The IPO Derby: Are There Consistent Losers and Winners on This Track?

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We examine the individual and joint relation of discretionary accounting accruals, underwriter reputation, and venture capital backing with the long-run performance of initial public offerings (IPOs). We find that although correlated to some extent, these variables do not manifest the same underlying phenomena in their relation to IPOs' performance. The confluence of the variables is more important than using any one of them individually to identify IPOs that exhibit abnormal long-run stock returns. The combination of their negative aspects helps identify extreme underperformers. We also identify a set of winner IPOs by combining the positive aspects of the three variables.

More than $500 billion has been raised by initial public offerings (IPOs) markets over the past two decades. Investors are keenly interested in searching for firm characteristics that help identify the IPOs that are more likely to outperform or underperform in the long run. Therefore, it is not surprising that IPOs have generated extensive research efforts.

Earlier papers show that various firm characteristics such as discretionary accounting accruals, underwriter reputation, and venture capital (VC) backing seem to be related to the cross-sectional variation of long-run IPO performance (see Table I). However, there are at least three concerns associated with these studies. First, they examine each firm characteristic in isolation and do not control for the other two variables. It is not clear whether the relation of the discretionary accruals (DA), underwriter reputation, and VC variables to IPOs is highly correlated, and therefore, whether each variable is related to the same underlying source of long-run return predictability or if they manifest as three distinct phenomena.

Second, some return anomalies, such as the size effect, either disappear or become weaker after they are well publicized. The earlier papers outlined in Table I use an IPO sample that covers the years only through 1992. Therefore, it is an open question whether the effects of the three variables persist when the sample analyzed includes the late 1990s, a period during which market prices were very volatile.

Finally, earlier research uses different sample specifications and statistical methods to examine the long-run performance of IPOs (see Table I). As a result, it is difficult to make direct

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Table I. Previous Studies Examining Long-Run Returns of IPOs

This table summarizes the previous studies examining the variables that are related to long-run performance of IPOs. BHAR means the buy-and-hold abnormal return approach. CTFG refers to the calendar-time factor regressions approach, while CSR refers to the event-time cross-sectional regression approach, FM denotes the Fama-MacBeth (1973) cross-sectional regression approach, EW represents equal-weighted, and VW represents the value-weighted scheme.

Study	Variable Examined	Sample Period	Cutoffs for Sample Selection	Methods Used to Measure Long-Run Returns	Controlled Factors	Portfolio Weight	Summarized Findings
Brav and Gompers (1997)	VC backing	1972-1992	Not mentioned	BHAR, CTFG, CSR	Market index, size, book-to-market, dividend-to-price	EW and VW	VC-backed IPOs outperform non-VC-backed IPOs only in equal-weighted portfolios. There is no abnormal performance for VC-backed IPOs. Non-VC-backed IPOs underperform only in equal-weighted portfolios.
Teoh, Welch, and Wong (1998)	Earnings management	1980–1992	$1 offer price; $20 million market cap.	BHAR,CTFG, CSR, FM	Market index, size, book-to-market, initial returns, change in profits, industry	EW and VW	IPOs with aggressive accruals underperform IPOs with conservative accruals. IPOs with high accruals underperform, but there is no abnormal performance for IPOs with low accruals.
Carter, Dark, and Singh (1998)	Underwriter reputation	1979-1991	$2 million proceeds	BHAR, CSR	Market index, proceeds, age, return volatility	EW	IPOs with prestigious underwriters outperform IPOs with low underwriter ranking.

comparisons or to ascertain whether the differences across these studies are driven by different sample periods, sample selection, or methods, all of which might affect the measurement of IPO long-run returns (Ritter and Welch, 2002). Moreover, Fama (1998) and Mitchell and Stafford (2000) argue that the buy-and-hold return method generally used in long-run event studies is biased and suffers from statistical problems, and that the abnormal returns disappear when evaluated using value-weighting schemes. Our goal is to address all of these issues.

In this paper, we focus exclusively on the individual and joint relation of DA, underwriter reputation, and VC backing with the long-run performance of IPOs. We obtain our IPO sample from 1980 to 2000, and thus have eight new, additional years of data compared with the previous studies. Using 3,626 observations, we find that each of the three previously documented results holds in our sample IPOs.

We find greater differentiating power when we simultaneously examine these three previously documented variables. We show that IPOs with high DA, low-reputation lead underwriters, and no VC backing ("loser" IPOs) significantly underperform the benchmark. Conversely, IPOs with low DA, prestigious lead underwriters, and VC backing ("winner" IPOs) significantly outperform in the long run. We believe that ours is the first study, without a look-ahead bias, to isolate a subsample of IPOs that outperform their benchmark. The difference in abnormal returns between winners and losers is 2.07% per month using value-weighted portfolios. Our results are particularly strong in the subsample of larger IPOs where the winners outperform losers by 2.36% per month. These findings suggest that a confluence of the three variables is more important in isolating winners and losers than any one of them individually. Thus, the three variables acting in conjunction help identify winners and losers in what we call the "IPO Derby."

We propose two competing hypotheses to explain the abnormal returns associated with IPO winners and losers, namely, mispricing and misspecification. We examine firm characteristics and operating performance to test these two hypotheses. We find that the negative drifts associated with loser IPOs are more likely due to mispricing. However, the winner IPO results are not consistent with the mispricing explanation and are more in line with a misspecification story.

The paper is organized as follows. Section I describes our sample selection and measure of variables. Section II discusses the methods we use to detect the IPO long-run abnormal returns. We present our empirical results in Section III. Section IV shows the tests on mispricing and misspecification hypotheses. Section V concludes and discusses some related issues.

I. Data

In this section, we discuss the sample selection and describe how we measure discretionary accounting accruals. We also present the summary statistics of our sample.

A. Sample Selection

We obtain our initial sample of 9,919 IPOs from Thomson Financial's SDC New Issues database for the period 1980-2000. We end our portfolio formation in 2000, even though our return information is available up to 2005 to ensure that the portfolio we use in our regression analysis is well seasoned. Our main conclusions do not change if we form IPO portfolios up to 2005.

We exclude 3,976 IPOs from the sample because they are either ADRs, closed-end funds, non-US firms, REITs, reverse LBOs, and unit offerings or spinoffs. To avoid the low-price stock effect (Loughran and Ritter, 1996), we delete 831 IPOs with an offering price less than $5.00 and IPOs with total proceeds less than $5 million. We drop 543 IPO firms that are not covered in either Compustat or CRSP. We discard 943 observations that do not have accounting information available to compute DA. Our final sample consists of 3,626 IPOs.

To be consistent with earnings management literature, we follow Sloan (1996) and Chan, Chan, Jegadeesh, and Lakonishok (2006) by defining accruals as in Equation (1). Compustat annual item numbers are in parentheses.

$$Total\ Accruals = (\Delta CA - \Delta Cash) - (\Delta CL - \Delta STD - \Delta TP) - DEP, \tag{1}$$

where ΔCA equals the change in current assets (4), $\Delta Cash$ equals the change in cash (1), ΔCL equals the change in current liabilities (5), ΔSTD equals the change in debt included in current liabilities (34), ΔTP equals the change in taxes payable (71), and DEP equals the depreciation and amortization expense (14).

We compute accruals based on two years' financial statements. However, since financial statement data are rarely available to compute accruals with exclusively pre-IPO data, we compute our total accruals as of the first fiscal year-end after the IPO date. Thus, the accruals are based on both pre- and post-IPO financial statements.

To control for firm size, we divide total accruals by the average of beginning and ending total assets. To compute DA, we require the sample firms to have data on changes in sales, and property, plant and equipment.

To examine whether IPO long-run performance is related to VC and underwriter reputation, we obtain the VC backing information from SDC, and the Carter and Manaster (1990) underwriter reputation ranks for the IPO's book underwriter from Jay Ritter's Web site at http://bear.cba.ufl.edu/ritter/ipodata.htm. Both the IPO's VC status and the reputation of the IPO's lead underwriter are observable at the time of the IPO.

B. Estimation of Earnings Management

Earnings management studies usually focus on the analysis of DA. The reason for this research focus is that nondiscretionary accruals (NDA), which we define as the difference between total accruals and DA, are a necessary component of earnings and reflect the business condition of the firm. For instance, high-growth firms normally have increasing accounts receivable and inventories as a consequence of rapidly growing sales. The resulting increase in current assets leads to an increase in total accruals. To control for this growth effect, we use the Jones (1991) model to measure the portion of accruals under the discretion of managers. We separate accruals into DA and NDA by regressing total accruals on the change in sales ($\Delta Sales$) and property, plant, and equipment (PPE), all of which are scaled by the average of beginning and ending total assets (TA), as shown in Equation (2).

$$\frac{Total\ Accruals_i}{TA_i} = a_0 \frac{1}{TA_i} + a_1 \frac{\Delta Sales_i}{TA_i} + a_2 \frac{PPE_i}{TA_i} + \varepsilon_i. \tag{2}$$

The NDA that we estimate from the fitted values of the regression are the expected accruals given the firm's growth in sales and level of property, plant, and equipment. DA, the residuals of the regression, are the unexpected accruals from the model.

Since most IPO firms do not have a long history of accounting information, estimates of DA and NDA from time-series data on each sample firm is not possible. Therefore, we follow Teoh, Welch, and Wong (1998) and run a separate cross-sectional regression using Equation (2) within each industry for each year. We collect all New York Stock Exchange (NYSE), American Stock Exchange (Amex), and Nasdaq stocks with available accounting data, and separate them into 48 industry groups based on the classification in Fama and French (1997). Then, in each calendar year and each industry, we run Equation (2). To assure that the regression estimates are meaningful, we drop all firms in an industry for a year in which the number of firms in that industry is less than 10. In such an event, we replace the coefficients for the industry with the coefficients based on a separate regression that uses all firms in that year. We obtain regression coefficients of Equation (2) for the calendar year prior to the first post-IPO fiscal year-end. We then compute NDA and DA for the IPO firm in Equations (3) and (4), where *TA* is the average of beginning and ending total assets.

$$NDA_t = (\hat{\alpha}_{0,t-1} + \hat{\alpha}_{1,t-1}\Delta Sales_t + \hat{\alpha}_{2,t-1}PPE_t)/TA. \quad (3)$$

$$DA_t = (Total\ Accruals_t - NDA_t)/TA. \quad (4)$$

To classify portfolios for return analysis, we use the DA decile ranking of IPOs relative to the stock universe. To determine the DA decile ranking, we compare the sample firm's DA to the DA for all Compustat firms with available data. To avoid a look-ahead bias, we obtain the decile cutoff points for Compustat firms for each year from 1979 to 1999 and use the decile cutoff points from the year preceding the sample IPO's first fiscal year-end.

Kothari, Leone, and Wasley (2005) suggest a performance-matched approach to control for the potential misspecification of estimating DA in Jones (1991) model. For robustness check, we compute the performance-matched abnormal DA by subtracting the DA of industry and performance-matched control firm from the DA of the sample firm, and use it to classify our IPOs. Our conclusions do not change by using this alternative DA measure.

C. Summary Statistics

Table II reports the sample distribution and summary statistics for our sample of 3,626 IPOs. In Panel A, except for business services (28%), there is no single industry that comprises more than 7% of the sample. More than 75% of our sample comes from IPOs in 1990s, as shown in Panel B. In Panel C, we present summary statistics for our sample. The mean total accruals are positive (0.039). Chan et al. (2006) show that, on average, general firms have small but negative accruals, which would suggest that IPO firms tend to have higher accruals than the average firm. The higher accruals for IPO firms may be due to high sales growth (mean = 335%) in the year prior to the first post-IPO fiscal year-end. However, after controlling for sales growth and property, plant, and equipment, DA is still high, with a median decile ranking of six. This result indicates the possibility of earnings manipulation by IPO firms.

