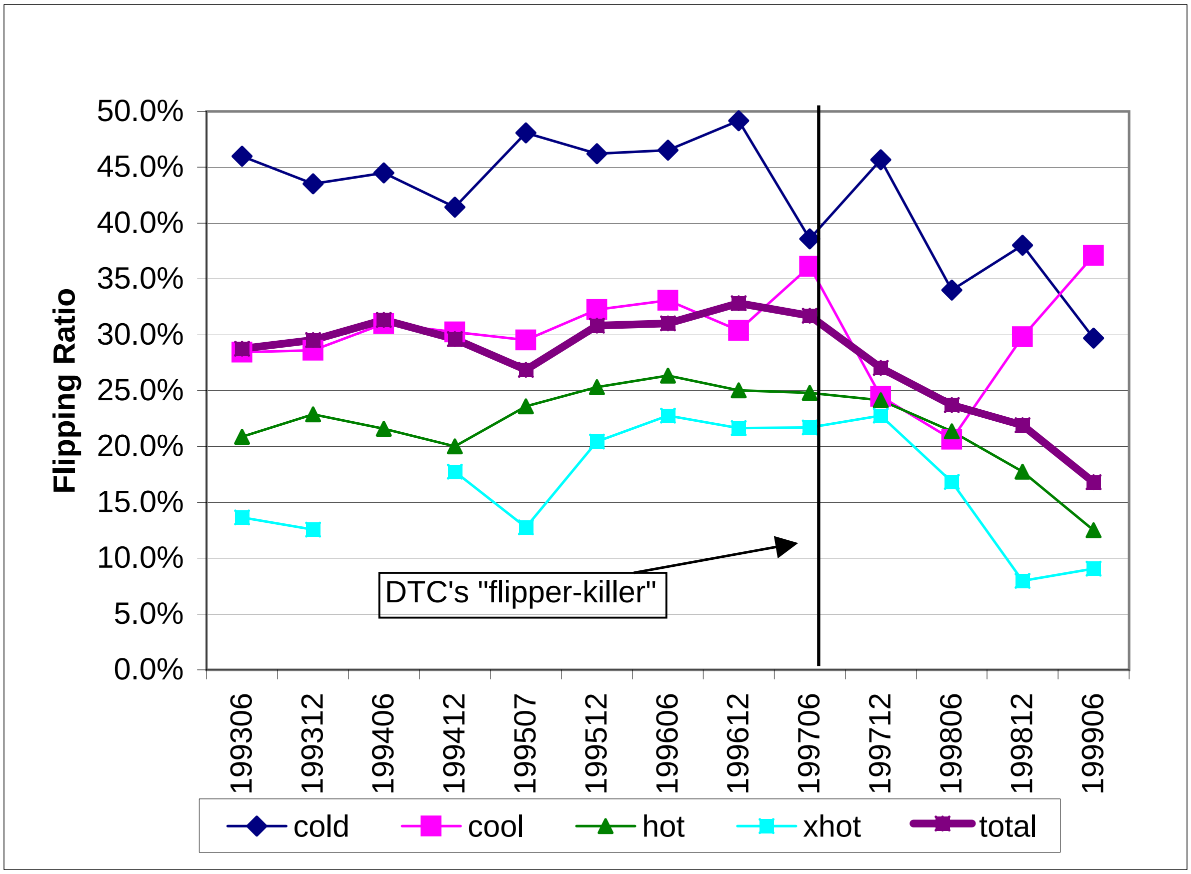