II. Method for Estimating Long-Term Abnormal Returns

To examine the long-horizon stock performance for IPOs, previous studies generally use the buy-and-hold abnormal return (BHAR) method. BHAR is preferable because the implied investment strategy is both simple and representative of the returns that a long-horizon investor might earn (Kothari and Warner, 2005).

However, as Fama (1998) and Mitchell and Stafford (2000) point out, BHAR may overstate the long-run performance since it can grow with the return horizon even when there is no abnormal return after the first period. Moreover, since we compute BHAR over a long horizon, many sample firms' BHARs may overlap in different months, making strong cross-sectional correlations among long-horizon returns. This cross-sectional dependence in sample observations can lead to poorly specified test statistics for BHAR (Fama, 1998; Lyon, Barber, and Tsai, 1999; Brav, 2000).

The solution proposed by Fama (1998) and Brav, Geczy, and Gompers (2000) is to run time-series regressions on a calendar-time portfolio. For each calendar month, we can obtain the return for each sample firm that has its IPO within a certain time period (e.g., within the last five years), and then get the portfolio return in that month. We reform the portfolio every month. As a result, we develop a time series of portfolio returns which we can use to run the four-factor model (Carhart, 1997) regressions as follows:

$$r_{p,t} - r_{f,t} = \alpha + \beta(r_{m,t} - r_{f,t}) + sSMB_t + hHML_t + pPRIOR_t + e_t, \quad (5)$$

Table II. Sample Distribution and Summary Statistics

The sample consists of 3,626 IPOs issued in 1980-2000 with an offering price of at least $5.00 and total proceeds of at least $5 million. We exclude closed-end funds, REITs, ADRs, non-US stocks, reverse LBOs, spin-offs, and units from the sample. We require that our sample firms have data available to compute accruals at the first post-IPO fiscal year-end. DA is the discretionary accruals, which we obtain from the residuals of the Jones (1991) model. Accruals are the firm's total accruals defined as changes in current assets excluding cash, minus changes in current liabilities excluding short-term debt and taxes payable, and minus depreciation. DA (Accruals) decile ranking is relative to all stocks with available DA (accruals). Cash flows are the difference between Earnings and Accruals. Earnings are operating income after depreciation. We normalize DA, Accruals, Cash flows, and Earnings by dividing by average total assets. CMR is Carter-Manaster (1990) ranking, as updated by Loughran and Ritter (2004), of the IPO's lead underwriter. VC is a dummy variable equal to one if the IPO is venture capital backed. Sales are expressed in millions of dollars. Sales growth is the one-year growth rate of sales, based on sales at the first post-IPO fiscal year and the year before. Size is market value of equity at the fourth month-end after the first post-IPO fiscal year-end, and is expressed in millions of dollars. BM is the book-to-market ratio, which we compute by dividing book value of equity by Size. Size (BM) decile ranking is relative to NYSE stocks only. Offer price is the IPO offer price. Initial return is the return from the IPO offer price to first available closing price. Total proceeds are in millions of dollars. We evaluate all accounting data items at the first post-IPO fiscal year. Panel A reports the industry distribution based on the Fama and French (1997) industry classifications. Panel B reports the sample distribution based on offering date and first post-IPO fiscal year. Panel C reports the summary statistics.

Panel A. Industry Distribution

Industry	No.	%	Industry	No.	%	Industry	No.	%
Agriculture	6	0.2	Construction materials	38	1.0	Telecommunications	144	4.0
Food	22	0.6	Construction	26	0.7	Personal services	64	1.8
Candy and soda	1	0.0	Steel	31	0.9	Business services	1007	27.8
Alcoholic beverages	10	0.3	Fabricated products	13	0.4	Computers	184	5.1
Tobacco	1	0.0	Machinery	81	2.2	Electronic equipment	206	5.7
Recreational	31	0.9	Electrical equipment	166	4.6	Measuring equipment	69	1.9
Entertainment	65	1.8	Miscellaneous	22	0.6	Business supplies	16	0.4
Printing and publishing	23	0.6	Automobiles	28	0.8	Shipping containers	8	0.2
Consumer goods	40	1.1	Aircraft	11	0.3	Transportation	101	2.8
Apparel	28	0.8	Shipbuilding	3	0.1	Wholesale	184	5.1
Healthcare	134	3.7	Defense	3	0.1	Retail	248	6.8
Medical equipment	115	3.2	Precious metals	1	0.0	Restaurants and hotels	97	2.7
Pharmaceuticals	157	4.3	Nonmetallic mining	2	0.1	Banking	7	0.2
Chemicals	35	1.0	Coal	2	0.1	Insurance	19	0.5
Rubber and plastic	30	0.8	Petroleum and gas	61	1.7	Real estate	10	0.3
Textiles	17	0.5	Utilities	41	1.1	Trading	18	0.5

Table II. Sample Distribution and Summary Statistics (*Continued*)

Panel B. Time Distribution

IPO Offering Year	No.	%	First Post-IPO Fiscal Year	No.	%
1980	31	0.9	1980	18	0.5
1981	90	2.5	1981	65	1.8
1982	25	0.7	1982	50	1.4
1983	200	5.5	1983	133	3.7
1984	76	2.1	1984	133	3.7
1985	58	1.6	1985	51	1.4
1986	182	5.0	1986	134	3.7
1987	131	3.6	1987	171	4.7
1988	58	1.6	1988	80	2.2
1989	52	1.4	1989	50	1.4
1990	59	1.6	1990	63	1.7
1991	158	4.4	1991	127	3.5
1992	199	5.5	1992	201	5.5
1993	284	7.8	1993	273	7.5
1994	240	6.6	1994	244	6.7
1995	301	8.3	1995	286	7.9
1996	445	12.3	1996	445	12.3
1997	293	8.1	1997	301	8.3
1998	179	4.9	1998	215	5.9
1999	334	9.2	1999	304	8.4
2000	231	6.4	2000	282	7.8
Total	3,626	100.0	Total	3,626	100.0

Panel C. Firm Characteristics

Statistics	Mean	Min.	25%	Median	75%	Max.	Std.
DA	0.030	−1.061	−0.046	0.014	0.094	1.343	0.150
Accruals	0.039	−0.878	−0.056	0.012	0.113	1.364	0.168
DA decile ranking	6.1	1	3	6	9	10	3.16
Accruals decile ranking	7.0	1	5	8	10	10	2.97
Cash flows	−0.024	−4.176	−0.162	0.050	0.181	0.919	0.338
Earnings	0.016	−4.178	−0.087	0.115	0.204	0.935	0.345
CMR	7.3	0.5	7	8	9	9	1.98
VC	0.50	0	0	0	1	1	0.50
Sales	110	0	16	38	89	27,052	539
Sales growth	3.35	−0.98	0.23	0.50	1.11	2,086.75	51.36
Size	309	0	42	97	231	33,405	1,139
BM	0.45	0.00	0.19	0.32	0.55	11.03	0.52
Size decile ranking	2.4	1	1	2	3	10	1.75
BM decile ranking	3.7	1	1	3	6	10	2.79
Offer price	12.3	5	9	12	15	50	4.56
Initial return (%)	23.37	−32.81	1.00	9.09	25.81	697.50	47.73
Total proceeds	45	5	15	28	49	5,470	109

where r_p is the portfolio return from the sample firms, r_f is the risk-free rate, r_m is the market portfolio return, *SMB* is the small-firm portfolio return minus the big-firm portfolio return, *HML* is the high book-to-market portfolio return minus the low book-to-market portfolio return, and *PRIOR* is the winner portfolio return minus the loser portfolio return based on the past 12-month return.

This approach is appealing because there is much less skewness using monthly returns and the time-series variation of monthly returns accurately captures the effects of correlation across event stocks (Fama, 1998). The abnormal returns can be tested based on the *t*-value of the regression intercept alphas.

To balance out all arguments on the computation of long-run returns, in our main results we follow Fama (1998) and use Equation (5) to detect long-run abnormal performance of IPOs.[1] Since the DA information is generally not available until after the first fiscal year following the IPO, to ensure full access to the IPO firms' level of earnings management and to prevent a look-ahead bias, we form our portfolios to measure the IPOs' long-run returns from the fifth month following the first post-IPO fiscal year-end. That is, we assume that there is a four-month reporting lag to collect the accounting information before the return calculation starts. For each month over the period of 1983-2000, we form an IPO calendar-time portfolio by including IPOs starting from the 5th month, up until the 52nd month (or the delisting date), after their first post-IPO fiscal year-end (i.e., a four-year period). The choice of 48 months (from the 5th to the 52nd month after the first fiscal year-end) is to facilitate the comparison with previous research. Long-run performance studies usually examine five-year returns after the announcement. Since our return calculation starts on the fifth month after the first fiscal year-end, which is already 4 to 15 months away from the IPO offering date, the 48-month horizon appropriately captures the 5-year long-run returns. To increase the power of the test, if for any month the number of IPOs is less than 10, we drop that month. Our results are robust to different minimum numbers of IPOs we require in a calendar-time portfolio.

For testing the difference in performance between two sets of IPOs, we follow the same approach, but now use the return difference between two portfolios as the dependent variable in Equation (5). Moreover, Mitchell and Stafford (2000) and Brav, Geczy, and Gompers (2000) argue that the underperformance of IPOs, if there is any, is present only when returns are equal-weighted. Therefore, we show both equal- and value-weighted results for robustness.

III. Empirical Results

In this section, we first report the univariate results, followed by multivariate analyses and cross-sectional regressions.

A. Univariate Analysis

Table III presents our univariate analysis results. In Panel A, we sort IPO firms into quartiles based on DA. We classify IPOs with the highest DA decile ranking into the highest DA quartile,

[1] For robustness, we also run the Fama-French (1993) three-factor model by taking out the momentum factor from Equation (5). Although not reported here, the results are similar to what we show in the paper. Furthermore, we also perform our analyses based on the BHAR approach by using size and book-to-market matched firms. The results, not reported here, are also consistent with those presented in this paper.