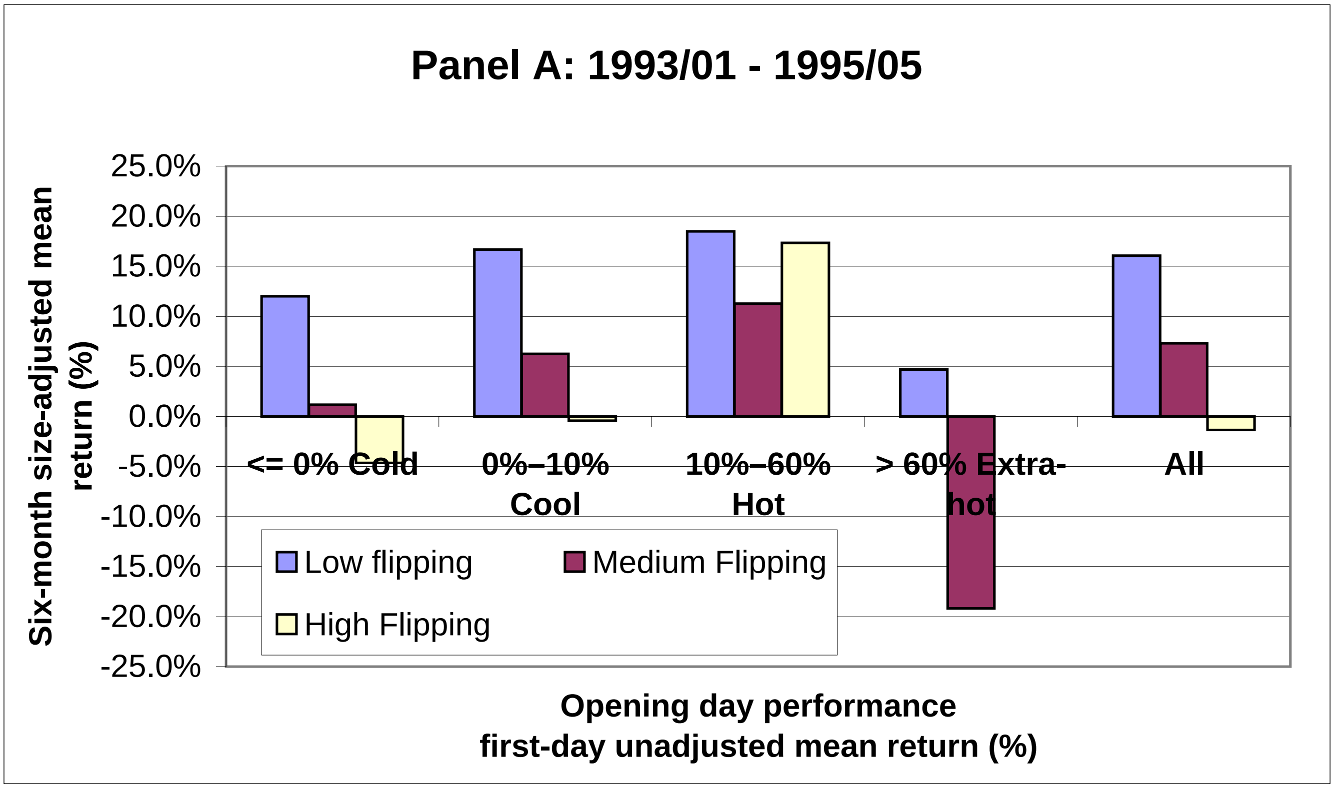