Table III. One-Way Classifications of Postissue Performance by Discretionary Accruals, Underwriter Reputation, and Venture Capital

The sample consists of 3,626 IPOs issued in 1980-2000 with an offering price of at least $5.00 and total proceeds of at least $5 million. We exclude closed-end funds, REITs, ADRs, non-US stocks, reverse LBOs, spin-offs, and units from the sample. We require that our sample firms have data available to compute accruals at the first post-IPO fiscal year-end. DA is the discretionary accruals, which we obtain from the residuals of the Jones (1991) model. DA decile ranking is relative to all stocks with available DA. Cash flows are the difference between earnings and accruals. Earnings are operating income after depreciation. We normalize DA, Cash flows, and Earnings by dividing by average total assets. CMR is Carter-Manaster (1990) ranking, as updated by Loughran and Ritter (2004), of the IPO's lead underwriter. VC is a dummy variable equal to one if the IPO is venture capital backed. Sales are expressed in millions of dollars. Sales growth is the one-year growth rate of sales, based on sales at the first post-IPO fiscal year and the year before. Size is market value of equity at the fourth month-end after the first post-IPO fiscal year-end, and is expressed in millions of dollars. BM is the book-to-market ratio, which we compute by dividing book value of equity by Size. Size (BM) decile ranking is relative to NYSE stocks only. Offer price is the IPO offer price. Initial return is the return from the IPO offer price to first available closing price. Total proceeds are in millions of dollars. We evaluate all accounting data items at the first post-IPO fiscal year. We measure long-run abnormal returns by using the intercept of the following Carhart (1997) four-factor regressions,

$$r_{p,t} - r_{f,t} = \alpha + \beta(r_{m,t} - r_{f,t}) + sSMB_t + hHML_t + pPRIOR_t + e_t,$$

where $r_{p,t}$ is IPO calendar-time portfolio return at month t. We include IPO firms in the portfolio starting from the 5th month after the first post-IPO fiscal year-end, and ending on the 52nd month after the first post-IPO fiscal year-end (or the delisted date). Numbers in the parentheses are the t-values of the regression intercepts. "# of months" is the number of months used to run Carhart four-factor regressions. In Panel A, the "Low" DA quartile includes IPOs with a DA decile ranking less than or equal to three, "2" for IPOs with a DA decile ranking from four to six, "3" for a DA decile ranking from seven to nine, and "High" for a DA decile ranking equal to 10. In Panel B, "Low" CMR quartile includes IPOs with CMR less than six, "2" for IPOs with CMR equal to or greater than six but less than eight, "3" for CMR equal to or greater than eight but less than nine, and "High" for CMR equal to nine. The t-statistics for the difference in firm characteristics between extreme portfolios are presented in the t-stat column.

Panel A. Sorted by Discretionary Accruals

	Low	2	3	High	Low-High *t*-Stat
Firm characteristics					
# of IPOs	1,028	810	1,039	749	
DA	−0.117	−0.010	0.060	0.236	−63.23***
DA decile ranking	2.0	4.9	8.2	10.0	−273.55***
Cash flows	0.036	0.004	0.002	−0.172	12.07***
Earnings	−0.066	−0.011	0.064	0.088	−8.66***
CMR	7.6	7.6	7.1	6.7	9.85***
VC	0.59	0.50	0.47	0.41	7.61***
Sales	111	110	134	75	2.18**
Size	466	363	243	126	5.48***
BM	0.45	0.45	0.45	0.46	−0.51
Size decile ranking	2.7	2.5	2.2	1.9	10.16***
BM decile ranking	3.4	3.9	3.9	3.9	−3.46***
Offer price	12.8	13.1	11.9	11.3	7.18***
Initial return (%)	31.99	25.54	18.39	16.08	6.69***
Total proceeds	48	57	45	29	7.98***
Long-run abnormal returns					
(equal-weighted)	0.26%	0.22%	−0.11%	−0.27%	0.54%**
	(1.34)	(1.10)	(−0.55)	(−1.06)	(2.51)
(value-weighted)	0.41%	−0.01%	−0.04%	−0.25%	0.65%*
	(1.53)	(−0.06)	(−0.14)	(−0.83)	(1.88)
# of months	216	216	216	216	216

Table III. One-Way Classifications of Postissue Performance by Discretionary Accruals, Underwriter Reputation, and Venture Capital (Continued)

Panel B. Sorted by Underwriter Reputation

	Low	2	3	High	High-Low *t*-Stat
Firm characteristics					
# of IPOs	656	721	1,278	971	
DA	0.071	0.054	0.023	−0.005	−9.9***
DA decile ranking	7.0	6.7	5.9	5.3	−10.7***
Cash flows	−0.103	0.028	−0.002	−0.038	3.4***
Earnings	−0.027	0.095	0.034	−0.039	−0.61
CMR	3.7	6.7	8.2	9.0	119.44***
VC	0.25	0.41	0.61	0.58	14.1***
Sales	31	61	83	234	5.13***
Size	52	112	209	761	8.7***
BM	0.48	0.45	0.44	0.45	−1.18
Size decile ranking	1.3	1.8	2.3	3.6	27.18***
BM decile ranking	4.1	3.8	3.6	3.6	−3.27***
Offer price	8.3	11.5	12.7	15.1	32.2***
Initial return (%)	14.53	14.20	19.18	41.64	9.12***
Total proceeds	14	25	38	92	10.1***
Long-run abnormal returns					
(equal-weighted)	−0.20%	−0.02%	0.07%	0.20%	0.40%
	(−0.63)	(−0.10)	(0.38)	(0.98)	(1.24)
(value-weighted)	−0.67%**	−0.33%	0.08%	0.29%	0.96%**
	(−2.43)	(−1.44)	(0.38)	(0.96)	(2.56)
# of months	216	216	216	216	216

Panel C. Sorted by Venture Capital

	Non-VC	VC	VC-Non-VC *t*-Stat
Firm characteristics			
# of IPOs	1,820	1,806	
DA	0.050	0.011	−7.77***
DA decile ranking	6.5	5.7	−8.06***
Cash flows	0.034	−0.083	−10.60***
Earnings	0.088	−0.058	−13.01***
CMR	6.7	7.8	17.28***
VC	0.00	1.00	N/A
Sales	155	64	−5.10***
Size	212	407	5.18***
BM	0.46	0.44	−1.07
Size decile ranking	2.1	2.6	8.46***
BM decile ranking	4.0	3.5	−5.12***
Offer price	11.8	12.7	6.11***
Initial return (%)	15.67	31.12	9.87***
Total proceeds	47	44	−0.90
Long-run abnormal returns			
(equal-weighted)	−0.37%*	0.45%**	0.82%***
	(−1.93)	(2.22)	(4.85)
(value-weighted)	−0.54%***	0.50%*	1.04%***
	(−3.50)	(1.74)	(3.45)
# of months	216	216	216

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

IPOs with a DA decile ranking of seven to nine as the third DA quartile, IPOs with a DA decile ranking four to six in the second DA quartile, and IPOs with a DA decile ranking less than or equal to three as the lowest DA quartile. This DA portfolio classification makes the distribution among the four DA quartiles roughly even, although the High DA quartile has fewer observations compared with others. By construction, the High DA quartile has a high level of DA. However, the corresponding cash flows are negative, but earnings are positive. This result suggests earnings manipulation (i.e., earnings are positive due to the high accruals, rather than high cash flows). The average Carter and Manaster (1990) reputation rank (CMR) for the IPO's lead underwriter is lowest for High DA firms. High DA IPOs also tend to be non-VC-backed, and are relatively smaller.

We find that for long-run performance, High DA firms have negative long-run abnormal returns and the Low DA firms have positive long-run abnormal returns, although neither performance is significantly different from zero. However, the difference in two extreme DA quartiles is significant and positive in both equal- and value-weighted results (0.54% and 0.65% per month, respectively), which indicate a DA effect in our sample.

In Panel B, we sort IPOs by the Carter and Manaster (1990) underwriter reputation ranks (CMR). The High CMR quartile has IPOs with a CMR of nine; quartile 3 has IPOs with a CMR equal to or greater than eight but less than nine; quartile 2 has IPOs with a CMR equal to or greater than six but less than eight; and the Low CMR quartile contains IPOs with a CMR less than six. The Low CMR quartile has higher DA, negative cash flows, and tends to include small, non-VC-backed firms. These results are similar to those observed for the High DA quartile in Panel A. However, the earnings for the Low CMR IPOs are negative, which is very different from the positive earnings shown in High DA offers. This difference suggests that although DA and CMR are correlated, the DA and CMR portfolio classifications are not the same.

The long-run return results indicate a monotonic increasing return pattern among CMR quartiles, but the difference in long-run returns between High and Low CMR quartiles is only significant with the value-weighting scheme. This return spread between the two extreme CMR quartiles is more than double for the value-weighted case than it is for the equal-weighted case, suggesting that the CMR effect is more significant for larger IPOs. Since the long-run return spread for the extreme DA portfolios is roughly the same in both equal- and value-weighted cases, and since the CMR effect is more evident in value-weighted case, it appears that the source of return predictability associated with DAs is not closely related to that of CMR.

Panel C consists of one-way results by the VC dummy. The Non-VC group has higher DA, cash flows, and earnings and the group also has lower market capitalization. This result is different from the Panel B result for the Low CMR group, for which the corresponding cash flows, earnings, and market capitalization are relatively low. The difference suggests that although VC and CMR are correlated, the VC and CMR classifications are not the same. Moreover, the higher DA, earnings, and smaller size in the Non-VC group appear to be consistent with the firm characteristics in the High DA group in Panel A. However, the cash flows in the Non-VC IPOs are positive and relatively high, but cash flows in High DA quartile are strongly negative, suggesting that VC and DA do not create the same grouping.

Over the long run, VC-backed IPOs outperform while non-VC-backed IPOs underperform the benchmark Carhart (1997) four-factor model returns. The VC effect is significant across both the equal- and value-weighted cases. This result is different from Brav and Gompers (1997), who find that the VC effect is primarily due to the underperformance of non-VC-backed IPOs, and is significant only in equal-weighted portfolios.

In summary, the univariate analysis shows that long-run returns are higher when discretionary accounting accruals are lower (the DA effect), when the IPO is led by a more reputable underwriter (the CMR effect), and when the IPO has VC backing (the VC effect). The univariate analysis also suggests that these three separate effects are not highly correlated, raising the possibility that a combination of the three effects could isolate a portfolio of IPO stocks that strongly underperforms, and another set of IPOs that outperforms its benchmark.

B. Univariate Analysis by Size

Previous studies (such as Brav, Geczy, Gompers, 2000 and Mitchell and Stafford, 2000) suggest that the mispricing, if there is any, occurs only in small firms. These papers recommend an examination of the long-term returns in both equal- and value-weighted cases. To fully assess the impact of firm size on our results, and as a robustness check, we divide our sample into small and big firms and report the results in Table IV. We classify IPOs whose market capitalizations are in the bottom size decile of NYSE stocks as small IPOs, and classify the rest as big IPOs. This size classification makes the number of IPOs in each subsample roughly even.

In Panel A of Table IV, the DA effect is significant for both small and big IPO firms, although it appears to be somewhat stronger for small IPO firms. In Panel B, we see that the distribution of IPOs brought to the market by different-quality investment bankers is closely related to firm size. The table shows that the majority of the small IPOs is brought to the market by lower-reputation underwriters and that a majority of the larger IPOs are managed by the more-prestigious investment bankers. For instance, 550 (34%) and 165 (10%) of the 1,606 small IPOs are brought to the market by the lowest- and highest-reputation underwriters, respectively. In contrast, 106 (5%) and 806 (40%) of the larger IPOs are managed by the least- and most-prestigious underwriters, respectively.

For long-run performance, we find that the underwriter reputation effect is relatively weak in the subsample of small IPO firms. However, there is a strong monotonic CMR effect for big IPO firms. Also, it appears that the CMR effect is driven primarily by the severe underperformance of large IPOs with low-reputation underwriters. Carter, Dark, and Singh (1998) document that IPOs brought to the market by more prestigious underwriters have better long-run performance. However, Logue, Rogalski, Seward, and Foster-Johnson (2002) do not find evidence of an underwriter reputation effect. The dissimilar effects across small versus large IPO firms shown in Panel B are one plausible reason for the different results in these two studies.

In Panel C, we see that the VC effect is significant for both small and big IPOs. The VC-backing status seems to generate a stronger return spread in big IPOs, especially for the value-weighted case (1.13% for big IPOs compared with 0.58% in small IPOs). The VC effect in big IPOs is primarily due to the underperformance of non-VC-backed IPOs. However, VC-backed IPOs also show marginally significant outperformance. Again, this result is not consistent with Brav and Gompers (1997).