Figure III: Mean Returns by First Day performance and Flipping Level



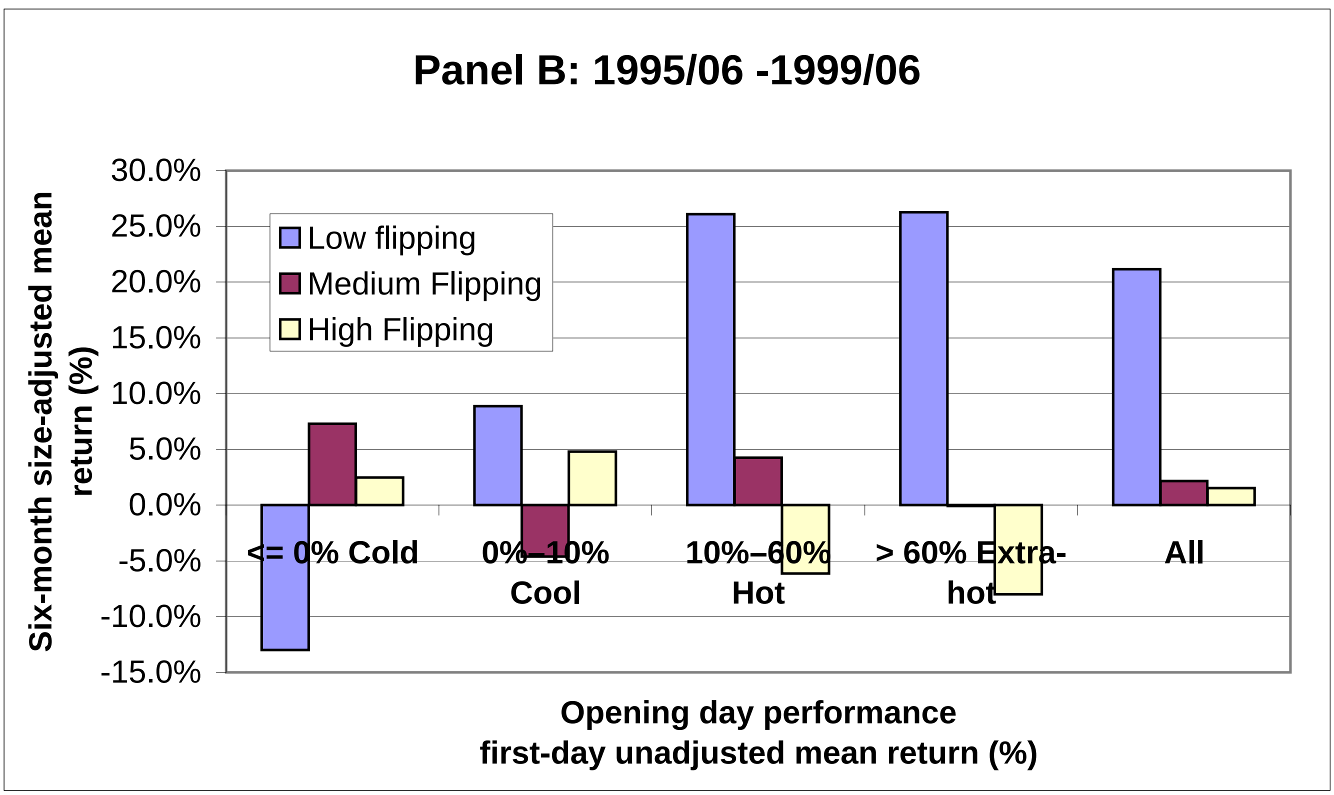


Figure IV: Quiet-period turnover partitioned by first day return
The sample is partitioned using raw return from offer price to first-day closing price. Cold IPOs are those with the return of 0% or less, cool are between 0% and 10%, hot are between 10% and 60%, and extra-hot are above 60%.