From the three panels of Table IV, it appears that the DA effect is remarkably different from the CMR effect. We observe the DA effect for both small and big IPOs, but see that it is stronger in small issuers. On the other hand, we can detect the CMR effect only in big IPOs. The VC effect is different from the CMR effect, since the VC effect is significant in both small and big IPOs. Moreover, even though both the CMR and VC effects are strong in big IPOs and are mainly driven by one extreme portfolio (Low CMR quartile and Non-VC, respectively), the CMR and VC groupings are not the same: in big IPOs, the Low CMR quartile has a very low BM compared with other CMR portfolios, while Non-VC IPOs have higher BM relative to VC-backed issuers.

There appears to be some correlation between the DA and VC effects, since both are significant in small and big IPOs. However, there are two differences between DA and VC sorts. First, the return spread based on the DA sort is higher for small IPOs, but the return spread based on the

Table IV. One-Way Classifications of Postissue Performance: Small Compared with Big IPOs

The sample consists of 3,626 IPOs issued in 1980-2000 with an offering price of at least \$5.00 and total proceeds of at least \$5 million. We exclude closed-end funds, REITs, ADRs, non-US stocks, reverse LBOs, spin-offs, and units from the sample. We require that our sample firms have data available to compute accruals at the first post-IPO fiscal year-end. DA is the discretionary accruals, which we obtain from the residuals of the Jones (1991) model. DA decile ranking is relative to all stocks with available DA. Cash flows are the difference between earnings and accruals. Earnings are operating income after depreciation. We normalize DA, Cash flows, and Earnings by dividing by average total assets. CMR is Carter-Manaster (1990) ranking, as updated by Loughran and Ritter (2004), of the IPO's lead underwriter. VC is a dummy variable equal to one if the IPO is venture capital-backed. Sales are expressed in millions of dollars. Sales growth is the one-year growth rate of sales, based on sales at the first post-IPO fiscal year and the year before. Size is market value of equity at the fourth month-end after the first post-IPO fiscal year-end, and is expressed in millions of dollars. BM is the book-to-market ratio, which we compute by dividing book value of equity by Size. Size (BM) decile ranking is relative to the NYSE stocks only. Offer price is the IPO offer price. Initial return is the return from the IPO offer price to first available closing price. Total proceeds are in millions of dollars. We evaluate all accounting data items at the first post-IPO fiscal year. We measure long-run abnormal returns by using the intercept of the following Carhart (1997) four-factor regressions,

$$r_{p,t} - r_{f,t} = \alpha + \beta(r_{m,t} - r_{f,t}) + sSMB_t + hHML_t + pPRIOR_t + e_t,$$

where $r_{p,t}$ is IPO calendar-time portfolio return at month t. We include IPO firms in the portfolio starting from the 5th month after the first post-IPO fiscal year-end, and ending on the 52nd month after the first post-IPO fiscal year-end (or the delisted date). Numbers in the parentheses are the t-values of the regression intercepts. The variable "# of months" is the number of months used to run Carhart four-factor regressions. Small IPOs are issuers whose size decile ranking is one, and the remaining sample firms are included in Big IPOs. In panel A, the "Low" DA quartile includes IPOs with a DA decile ranking less than or equal to three, "2" for IPOs with a DA decile ranking from four to six, "3" for a DA decile ranking from seven to nine, and "High" for a DA decile ranking equal to 10. In panel B, "Low" CMR quartile includes IPOs with CMR less than six, "2" for IPOs with CMR equal to or greater than six but less than eight, "3" for CMR equal to or greater than eight but less than nine, and "High" for CMR equal to nine. The t-statistics for the difference in firm characteristics between extreme portfolios are presented in the t-stat column.

Panel A. Sorted by Discretionary Accruals

	Small IPOs				Low-High	Big IPOs				Low-High
	Low	2	3	High	t-Stat	Low	2	3	High	t-Stat
Firm characteristics										
# of IPOs	389	313	489	415		639	497	550	334	
DA	−0.122	−0.009	0.062	0.248	−40.77***	−0.114	−0.010	0.058	0.221	−47.56***
DA decile ranking	2.0	4.9	8.3	10.0	−205.28***	2.0	4.9	8.2	10.0	−181.71***

Table IV. One-Way Classifications of Postissue Performance: Small Compared with Big IPOs (*Continued*)

Panel A. Sorted by Discretionary Accruals (Continued)

	Small IPOs				Low-High	Big IPOs				Low-High
	Low	2	3	High	*t*-Stat	Low	2	3	High	*t*-Stat
Cash flows	−0.032	−0.025	−0.036	−0.213	6.74***	0.078	0.022	0.035	−0.121	8.83***
Earnings	−0.144	−0.044	0.021	0.048	−6.99***	−0.018	0.009	0.103	0.139	−6.72***
CMR	6.6	6.6	6.1	5.9	4.75***	8.2	8.3	8.0	7.7	6.03***
VC	0.49	0.47	0.38	0.32	5.00***	0.65	0.53	0.55	0.52	3.92***
Sales	45	38	46	50	−0.84	150	155	212	106	1.47
Size	47	47	41	40	3.18***	722	561	423	233	4.23***
BM	0.75	0.64	0.62	0.61	2.44**	0.27	0.33	0.30	0.29	−1.01
Size decile ranking	1.0	1.0	1.0	1.0	N/A	3.8	3.5	3.3	3.0	7.08***
BM decile ranking	5.2	5.5	5.3	5.0	0.84	2.3	2.9	2.7	2.4	−0.78
Offering price	10.3	10.3	9.8	9.6	3.15***	14.3	14.8	13.8	13.4	3.05***
Initial return (%)	15.55	9.87	10.84	12.48	1.39	42.00	35.40	25.11	20.54	5.38***
Total proceeds	26	23	20	18	5.49***	62	79	66	42	4.68***
Long-run abnormal returns										
(equal-weighted)	0.40%	0.48%	0.05%	−0.26%	0.65%**	0.22%	0.02%	−0.22%	−0.26%	0.48%*
	(1.23)	(1.50)	(0.16)	(−0.75)	(2.07)	(1.10)	(0.10)	(−1.09)	(−1.03)	(1.89)
(value-weighted)	0.10%	0.29%	−0.10%	−0.68%**	0.78%*	0.46%	−0.03%	−0.02%	−0.19%	0.64%*
	(0.36)	(0.91)	(−0.43)	(−2.03)	(1.78)	(1.57)	(−0.11)	(−0.05)	(−0.57)	(1.67)
# of months	216	216	216	216	216	216	216	216	216	216

Table IV. One-Way Classifications of Postissue Performance: Small Compared with Big IPOs (*Continued*)

Panel B. Sorted by Underwriter Reputation

	Small IPOs				High-Low	Big IPOs				High-Low
	Low	2	3	High	*t*-Stat	Low	2	3	High	*t*-Stat
Firm characteristics										
# of IPOs	550	422	469	165		106	299	809	806	
DA	0.072	0.062	0.030	0.017	−3.51***	0.067	0.043	0.019	−0.009	−5.65***
DA decile ranking	7.0	6.8	6.1	5.8	−4.31***	6.9	6.4	5.8	5.2	−5.51***
Cash flows	−0.129	0.006	−0.061	−0.178	−1.31	0.036	0.058	0.032	−0.009	−1.32
Earnings	−0.059	0.076	−0.028	−0.160	−2.76***	0.137	0.123	0.070	−0.014	−4.20***
CMR	3.5	6.7	8.1	9.0	50.44***	4.3	6.8	8.2	9.0	109.12***
VC	0.23	0.39	0.56	0.62	10.27***	0.34	0.45	0.65	0.57	4.54***
Sales	26	47	55	78	7.80***	54	82	99	266	1.97***
Size	31	43	51	62	14.18***	162	209	300	904	3.37***
BM	0.53	0.59	0.72	1.01	8.56***	0.22	0.26	0.28	0.33	3.34***
Size decile ranking	1.0	1.0	1.0	1.0	N/A	2.5	2.8	3.1	4.2	8.22***
BM decile ranking	4.5	5.1	5.8	6.5	7.92***	1.8	2.1	2.4	3.0	5.21***
Offering price	7.8	10.2	11.5	12.3	18.26***	11.0	13.2	13.3	15.7	9.49***
Initial return (%)	13.66	10.29	10.22	18.02	1.79*	19.04	19.73	24.38	46.48	3.59***
Total proceeds	12	19	28	44	21.56***	23	33	44	102	3.76***
Long-run abnormal returns										
(equal-weighted)	0.06%	0.13%	0.15%	0.82%	0.73%	−1.43%***	−0.32%	0.05%	0.15%	1.61%***
	(0.17)	(0.44)	(0.50)	(1.59)	(1.42)	(−3.05)	(−1.28)	(0.29)	(0.70)	(3.36)
(value-weighted)	−0.05%	−0.01%	−0.43%*	0.26%	0.25%	−1.51%***	−0.44%	0.15%	0.31%	1.83%***
	(−0.17)	(−0.03)	(−1.67)	(0.63)	(0.48)	(−3.34)	(−1.62)	(0.66)	(0.98)	(3.44)
# of months	216	216	216	200	200	206	206	216	216	206

Table IV. One-Way Classifications of Postissue Performance: Small Compared with Big IPOs (*Continued*)

Panel C. Sorted by Venture Capital

	Small IPOs		VC-Non-VC	Big IPOs		VC-Non-VC
	Non-VC	VC	*t*-Stat	Non-VC	VC	*t*-Stat
Firm characteristics						
# of IPOs	953	653		867	1153	
DA	0.068	0.027	−5.06***	0.029	0.002	−4.34***
DA decile ranking	6.9	6.0	−5.32***	6.1	5.5	−4.53***
Cash flows	−0.040	−0.135	−5.32***	0.116	−0.053	−12.31***
Earnings	0.031	−0.106	−7.57***	0.151	−0.030	−12.83***
CMR	5.7	7.1	13.21***	7.9	8.2	6.09***
VC	0.00	1.00	N/A	0.00	1.00	N/A
Sales	50	38	−3.21***	270	79	−6.01***
Size	40	49	6.46***	401	610	3.13***
BM	0.59	0.74	4.25***	0.32	0.28	−3.43***
Size decile ranking	1.0	1.0	N/A	3.3	3.5	2.20**
BM decile ranking	5.1	5.5	2.87***	2.8	2.4	−4.30***
Offering price	9.6	10.5	5.58***	14.3	14.0	−1.49
Initial return (%)	11.77	12.87	0.83	19.96	41.45	8.38***
Total proceeds	18	27	9.62***	79	53	−4.06***
Long-run abnormal returns						
(equal-weighted)	−0.25%	0.62%**	0.87%***	−0.54%***	0.36%*	0.90%***
	(−0.92)	(2.05)	(3.56)	(−3.28)	(1.68)	(4.05)
(value-weighted)	−0.37%*	0.20%	0.58%*	−0.58%***	0.55%*	1.13%***
	(−1.87)	(0.81)	(1.97)	(−3.33)	(1.80)	(3.39)
# of months	216	216	216	216	216	216

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

VC sort is higher for big issuers. Second, Non-VC and High DA offers have different levels of cash flows. Among the big IPOs, the Non-VC issuers have high cash flows, but the High DA firms have negative cash flows. In small IPOs, Non-VC issuers have small negative cash flows, but High DA issuers have very negative cash flows.