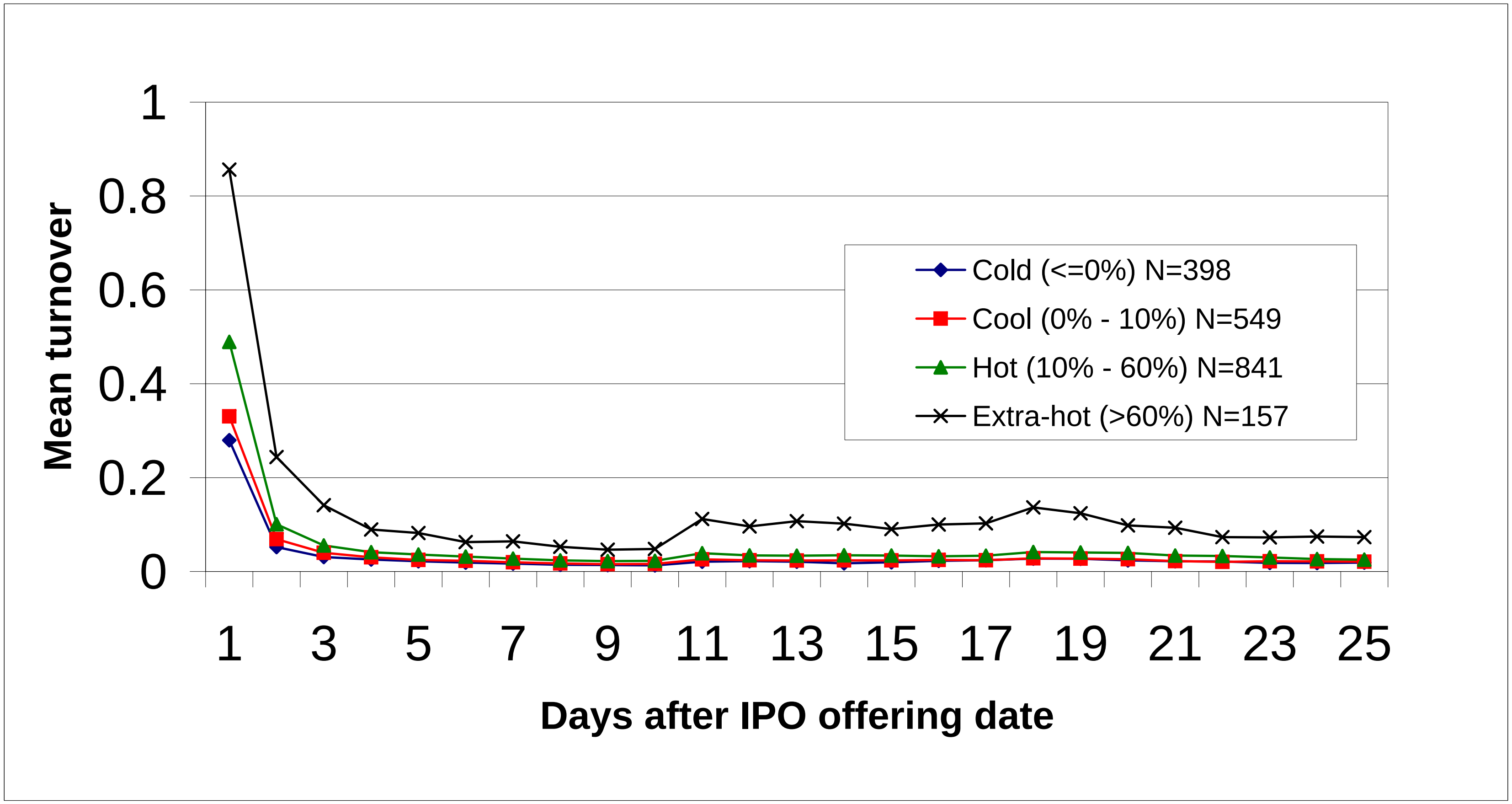


Figure V: Size-adjusted performance partitioned by quiet-period turnover

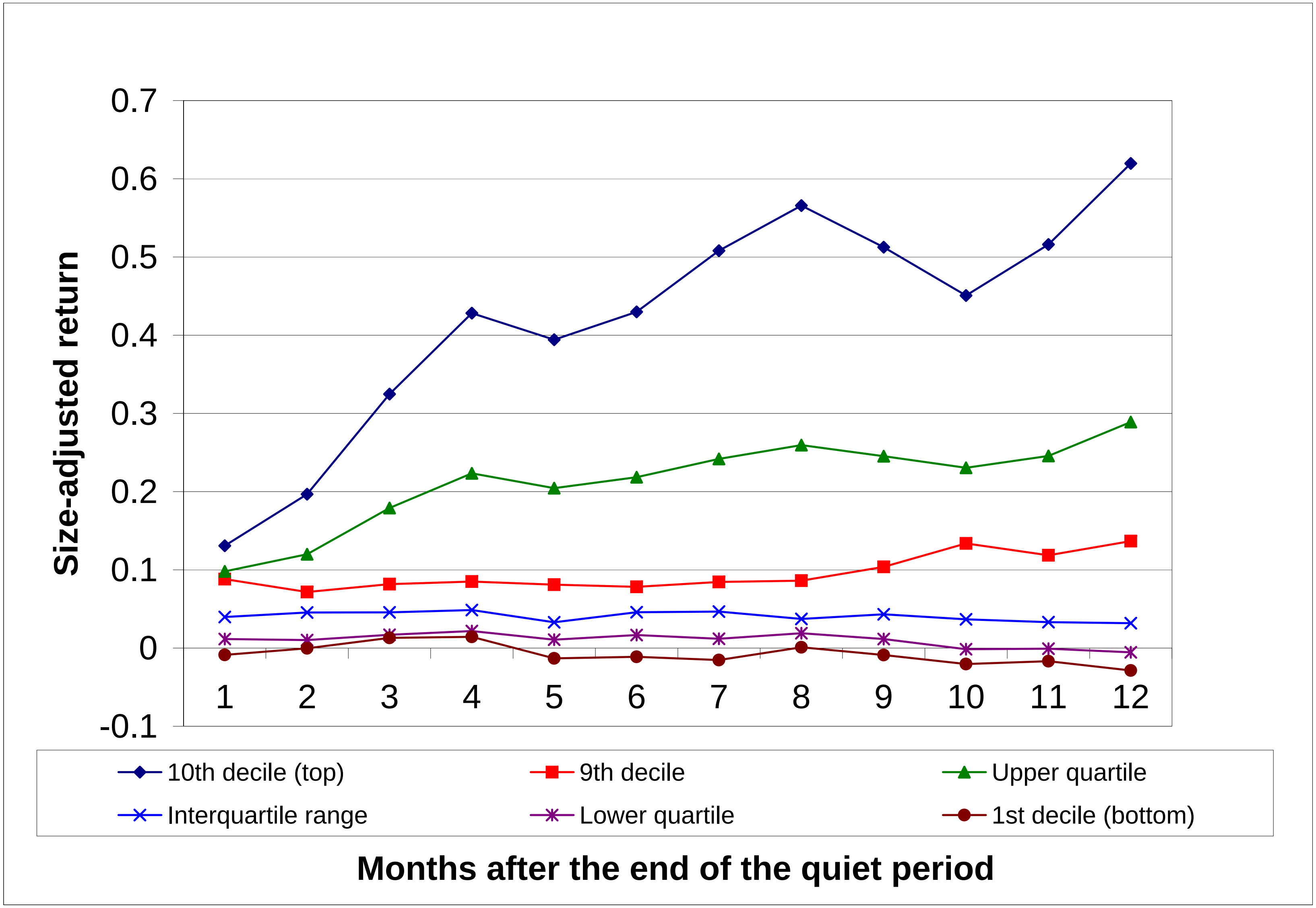


Figure VI: Size-adjusted returns partitioned by quiet-period equilibrium turnover and cumulative flipping. Low is the bottom quartile, high is the top quartile, and medium is interquartile range. Equilibrium turnover is defined as average turnover from day 5 through 25 of an IPO. Cumulative flipping is the fraction of block (10,000 shares or more) sell-signed volume from days 3 through 25 to total volume.