The analysis by size suggests that each of the three variables, namely, DA, CMR, and VC, is related to different sources of return predictability. The relations of these three variables with IPO stock returns are not the manifestation of one phenomenon. Introducing all three together should help in identifying IPOs that generate abnormal returns.

C. Multivariate Analysis

Our main results are presented in Table V, where we examine the effects of all three variables simultaneously. In Panel A, we examine the full sample, and then sort by size in Panels B and C. To maintain a reasonable number of IPOs in each cell, we use dichotomous cuts for each of the three variables. We combine the top two (bottom two) DA quartiles from Tables III and IV as the High (Low) DA firms, and combine the top two (bottom two) CMR quartiles as the High (Low) CMR IPOs.

One important result of our three-way analyses is that the combined effect of the three variables is generally stronger than each of their individual effects. The return spread between the two extreme portfolios (Low DA/High CMR/VC, Column (6), minus High DA/Low CMR/Non-VC, Column (3)) is significant and economically large for the full sample (1.31% and 2.07%, respectively, for equal- and value-weighted portfolios). Even though we use only dichotomous cuts for DA and CMR in Table V and quartile cuts in Table III, this return spread is bigger than any sort in Table III. The return spread is especially large for the sample of big IPOs (2.05% and 2.36%, respectively, for equal- and value-weighted portfolios). None of the one-way sorts in Table IV creates such a large return difference. For small IPOs, the equal-weighted results show a significant return spread equal to 1.17%, but the value-weighted return spread is not significant.

Another interesting finding is that by combining positive aspects of DA, CMR, and VC, we create an IPO-winner portfolio that significantly outperforms the benchmark, while the grouping of negative aspects of these three variables generates IPO losers with large negative stock returns. IPOs with Low DA, High CMR, and VC backing (Column (6)) outperform the Carhart (1997) four-factors by 0.77% (0.98%) per month in the equal- (value-) weighted case. On the other hand, the IPO losers, that is, High DA, Low CMR, Non-VC (Column (3)), exhibit an abnormal return of −0.54% (−1.09%) per month in equal- (value-) weighted case. When we further condition on firm size, we do not find consistent results in small IPOs. However, in larger IPOs, combining the negative aspect of each of the three variables produces losers, and the combination of the positive attributes produces winners. The result holds for both equal- and value-weighted portfolios.

In summary, each of the three variables examined in our study—the level of DA, the reputation of the underwriter, and VC backing—has a positive and a negative association with IPO long-run returns. We use these three variables jointly to identify IPO winners and losers.

D. Cross-Sectional Regressions

In Table VI, we report the results of event-time cross-sectional regressions that incorporate the interaction among the variables presented in previous tables. The dependent variable is the four-year BHAR, which we obtain by compounding the monthly returns of an IPO from the fifth month after its first post-IPO fiscal year-end, and then subtracting the compounded return over the same period of its corresponding size and book-to-market matched control firm. We winsorize the returns at 1% and 99% to control for the impact of outliers.

Table V. Three-Way Classifications of Postissue Performance by Discretionary Accruals, Underwriter Reputation, and Venture Capital

This table presents the long-run abnormal returns sorted by DA, CMR, and VC. DA denotes discretionary accruals, CMR denotes the Carter-Manaster (1990) ranking, as updated by Loughran and Ritter (2004), of the IPO's lead underwriter, and VC is a dummy variable equal to one if the IPO is venture capital-backed. Low DA includes IPOs with a DA decile ranking less than or equal to six, and High DA includes IPOs with a DA decile ranking greater than six. Low CMR has IPOs with CMR less than eight, and High CMR for CMR equal to or greater than eight. We measure the long-run abnormal returns by using the intercept of Carhart (1997) four-factor regressions. Numbers in the parentheses are the *t*-values of the regression intercepts. The variable "# of months" is the number of months used to run regressions. Small IPOs are issuers whose size decile ranking is one, and the remaining sample firms are included in Big IPOs. Size decile ranking is relative to the NYSE stocks only. Column (9) shows the *t*-statistic of testing IPO winners (Low DA, High CMR, and VC, Column (6)) compared to IPO losers (High DA, Low CMR, and Non-VC, Column (3)).

Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
VC	**Non-VC**				**VC**				**Winner-Loser**
DA	**Low**		**High**		**Low**		**High**		
CMR	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**	
Panel A. Full Sample									
# of IPOs	338	486	579	417	210	804	250	542	
(equal-weighted)	−0.22%	−0.22%	−0.54%**	−0.45%*	0.85%**	0.77%***	0.50%	0.22%	1.31%***
	(−0.80)	(−1.14)	(−2.01)	(−1.85)	(2.33)	(2.93)	(1.55)	(0.91)	(4.58)
(value-weighted)	−0.21%	−0.47%**	−1.09%***	−0.53%**	0.35%	0.98%***	0.08%	0.45%	2.07%***
	(−0.67)	(−2.27)	(−4.38)	(−2.03)	(0.85)	(2.76)	(0.23)	(1.18)	(5.15)
# of months	216	216	216	216	216	216	216	216	216

Table V. Three-Way Classifications of Postissue Performance by Discretionary Accruals, Underwriter Reputation, and Venture Capital (*Continued*)

Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VC	Non-VC				VC				Winner-Loser
DA	Low		High		Low		High		
CMR	Low	High	Low	High	Low	High	Low	High	
Panel B. Small IPOs									
# of IPOs	243	122	440	148	129	208	160	156	
(equal-weighted)	0.01%	0.17%	−0.30%	−0.58%	1.14%***	0.93%**	0.49%	0.57%	1.17%***
	(0.04)	(0.42)	(−0.94)	(−1.51)	(2.61)	(2.07)	(1.25)	(1.40)	(2.91)
(value-weighted)	0.27%	−0.03%	−0.69%**	−0.83%**	0.92%*	−0.03%	0.03%	0.22%	0.62%
	(0.71)	(−0.08)	(−2.26)	(−2.16)	(1.82)	(−0.07)	(0.06)	(0.52)	(1.34)
# of months	216	197	216	206	203	188	216	200	188
Panel C. Big IPOs									
# of IPOs	95	364	139	269	81	596	90	386	
(equal-weighted)	−0.84%**	−0.25%	−1.18%***	−0.43%*	0.11%	0.87%***	−0.19%	0.10%	2.05%***
	(−2.03)	(−1.15)	(−3.92)	(−1.70)	(0.20)	(2.91)	(0.42)	(0.38)	(5.30)
(value-weighted)	−0.59%	−0.47%**	−1.26%***	−0.51%*	−0.33%	1.10%***	−0.18%	0.47%	2.36%***
	(−1.42)	(−2.14)	(−3.71)	(−1.79)	(−0.51)	(2.92)	(−0.36)	(1.20)	(4.81)
# of months	216	216	216	216	168	216	197	216	216

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

Table VI. Cross-Sectional Regressions

The dependent variable is the four-year buy-and-hold abnormal return (BHAR). We compute this variable by compounding monthly returns of an IPO from the fifth month after its first post-IPO fiscal year-end and then subtracting the compounded return over the same period of its corresponding size and book-to-market matched control firm. We winsorize the returns at 1% and 99%. Size is market value of equity at the fourth month-end after the first post-IPO fiscal year-end, and is expressed in millions of dollars. BM is the book-to-market ratio, which we compute by dividing book value of equity by Size. Initial return is the return from the IPO offer price to first available closing price. DA is the discretionary accruals, which we obtain from the residuals of the Jones (1991) model. CMR is Carter-Manaster (1990) ranking, as updated by Loughran and Ritter (2004), of the IPO's lead underwriter. DA (CMR) quartile assigns values of 0, 0.333, 0.667, and 1 to the lowest DA (CMR) quartile, the next two quartiles and the highest DA (CMR) quartile, respectively. VC is a dummy variable equal to one if the IPO is venture capital-backed. Winner dummy is equal to one if the IPO has a DA decile ranking less than or equal to six, a CMR equal to or greater than eight, and is VC-backed. Loser dummy is equal to one if the IPO has a DA decile ranking greater than six, a CMR less than eight, and is not VC-backed. Numbers in the parentheses are *t*-statistics based on White (1980) heteroskedasticity-consistent standard errors. We include, but do not report, year dummy variables in the regressions.

Panel A. Full Sample

Model	**1**	**2**	**3**	**4**	**5**	**6**
Intercept	−0.624**	−0.348**	−0.629***	−0.576**	−0.901***	−0.619**
	(−2.35)	(−2.49)	(−3.58)	(−2.16)	(−3.48)	(−2.27)
Log(size)	0.042	−0.100	−0.013	−0.032	−0.056	0.002
	(1.25)	(−0.70)	(−1.32)	(−0.81)	(−1.38)	(0.00)
Log (1+ BM)	0.238	−0.465	−0.114	0.093	0.024	0.151
	(1.32)	(−0.37)	(−1.41)	(0.50)	(0.14)	(0.83)
IPO initial return	−0.132	0.022	−0.033*	−0.131	−0.112	−0.149*
	(−1.52)	(1.18)	(−1.78)	(−1.51)	(−1.28)	(−1.73)
DA quartile	−0.329***	—	—	−0.287***	—	—
	(−3.49)			(−3.03)		
CMR quartile	—	0.569***	—	0.318**	—	—
		(3.31)		(2.55)		
VC	—	—	0.246***	0.190***	0.163**	—
			(3.31)	(2.65)	(2.26)	
DA	—	—	—	—	−0.809***	—
					(−3.71)	
CMR	—	—	—	—	0.077***	—
					(3.53)	
Winner dummy	—	—	—	—	—	0.349***
						(3.68)
Loser dummy	—	—	—	—	—	−0.250***
						(−2.60)
Adjusted R squared (%)	1.41	1.37	1.39	1.77	2.01	1.74
Number of observations	3,626	3,626	3,626	3,626	3,626	3,626

Table VI. Cross-Sectional Regressions (*Continued*)

Panel B. Small versus Big IPOs

	Small IPOs						Big IPOs					
Model	**1**	**2**	**3**	**4**	**5**	**6**	**1**	**2**	**3**	**4**	**5**	**6**
Intercept	−0.715*	−0.746*	−0.913**	−0.612	−0.798*	−0.690	−0.214	−0.348	−0.629	−0.439	−1.173***	−0.332
	(−1.69)	(−1.77)	(−2.22)	(−1.43)	(−1.94)	(−1.57)	(−0.51)	(−0.84)	(−1.50)	(−1.03)	(−2.67)	(−0.78)
Log(size)	0.117*	0.069	0.105	0.055	0.015	0.078	−0.036	−0.100	−0.013	−0.088	−0.093	−0.052
	(1.78)	(0.89)	(1.57)	(0.71)	(0.17)	(1.10)	(−0.62)	(−1.57)	(−0.22)	(−1.40)	(−1.49)	(−0.88)
Log (1+ BM)	0.414*	0.310	0.389*	0.299	0.207	0.323	−0.208	−0.465	−0.114	−0.353	−0.371	−0.235
	(1.95)	(1.41)	(1.84)	(1.36)	(0.92)	(1.48)	(−0.57)	(−1.26)	(−0.32)	(−0.95)	(−1.00)	(−0.65)
IPO initial return	−0.446*	−0.436*	−0.447*	−0.413*	−0.412*	−0.424*	0.006	0.022	−0.033	−0.025	−0.020	−0.047
	(−1.83)	(−1.78)	(−1.85)	(−1.68)	(−1.66)	(−1.76)	(0.00)	(0.24)	(−0.36)	(−0.28)	(−0.22)	(−0.51)
DA quartile	−0.411***	—	—	−0.383***	—	—	−0.250*	—	—	−0.198	—	—
	(−3.18)			(−2.91)			(−1.85)			(−1.47)		
CMR quartile	—	0.247	—	0.163	—	—	—	0.569***	—	0.497***	—	—
		(1.35)		(0.89)				(3.42)		(2.96)		
VC	—	—	0.181	0.129	0.107	—	—	—	0.246**	0.209**	0.187*	—
			(1.63)	(1.15)	(0.94)				(2.57)	(2.19)	(1.95)	
DA	—	—	—	—	−0.911***	—	—	—	—	—	−0.685**	—
					(−3.27)						(−1.98)	
CMR	—	—	—	—	0.050*	—	—	—	—	—	0.132***	—
					(1.68)						(3.82)	
Winner dummy	—	—	—	—	—	0.188	—	—	—	—	—	0.383***
						(1.20)						(3.24)
Loser dummy	—	—	—	—	—	−0.189	—	—	—	—	—	−0.387**
						(−1.53)						(−2.48)
Adjusted R square (%)	0.70	0.28	0.34	0.74	0.95	0.38	2.50	2.78	2.64	3.02	3.23	3.20
Number of observations	1,606	1,606	1,606	1,606	1,606	1,606	2,020	2,020	2,020	2,020	2,020	2,020