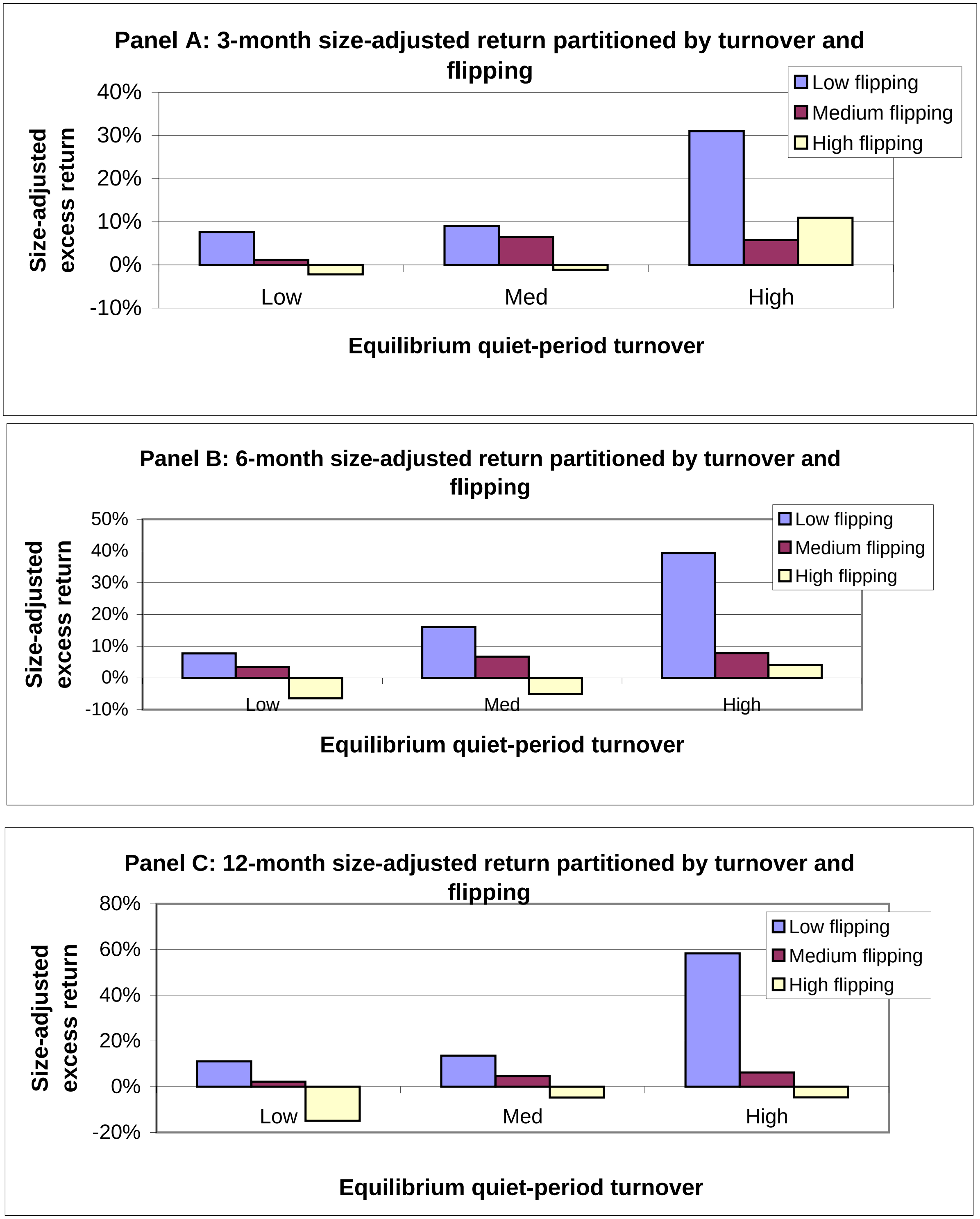


Table I*: Descriptive Statistics

First-day volume is reported unadjusted and adjusted for the double-counting of NASDAQ trades (see Atkins and Dyl (1997))

	Replica results (1993/01-1995/05)						Extension results (1995/06-1999/06)					
	Cold IPOs <=0%	Cool IPOs 0% – 10%	Hot IPOs 10% – 60%	Extra-Hot IPOs >60%	Kruskal-Wallis test $\chi 2$	p-value	Cold IPOs <=0%	Cool IPOs 0% – 10%	Hot IPOs 10% – 60%	Extra-Hot IPOs >60%	Kruskal-Wallis test $\chi 2$	p-value
N	137	219	225	23			261	330	616	134		
First-day Return												
Mean	-1.7%	4.6%	25.1%	83.9%			-2.6%	4.6%	25.8%	127.6%		
Median	0.0%	4.2%	21.7%	81.7%			0.0%	4.3%	22.5%	99.8%		
First-day volume as percentage of shares offered												
Mean	48.1%	51.8%	83.3%	134.8%	185.1	0.0000	56.9%	53.5%	81.2%	161.8%	381.3	0.0000
Adjusted Mean	29.4%	34.3%	46.7%	70.3%	136.6	0.0000	33.0%	31.9%	46.7%	82.6%	346.6	0.0000
One-month excess return												
Mean	-1.5%	2.4%	7.4%	-1.0%	26.7	0.0000	-0.3%	1.1%	6.3%	7.5%	22.4	0.0001
Median	-0.9%	1.6%	4.5%	-4.6%			-3.1%	-1.4%	3.0%	4.1%		
Six-month excess return												
Mean	-2.0%	7.0%	14.1%	-0.5%	21.7	0.0001	3.1%	0.9%	9.2%	17.2%	5.0	0.1744
Median	-10.7%	2.8%	9.2%	-15.5%			-6.9%	-6.2%	-2.7%	-15.7%		
Second-day return (mean)	1.3%	0.0%	0.5%	-0.6%	1.1	0.7834	-0.9%	-0.5%	0.8%	1.7%	7.3	0.0626
Pro-forma market capitalization ($ millions)												
Mean	$211.70	$234.10	$253.90	$205.26	6.4	0.0951	$385.70	$460.86	$372.65	$420.91	51.0	0.0000
Median	$106.90	$114.10	$116.20	$180.10			$122.10	$133.35	$154.25	$233.10		
Proceeds of offering ($ million)												
Mean	$75.06	$73.98	$67.88	$48.08	1.2	0.7437	$105.42	$140.77	$95.52	$82.42	31.5	0.0000
Median	$35.18	$40.48	$40.50	$42.90			$41.60	$46.00	$52.05	$57.89		

*** Corresponds to Table II in KSW.**

Table II*: Returns partitioned by first-day performance and flipping activity

Sample is partitioned by flipping activity: low is the lowest quartile, medium is interquartile range, and high is the upper quartile.
Returns are calculated starting on the 3rd day of the IPO.

Replica (1993/01-1995/05) one-month return

	Cold IPOs (N=137)		Cool IPOs (N=219)		Hot IPOs (N=225)		Extra-hot IPOs (N=23)		All IPOs (N=604)	
Flipping level	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
Low	1.2%	1.8%	7.7%	6.6%	7.7%	4.8%	-0.9%	-6.7%	6.5%	4.7%
Medium	0.6%	-0.9%	2.2%	1.2%	7.3%	4.5%	-1.3%	-1.0%	4.2%	2.3%
High	-2.9%	-1.0%	-1.9%	-4.1%	6.0%	1.9%			-1.8%	-2.0%

Replica (1993/01-1995/05) six-month return

	Cold IPOs (N=137)		Cool IPOs (N=219)		Hot IPOs (N=225)		Extra-hot IPOs (N=23)		All IPOs (N=604)	
Flipping level	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
Low	12.2%	12.5%	16.6%	9.4%	18.5%	14.2%	4.8%	-18.4%	16.0%	8.4%
Medium	1.1%	-3.5%	6.2%	5.8%	11.3%	8.5%	-19.3%	-3.4%	7.3%	5.6%
High	-4.7%	-16.5%	-0.4%	-2.8%	17.4%	16.5%			-1.3%	-8.6%

Extension (1995/06-1999/06) one-month return

	Cold IPOs (N=261)		Cool IPOs (N=330)		Hot IPOs (N=616)		Extra-hot IPOs (N=134)		All IPOs (N=1341)	
Flipping level	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
Low	-5.5%	-3.0%	1.5%	0.0%	10.5%	4.0%	9.3%	1.5%	7.8%	2.0%
Medium	2.2%	-3.0%	1.8%	-2.5%	5.4%	2.0%	4.2%	6.0%	4.0%	1.0%
High	-1.0%	-4.0%	-0.2%	-4.0%	1.0%	0.0%	-4.0%	-4.0%	-0.4%	-3.0%