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

To be consistent with previous tables, we use variables in the regressions to represent different IPO groups. For example, the variable DA quartile takes values of 0, 0.333, 0.667, and 1 for the lowest DA quartile, the next two quartiles, and the highest DA quartile, respectively. As a result, the coefficient of the DA quartile indicates the difference of long-run returns between extreme DA quartiles. We define the variable CMR quartile in a similar fashion. We also use continuous DA and CMR values to perform robustness checks, and we add log (market capitalization), log (1 + book-to-market ratio), and IPO initial return in the regressions as control variables. We include, but do not report, year dummy variables in the regressions.

If the market is efficient, under the null hypothesis, abnormal stock returns are not predictable. Therefore, we would not expect to observe significant coefficients associated with DA quartile, CMR quartile, and VC.

Panel A of Table VI shows the regression results for the full sample. Model 1 shows that high DA IPOs significantly underperform low DA by 32.9% over four years, which is about 0.6% per month (geometric average). This result is consistent with the findings reported in Table III. The CMR effect also exists in our full sample (Model 2). Issuers with VC backing significantly outperform non-VC-backed IPOs (Model 3). In Model 4, we combine all three variables in the same regression and find that the DA quartile, CMR quartile, and VC are all significantly related to IPO long-run returns. We reach similar conclusions when we use continuous variables (Model 5).

Combining the positive and negative aspects of DA, CMR, and VC together (Model 6), we find that Low DA/High CMR/VC IPOs (winner IPOs) outperform and High DA/Low CMR/Non-VC IPOs (loser IPOs) underperform their matching firms. The difference between winners and losers is about 60% over four years, or 1% per month (geometric average), which is comparable to Table V (Column (9) of Panel A). All of these results are consistent with the results of our three-way analyses presented in Table V.

In Panel B, we run separate regressions for small and big IPOs. Generally, the results confirm those in previous tables. The DA effect exists for both small and big IPOs and is stronger in small IPOs, while the VC and CMR effects are strong in big IPOs. In big IPOs, since both CMR and VC are significant in the same regression (Models 4 and 5), CMR and VC effects apparently do not subsume each other. For the IPO extreme groups, winner IPOs outperform and loser IPOs underperform their matching benchmarks in the big IPO subsample.

IV. Tests of Mispricing and Misspecification Hypotheses

Why do our IPO winners and losers exhibit abnormal long-run stock returns? We consider two competing hypotheses on performance, mispricing, and model misspecification.

The mispricing story argues that DA, underwriter ranking, and VC may contain vital information regarding IPO future prospects, or that these three attributes are associated with certain firm characteristics which are closely related to long-run returns. However, investors do not fully incorporate these effects into pricing initially. As more information is released over time, investors are surprised by the changes in fundamentals and revise their expectations accordingly. As a result, under this scenario, we would expect that loser IPOs exhibit deteriorating operating performance but winners show an improvement. We also expect that loser and winner IPOs tend to covary with certain firm characteristics that have been documented in the literature to be related to future stock returns.

Alternatively, our results could be driven by omitted risk factors in the asset pricing models employed to detect the abnormal stock returns of IPOs. Thus a "bad or poor" asset pricing model problem will manifest itself in spurious long-run abnormal returns (Fama, 1998). This risk explanation also raises concerns about the methodology used to gauge long-run stock returns (Brav, Geczy, and Gompers, 2000; Jegadeesh, 2000; Mitchell and Stafford, 2000). Under this alternative hypothesis, the abnormal stock performance of winner and loser IPOs will disappear when appropriate risk factors are controlled for and/or correct methods are used. Therefore, if our results are driven by model misspecifications, we would neither expect to see abnormal patterns in subsequent operating performance nor to observe consistent firm characteristics correlated with future returns.

In this section, we use operating performance following IPOs and firm characteristics at the time when we form IPO portfolios to disentangle the mispricing and misspecification explanations.

A. Firm Characteristics

Table VII shows the firm characteristics for the three-way sorts by DA, CMR, and VC for small IPOs (Panel A) and big IPOs (Panel B). These are the same sorts as in Table V, with loser IPOs in Column (3) and winner IPOs in Column (6). We focus on big IPOs, although we can draw similar (albeit somewhat weaker) conclusions from the subsample of small IPOs.

For big IPOs, losers have high earnings. In fact, their earnings are the highest among the eight portfolios in the three-way sort. However, the high earnings are mainly due to the very large accruals and, by construction, high DA. Meanwhile, these loser IPOs have low book-to-market ratios (BM), indicating the high expectation that the market has for their future growth potential. Prior research argues that these firm characteristics found in our loser IPOs are associated with poor future stock returns. Thus, the characteristics of the losing IPO firms seem to suggest a mispricing story. At the time of the first post-IPO fiscal year-end, investors are overly optimistic about issuers' future prospects. They put too much weight on the bottom-line performance measure while ignoring the poor fundamentals indicated by high accruals. When negative information is subsequently released, investors revise their expectation downward and the stock price drops. In view of the negative signals implied from the non-VC-backed status and the low ranking of lead underwriters of the losing IPO firms, it is also likely that investors do not discount stock prices sufficiently.

Unlike loser IPOs, the firm characteristics of winner IPOs do not seem to provide consistent evidence to support the mispricing story. For example, the winner IPOs in Panel B have relatively poor earnings, low accruals, and thus low DA. This result seems to be consistent with the other studies that find that future stock returns tend to be high for firms with lower earnings (Cooper, Gulen, and Schill, 2007), low accruals (Sloan, 1996), and low DA (Xie, 2001; Chan et al., 2006). However, the winner IPOs are also associated with negative cash flows and low BM, which are indications of lower future stock returns (Lakonishok, Shleifer, and Vishny, 1994; Desai, Rajgopal, and Venkatachalam, 2004). Thus, our results do not seem to support the mispricing story but are instead more consistent with the misspecification hypothesis.

B. Operating Performance

Although firm characteristics support the mispricing story for loser IPOs, we cannot rule out the possibility that model misspecification may account for the negative abnormal returns of IPO losers. Moreover, it is not obvious that winner IPOs exhibit fundamentals in a pattern that is consistent with their stock performance.

Table VII. Firm Characteristics of Three-Way Classifications by Discretionary Accruals, Underwriter Reputation, and Venture Capital: Small Compared with Big IPOs

This table presents the firm characteristics for three-way sorts by DA, CMR, and VC. DA is the discretionary accruals, which we obtain from the residuals of the Jones (1991) model. DA decile ranking is relative to all stocks with available DA. Accruals are the firm's total accruals defined as changes in current assets excluding cash, minus changes in current liabilities excluding short-term debt and taxes payable, and minus depreciation. Cash flows are the difference between earnings and accruals. Earnings are operating income after depreciation. We normalize DA, Accruals, Cash flows, and Earnings by dividing by average total assets. CMR is Carter-Manaster (1990) ranking, as updated by Loughran and Ritter (2004), of the IPO's lead underwriter. VC is a dummy variable equal to one if the IPO is venture capital-backed. Sales are expressed in millions of dollars. Size is market value of equity at the fourth month-end after the first post-IPO fiscal year-end, and is expressed in millions of dollars. BM is the book-to-market ratio, which we compute by dividing book value of equity by Size. Size (BM) decile ranking is relative to the NYSE stocks only. Small IPOs are issuers whose size decile ranking is one. The remaining sample firms are included in Big IPOs. Low DA includes IPOs with a DA decile ranking less than or equal to six, and High DA includes IPOs with a DA decile ranking greater than six. Low CMR has IPOs with CMR less than eight, and high CMR for CMR equal to or greater than eight. Column (9) shows the t-statistics of testing IPO winners (Low DA, High CMR, and VC, Column (6)) compared with IPO losers (High DA, Low CMR, and Non-VC, Column (3)).

Column	**(1)**	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**
VC	**Non-VC**				**VC**				***t*-Stat of Winner-Loser (6)-(3)**
DA	**Low**		**High**		**Low**		**High**		
CMR	**Low**	**High**	**Low**	**High**	**Low**	**High**	**Low**	**High**	
Panel A. Small IPOs									
# of IPOs	243	122	440	148	129	208	160	156	
DA	−0.077	−0.066	0.161	0.142	−0.074	−0.067	0.144	0.116	−25.38***
DA decile ranking	3.2	3.5	9.1	9.0	3.3	3.3	9.1	8.8	−48.50***
Accruals	−0.071	−0.070	0.161	0.151	−0.069	−0.072	0.145	0.125	−21.98***
Cash flows	0.037	0.084	−0.121	−0.027	−0.031	−0.171	−0.126	−0.183	−1.56
Earnings	−0.034	0.015	0.040	0.124	−0.100	−0.243	0.019	−0.058	−8.48***

Table VII. Firm Characteristics of Three-Way Classifications by Discretionary Accruals, Underwriter Reputation, and Venture Capital: Small Compared with Big IPOs (*Continued*)

Column	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VC	Non-VC				VC				*t*-Stat of Winner-Loser (6)-(3)
DA	Low		High		Low		High		
CMR	Low	High	Low	High	Low	High	Low	High	
Panel A. Small IPOs (Continued)									
CMR	4.8	8.4	4.6	8.3	5.7	8.4	5.5	8.4	37.93***
VC	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00	N/A
Sales	37	71	38	94	30	39	31	52	0.18
Size	37	54	34	50	45	56	36	55	9.36***
BM	0.57	0.64	0.53	0.76	0.60	0.95	0.57	0.75	4.54***
Size decile ranking	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	N/A
BM decile ranking	4.9	5.5	4.7	6.0	4.6	6.1	4.8	6.0	6.24***
Panel B. Big IPOs									
# of IPOs	95	364	139	269	81	596	90	386	
DA	−0.064	−0.057	0.142	0.119	−0.067	−0.077	0.128	0.111	−18.17***
DA decile ranking	3.4	3.6	9.1	8.8	3.2	3.1	9.1	8.8	−55.13***
Accruals	−0.060	−0.055	0.167	0.122	−0.052	−0.063	0.188	0.132	−15.44***
Cash flows	0.214	0.178	0.025	0.044	−0.001	−0.041	−0.030	−0.087	−2.39**
Earnings	0.153	0.124	0.192	0.166	−0.053	−0.104	0.158	0.045	−11.50***
CMR	6.0	8.7	6.0	8.6	6.3	8.6	6.3	8.5	20.79***
VC	0.00	0.00	0.00	0.00	1.00	1.00	1.00	1.00	N/A
Sales	87	320	87	362	54	74	61	95	−1.17
Size	208	515	177	431	250	861	168	402	6.61***
BM	0.25	0.35	0.24	0.34	0.24	0.28	0.27	0.28	2.23**
Size decile ranking	2.7	3.7	2.5	3.4	2.9	3.8	2.9	3.3	12.15***
BM decile ranking	2.0	3.0	2.0	3.2	2.0	2.4	1.9	2.5	2.91***

***Significant at the 0.01 level.

**Significant at the 0.05 level.

In Table VIII, we examine operating performance to test the two hypotheses.[2] To match the stock-return horizon we measure in previous tables, we examine the median abnormal operating performance in the four years following the first post-IPO fiscal year-end. Since there are some outliers in earnings, Barber and Lyon (1996) suggest examining the median rather than the mean values of operating performance. We also look at the mean operating performance (not reported), and the results are qualitatively similar. We use EBITDA (operating income before depreciation, Compustat item 13) scaled by total assets to gauge the operating performance. EBITDA is recommended by Barber and Lyon (1996) to detect abnormal operating performance because it is not affected by a change in capital structure or affected by special items and income taxes that influence other measures of earnings. Moreover, EBITDA is the most popular measure in the literature examining operating performance (e.g., Jain and Kini, 1994, for IPOs; Loughran and Ritter, 1997, for SEOs; and Grullon and Michaely, 2004, for repurchases).

We measure abnormal operating performance by using an industry-matched control benchmark. We first classify all firms covered in Compustat with available returns on assets (ROAs; i.e., EBITDA/Assets) into 48 industries based on the Fama and French (1997) industry classification. We exclude all IPOs, even those IPOs we do not include in our sample, from the corresponding industries until five years after their offering date. We obtain the abnormal operating performance of a sample IPO firm by subtracting the median ROA of its corresponding industry.[3] To detect the abnormal performance of our sample IPOs following the first post-issue fiscal year-end, we focus on the changes in abnormal operating performance. In doing so, we follow Barber and Lyon (1996), who suggest that test statistics based on changes in operating performance yield more powerful tests than do those based on levels.

Panel A shows the abnormal operating performance classified by DA quartiles. High DA issuers tend to have a better level of abnormal performance in the year in which we form the portfolios, while Low DA IPOs perform poorly. However, the fundamentals change dramatically in the next year. High DA firms' abnormal ROA drops by 3.3%, but there is only a small decrease for the Low DA group. The fundamentals of High DA firms continue to deteriorate over time, and the drop in abnormal ROAs is significantly larger than that for Low DA firms. This pattern shows up in both small and big IPOs. These results are consistent with the previous tables showing that the DA effect in stock returns is significant in both small and big IPOs.

Panel B presents the results sorted by CMR quartiles. In small IPOs, there is no significant difference in operating performance changes between extreme CMR portfolios. In big IPOs, low CMR firms initially exhibit a much better ROA than high CMR issuers (4.7% compared to 0.3%), but the relation reverses over the subsequent four-year period: low CMR issuers experience a decline in ROA of 8.5% and high CMR IPOs earnings decrease only by 1.5%.

The same pattern holds in Panel C, where we group operating performance by VC-backing status. Non-VC-backed firms have superior earnings initially, but their earnings deteriorate significantly in the following years. Thus, there is a significant difference in operating performance between VC-backed and non-VC-backed issuers, especially for big IPOs. The results in Panels A to C are consistent with our previous tables of stock returns: the DA effect holds for both small and big IPOs, and the CMR and VC effects exist in big IPOs.

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[2]It is possible that the "winner" and "loser" IPO portfolios have differences in cash flow characteristics that dictate different expected returns. In such cases, there could be differences in operating performance and stock returns. We are grateful to the referee for pointing out this possibility.

[3]We also follow a similar procedure used in Lie (2001) and Grullon and Michaely (2004) to find an industry and preevent performance-matched control firm as the benchmark for each IPO to detect the abnormal operating performance. In particular, we search the same industry as the IPO firm to find its matching firm with the closest ROA and book-to-market ratio at the time of first post-IPO fiscal year-end. Although not reported here, the results are qualitatively similar.

Table VIII. Abnormal Operating Performance

This table presents the median abnormal operating performance at the first post-IPO fiscal year (Year 0) and median change in abnormal operating performance in the four years after Year 0. We measure operating performance by return-on-assets (ROAs), which we define as operating income before depreciation divided by total assets. We compute the abnormal operating performance by subtracting the industry median of ROAs from the sample firms' ROAs. We exclude all IPOs, even for those IPOs not included in our sample, when we compute industry medians of ROAs. Panel A shows the results sorted by DA quartiles, by CMR quartiles in Panel B, by VC status in Panel C, and Panel D presents results for IPO winners and losers. IPO Winners are IPOs with DA decile ranking less than or equal to six, CMR equal to or greater than eight, with VC backing, and IPO Losers are IPOs with DA decile ranking greater than six, with CMR less than eight, and no VC backing. Each panel presents the results for the full sample, small IPOs (with size decile ranking equal to one), and big IPOs (with size decile ranking greater than one). Size decile ranking is relative to the NYSE stocks only. The last row in each panel shows the *p*-values of Wilcoxon median tests for comparing two extreme groups (e.g., Low/High DA, High/Low CMR, VC/NonVC, and IPO Winners/IPO Losers). In Panel A, "Low" DA quartile includes IPOs with a DA decile ranking less than or equal to three, "2" for IPOs with a DA decile ranking from four to six, "3" for a DA decile ranking from seven to nine, and "High" for a DA decile ranking equal to 10. In Panel B, "Low" CMR quartile includes IPOs with CMR less than six, "2" for IPOs with CMR equal to or greater than six but less than eight, "3" for CMR equal to or greater than eight but less than nine, and "High" for CMR equal to nine. In Panel D, the numbers in parentheses are *p*-values of Wilcoxon signed rank tests for testing if the median of IPO Losers and IPO Winners, respectively, is zero.

Year	Full Sample					Small IPOs					Big IPOs				
	0	0–1	0–2	0–3	0–4	0	0–1	0–2	0–3	0–4	0	0–1	0–2	0–3	0–4
Panel A. Sorted by Discretionary Accruals															
Low	−0.018	−0.003	−0.013	−0.019	−0.019	−0.040	−0.033	−0.017	−0.008	−0.019	0.001	0.005	−0.010	−0.023	−0.019
2	0.002	−0.018	−0.034	−0.024	−0.027	−0.025	−0.033	−0.037	−0.030	−0.030	0.010	−0.010	−0.030	−0.018	−0.025
3	0.028	−0.017	−0.029	−0.029	−0.036	0.014	−0.036	−0.033	−0.029	−0.038	0.041	−0.004	−0.021	−0.030	−0.034
High	0.025	−0.033	−0.048	−0.049	−0.049	0.009	−0.046	−0.061	−0.057	−0.054	0.043	−0.017	−0.035	−0.042	−0.045
Low-High	0.000	0.000	0.000	0.000	0.000	0.000	0.014	0.003	0.001	0.000	0.000	0.000	0.003	0.007	0.005

Table VIII. Abnormal Operating Performance (*Continued*)

Year	Full Sample					Small IPOs					Big IPOs				
	0	0–1	0–2	0–3	0–4	0	0–1	0–2	0–3	0–4	0	0–1	0–2	0–3	0–4
Panel B. Sorted by Underwriter Reputation															
Low	−0.012	−0.030	−0.041	−0.041	−0.031	−0.025	−0.035	−0.037	−0.029	−0.027	0.047	−0.009	−0.065	−0.094	−0.085
2	0.042	−0.026	−0.038	−0.043	−0.045	0.036	−0.030	−0.037	−0.040	−0.045	0.049	−0.020	−0.041	−0.049	−0.041
3	0.017	−0.015	−0.027	−0.033	−0.036	−0.006	−0.043	−0.037	−0.035	−0.044	0.029	−0.004	−0.023	−0.031	−0.034
High	−0.007	−0.003	−0.011	−0.013	−0.012	−0.066	−0.050	−0.025	−0.004	0.007	0.003	0.001	−0.010	−0.014	−0.015
High-Low	0.855	0.000	0.000	0.002	0.017	0.010	0.794	0.301	0.180	0.246	0.000	0.225	0.000	0.000	0.001
Panel C. Sorted by Venture Capital															
Non-VC	0.041	−0.022	−0.034	−0.041	−0.045	0.018	−0.033	−0.034	−0.040	−0.047	0.056	−0.011	−0.033	−0.044	−0.042
VC	−0.030	−0.010	−0.019	−0.013	−0.011	−0.046	−0.045	−0.037	−0.022	−0.015	−0.022	0.002	−0.011	−0.010	−0.010
VC-Non-VC	0.000	0.000	0.005	0.000	0.000	0.000	0.165	0.572	0.050	0.002	0.000	0.000	0.000	0.000	0.000
Panel D. Winner versus Loser															
IPO loser	0.032	−0.032	−0.048	−0.059	−0.071	0.018	−0.038	−0.049	−0.052	−0.065	0.083	−0.017	−0.047	−0.066	−0.081
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.183)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.012)	(0.000)	(0.000)	(0.000)
IPO winner	−0.076	0.000	−0.006	0.002	−0.005	−0.138	−0.049	−0.028	−0.018	−0.025	−0.063	0.008	0.003	0.008	0.000
	(0.000)	(0.117)	(0.003)	(0.404)	(0.806)	(0.000)	(0.000)	(0.004)	(0.084)	(0.267)	(0.000)	(0.157)	(0.082)	(0.966)	(0.698)
Winner-Loser	0.000	0.000	0.000	0.000	0.000	0.000	0.832	0.524	0.087	0.019	0.000	0.006	0.006	0.000	0.000

Table IX. Regressions of Changes in Abnormal Operating Performance

This table presents the regressions of changes in abnormal operating performance. We measure operating performance by return-on-assets (ROAs), which we define as operating income before depreciation divided by total assets. We compute the abnormal operating performance by subtracting the industry median of ROAs from the sample firms' ROAs. We exclude all IPOs, even for those IPOs not included in our sample, when we compute industry medians of ROAs. The dependent variable is the four-year change in abnormal operating performance, defined as abnormal ROAs at Year 4 minus abnormal ROAs at Year 0, where Year 0 is the first post-IPO fiscal year. To reduce the impact of outliers, we winsorize the top and bottom 1% of changes in abnormal ROAs. Size is market value of equity at the fourth month-end after the first post-IPO fiscal year-end, and is expressed in millions of dollars. BM is book-to-market ratio computed by dividing book value of equity by Size. DA quartile assigns a value of one to the lowest DA quartile consisting of IPOs with DA decile ranking less than or equal to three, two for IPOs with a DA decile ranking from four to six, three for a DA decile ranking from seven to nine, and four for IPOs with a DA decile ranking equal to 10. CMR quartile assigns a value of one to the lowest CMR quartile consisting of IPOs with CMR less than six, two for IPOs with CMR equal to or greater than six but less than eight, three for CMR equal to or greater than eight but less than nine, and four for IPOs with CMR equal to nine. VC is equal to one if the IPO is venture capital-backed. Winner dummy is equal to one if the IPO has a DA decile ranking less than or equal to six, a CMR equal to or greater than eight, and is VC-backed. Loser dummy is equal to one if the IPO has a DA decile ranking greater than six, a CMR less than eight, and is not VC-backed. Numbers in the parentheses are *t* statistics. We include, but do not report, year dummy variables in the regressions.