Extension (1995/06-1999/06) six-month return

	Cold IPOs (N=261)		Cool IPOs (N=330)		Hot IPOs (N=616)		Extra-hot IPOs (N=134)		All IPOs (N=1341)	
Flipping level	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**	**Mean**	**Median**
Low	-13.0%	-12.0%	8.9%	-5.0%	26.1%	0.5%	26.3%	-18.0%	21.2%	-4.5%
Medium	7.3%	-7.0%	-4.6%	-7.5%	4.3%	-3.0%	-0.1%	-13.0%	2.2%	-4.0%
High	2.5%	-6.0%	4.8%	-3.0%	-6.1%	-11.5%	-8.0%	-8.0%	1.5%	-7.0%

*** Corresponds to Table V in KSW.**

Table III: Cross-sectional OLS regressions with 3-, 6-, and 12-month size-adjusted returns as dependent variables. Returns are calculated starting on the 26th day of the IPO, at the end of the quiet period. Heteroskedasticity-adjusted t-statistics are reported in parentheses.

	3-month excess return	6-month excess return	12-month excess return
Intercept	0.174	0.126	0.125
	(4.22)	(5.54)	(5.65)
First day raw return (underpricing)	-0.134	-0.170	0.005
	-(2.96)	-(2.37)	(0.05)
Flipping level (first and second day combined)	-0.002	-0.002	-0.001
	-(2.31)	-(2.55)	-(1.03)
Flipping level (cumulative from day 3 through 25)	-0.004	-0.007	-0.010
	-(4.28)	-(5.89)	-(5.38)
Equilibrium turnover (mean turnover from day 5 through 25)	2.141	2.287	1.813
	(2.25)	(1.54)	(1.18)
F-value	9.39	14.62	9.43
R^2	5.00%	5.21%	2.96%
N	1945	1945	1945

Table IV: Size-adjusted returns partitioned by equilibrium turnover and cumulative flipping.
Low is the bottom quartile, high is the top quartile, and medium is interquartile range. Equilibrium turnover is defined as average turnover from day 5 through 25 of an IPO. Cumulative flipping is the fraction of block (10,000 shares or more) sell-signed volume from days 3 through 25 to total volume. Returns are calculated starting on the 26th day of the IPO, at the end of the quiet period.

3-month size-adjusted return

	EquilibriumTurnover								
	Low			**Medium**			**High**		
	Mean	Median	N	Mean	Median	N	Mean	Median	N
Low flipping	7.64%	2.40%	106	9.05%	3.79%	157	30.96%	1.90%	222
Medium flipping	1.21%	-0.02%	244	6.47%	2.24%	521	5.77%	0.68%	207
High flipping	-2.16%	-3.09%	133	-1.14%	-5.39%	298	10.94%	-0.35%	55

6-month size-adjusted return

	EquilibriumTurnover								
	Low			**Medium**			**High**		
	Mean	Median	N	Mean	Median	N	Mean	Median	N
Low flipping	7.73%	-0.26%	106	16.02%	4.23%	157	39.36%	5.69%	222
Medium flipping	3.45%	-1.29%	244	6.68%	-0.35%	521	7.77%	-6.02%	207
High flipping	-6.45%	-9.37%	133	-5.13%	-10.24%	298	4.06%	-3.15%	55

12-month size-adjusted return

	EquilibriumTurnover								
	Low			**Medium**			**High**		
	Mean	Median	N	Mean	Median	N	Mean	Median	N
Low flipping	11.11%	-0.52%	106	13.60%	-14.21%	157	58.36%	-26.18%	222
Medium flipping	2.23%	-3.65%	244	4.56%	-8.28%	521	6.22%	-19.54%	207
High flipping	-14.93%	-23.54%	133	-4.73%	-15.76%	298	-4.64%	-29.50%	55