Intercept	Log(size)	Log(1 + BM)	DA Quartile	CMR Quartile	VC	Winner Dummy	Loser Dummy
Panel A. Full Sample							
−0.044	0.007	0.033	−0.025***	0.004	0.024*	—	—
(−0.46)	(0.87)	(0.87)	(−4.03)	(0.47)	(1.77)		
−0.074	0.005	0.021	—	—	—	0.038**	−0.051***
(−0.78)	(0.71)	(0.58)				(2.21)	(−2.65)
Panel B. Small IPOs							
0.020	0.028	0.056	−0.041***	−0.023	0.031	—	—
(0.09)	(1.04)	(0.80)	(−3.40)	(−1.36)	(1.12)		
−0.007	0.003	−0.007	—	—	—	0.025	−0.059*
(−0.03)	(0.13)	(−0.11)				(0.56)	(−1.88)
Panel C. Big IPOs							
−0.135	0.003	−0.006	−0.014**	0.025***	0.028**	—	—
(−1.55)	(0.40)	(−0.14)	(−2.41)	(3.15)	(2.29)		
−0.118	0.009	0.011	—	—	—	0.050***	−0.053**
(−1.40)	(1.13)	(0.27)				(3.62)	(−2.19)

***Significant at the 0.01 level.
**Significant at the 0.05 level.
*Significant at the 0.10 level.

In Panel D, we examine winner and loser IPOs. The loser IPOs perform significantly better than does the median firm in their industry at year zero. However, these good fundamentals reverse quickly, dropping by 3.2% in the first year and by 7.1% over four years. The plummeting pattern of earnings of loser IPOs is more severe in the big IPO subsample. This evidence of loser IPOs supports the mispricing story but not the misspecification explanation. It appears that investors are too optimistic about the strong earnings of IPOs with high DA, low CMR, and no VC backing, and overestimate the likelihood that these sound fundamentals can be sustained in the future. Later, investors are surprised by the substantial deterioration in earnings. They correct their expectation downward, leading to poor future stock returns.

Unlike the loser IPOs, the winner IPOs do not show a clear reversal pattern in operating performance. Their earnings are very poor at year 0, 7.6% below the industry median. The poor fundamentals of winner IPOs do not improve subsequently in the "Full" sample, and even deteriorate in the "Small" sample.

For big IPOs, the earnings improvement over the different horizons that we examine is not significant, except in the window of event years (0, 2). However, even for this particular window, the positive change in abnormal operating performance is only marginally significant (p value is 0.082). These results do not seem to support the mispricing story where investors are surprised by the strong improvement in fundamentals of winner IPOs and thus revise their stock price accordingly. Similar to the firm characteristics we document in Table VII, the lack of consistent evidence to back up the mispricing hypothesis seems to validate the misspecification argument for the positive drifts associated with winner IPOs.

To check the robustness of our results in operating performance, in Table IX we regress changes in abnormal operating performance on various dummy variables. The results are consistent with our earlier findings. The DA effect is stronger in small IPOs, and both CMR and VC are positively related to issuers' operating performance in big IPOs. Since both coefficients of CMR and VC are significant in the same regression in big IPOs, the two apparently do not subsume each other. The performance of IPO winners dominates losers, especially in the subsample of big IPOs.

V. Conclusion

Starting with Ritter (1991), there has been extensive investigation of IPO long-run performance. Subsequent studies show that DA, underwriter reputation, and the backing of VC, among other variables, are significantly related to the IPO long-run returns. However, it is possible that these variables are highly correlated and that all are related to the same source of return predictability. Therefore, it is not clear whether all three relations exist simultaneously in IPO returns. Moreover, previous papers examine IPOs through the early 1990s, so it is an empirical question whether their results persist when the sample consists of IPOs from the late 1990s.

In this paper, we reexamine the three variables based on an IPO sample from 1980 to 2000. We test how they are related to IPO long-run performance, individually and jointly.[4]

Our empirical results show that the previously documented association of the DA, underwriter reputation, and VC variables with IPO long-run performance hold in our sample. Issuers with

[4]Ritter and Welch (2002) list some other variables that are associated with IPO long-run returns such as flipping by institutional investors (Houge, Loughran, Suchanek, and Yan, 2001). Field and Lowry (2005) find that the institutional ownership is positively related to future returns of IPOs. Bradley, Cooney, Dolvin, and Jordan (2006) find that penny stock IPOs have lower long-run performance relative to other IPOs. We have taken a parsimonious set of established variables that are readily accessible, to examine their joint relations to long-run returns. We do not claim that this is an exhaustive set and leave it to future research to examine the efficacy of other variables in providing results similar to ours.

low DA outperform those with high DA, IPOs with prestigious underwriters perform better than those managed by low-ranking underwriters, and VC-backed IPOs outperform non-VC-backed IPOs. The association of DA with IPO performance is particularly strong in small IPOs, while underwriter reputation and VC relations are stronger in big IPOs. The firm characteristics and long-run stock returns suggest that the association of these three variables with IPO long-run performance is not the manifestation of the same underlying phenomenon.

Given that the three variables are not highly correlated, we further partition our sample by introducing them simultaneously. We find that IPOs with positive aspects of these variables, that is, IPOs with low DA, prestigious underwriters, and VC backing ("winner" IPOs), significantly outperform the Carhart (1997) four-factor model in the long run. On the other hand, IPOs with high DA, low-ranking underwriters, and no VC backing ("loser" IPOs) underperform. The return spread between IPO winners and losers, over the four years following the first post-IPO fiscal year-end, is 1.3% and 2.1% per month, respectively, using equal- and value-weighted portfolios. This return spread is especially high for big IPOs, amounting to 2.1% and 2.4% per month, respectively.

It is possible that our results for IPO winners and losers are driven by omitted risk factors in the asset pricing models or by using an incorrect method to detect long-run abnormal returns. That is, the "bad model" problem (Fama, 1998) or a biased return calculation method (Brav, Geczy, and Gompers, 2000; Mitchell and Stafford, 2000) could create a spurious abnormal long-run performance for IPOs when none exists. However, it is less likely that these model misspecifications would explain differences in firm characteristics and abnormal operating performance associated with IPO winners and losers. Therefore, we examine firm characteristics when we form IPO portfolios, and operating performance in the four years following the first post-IPO fiscal year-end. We wish to see if they exhibit a pattern consistent with long-run abnormal stock returns.

We find that initially, IPO losers tend to be profitable growth firms. The significant abnormal earnings associated with losers seem to be due to their corresponding extreme accruals. Yet, this remarkable performance pattern changes dramatically over time. Their subsequent fundamentals significantly deteriorate, especially those of the big IPO subsample. These results are consistent with a mispricing hypothesis, which suggests that investors initially overvalue the IPO losers. When the subsequent fundamentals do not support the original market expectations, investors revise the stock prices accordingly, leading to negative long-run stock returns for losers.

Winner IPOs are initially unprofitable, with low accruals. These firm characteristics seem to suggest a positive return drift (Cooper, Gulen, and Schill, 2007). However, their cash flows are also negative, an indicator that is not consistent with higher future returns. Although there is weak evidence of earnings improvement for winners in big IPOs, in most cases we do not observe significant increases in earnings. These results do not seem to support the mispricing story but instead are more consistent with the misspecification hypothesis. We are still confronted with the puzzle of why winner IPOs outperform. We leave the solution to future research.

Our interpretation of IPO losers is consistent with the behavioral finance literature regarding asset pricing. For example, Lakonishok, Shleifer, and Vishny (1994) find that growth firms underperform for five years and traditional risk measures cannot explain this poor return. They argue that investors put too much weight on recent performance in valuing stock and extrapolate it too far into the future, thus creating overreaction. Yet, the market takes a long time to correct the price. Moreover, Sloan (1996) documents that accounting accruals are negatively related to future stock returns. His results suggest that investors fixate on reported earnings while ignoring the fact that the accrual component of current earnings tend to reverse in the future. Sloan's (1996) mispricing story is recently supported by Hirshleifer, Hou, and Teoh (2006). Teoh and

Wong (2002) find that analysts are optimistic for several years pursuant to an IPO and conclude that analysts' credulity about accruals management contributes to abnormal long-run returns. Bradshaw, Richardson, and Sloan (2001) also examine the forecasts of sell-side analysts and show that analysts do not incorporate the predictable future earning decline associated with high accruals. Richardson (2003) further shows that short sellers do not exploit the predictability in stock returns associated with earnings quality. With strong earnings and high accruals at the time of portfolio formation, our IPO losers fit exactly the group of stocks that investors tend to misprice.

Why are the abnormal returns associated with IPO losers not arbitraged away? A possibility is that our IPO losers tend to be firms with high transaction costs and these high costs prohibit arbitrageurs from correcting the stock price (Geczy, Musto, and Reed, 2002). However, we have excluded IPOs with an offer price below \$5 or proceeds less than \$5 million from our IPO sample. In addition, our abnormal returns are more significant and accentuated in big IPOs (whose market capitalization is larger than the bottom size decile based on NYSE breakpoints). Therefore, it is less likely that our results are driven by very small firms that are believed to have large transaction costs (see, e.g., Chan and Lakonishok, 1997). As a result, the transactions cost explanation may not well account for our loser results. Another possibility is that IPO losers tend to be firms with characteristics that institutional investors try to avoid (such as smaller market caps and higher volatility) and thus do not play an active role to make arbitrage trades (Lev and Nissim, 2006). Finally, Brav and Heaton (2006) find that the underperformance of growth stocks occurs only when the limits of arbitrage are high. Since our IPO losers tend to be growth firms, therefore, it could also be the case that the loser IPO firms have high limits of arbitrage, such as high idiosyncratic risks, which prevent underdiversified arbitrageurs from hedging against them.

Regardless of why some IPOs perform so differently, our results have several implications. First, the three variables seem to capture those IPO firms that tend to have abnormal long-run performance. For larger IPOs, the reputation of the lead-underwriter and the support of VC covary closely with the return predictability. For smaller IPOs, the level of earnings management is strongly related to future performance. Second, since the underwriter reputation and VC variables do not subsume one another, their association with IPO returns may be the manifestation of dissimilar pieces of vital information about issuers. Our results suggest that these professionals are important, and that their presence is associated with long-run IPO returns. Third, we find that DA are related to IPO long-run performance, even after controlling for underwriter reputation and VC-backing status, suggesting that neither the venture capitalists nor investment bankers can fully detect the level of earnings management. This result probably explains why earnings quality is such an important issue for investors.

There are three caveats on the results in this paper that we wish to point out. First, our sample period overlaps the period used in prior studies, so it may not be surprising that by combining these three variables used in previous research, we find stronger abnormal returns. Second, although DA, underwriter reputation, and VC backing appear to be empirically associated with the abnormal performance for IPOs, they do not represent the cause of long-run return drifts. Finally, even though our results suggest that there are winners and losers in the IPO market, we cannot preclude the possibility that we get these results by chance. Nevertheless, we identify IPOs that tend to have abnormal performance and we provide a trading strategy. Whether these IPOs will continue to generate abnormal returns and why the market does not eliminate these abnormal returns, especially the positive drift for the winner portfolios, are questions that we leave for future research. ■

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