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Analyst Following of Initial Public Offerings

RAGHURAM RAJAN and HENRI SERVAES*

ABSTRACT

We examine data on analyst following for a sample of initial public offerings completed between 1975 and 1987 to see how they relate to three well-documented IPO anomalies. We find that higher underpricing leads to increased analyst following. Analysts are overoptimistic about the earnings potential and long term growth prospects of recent IPOs. More firms complete IPOs when analysts are particularly optimistic about the growth prospects of recent IPOs. In the long run, IPOs have better stock performance when analysts ascribe low growth potential rather than high growth potential. These results suggest that the anomalies may be partially driven by overoptimism.

THREE WELL-DOCUMENTED “ANOMALIES” associated with initial public offerings (IPO) are underpricing, hot issue markets, and long-run underperformance. Can data on analyst following or analyst forecast accuracy help us understand these phenomena better? There is an ongoing debate about whether these anomalies are examples of market inefficiency, and if so, whether they are caused by the behavior of irrational investors or whether they reflect institutional constraints. Consider the long run underperformance of initial public offerings documented by Ritter (1991). The immediate question is whether the underperformance persists after precise adjustment for priced risk. If indeed IPOs underperform on a risk adjusted basis, the next question is whether the underperformance is because of institutional constraints—such as short sales restrictions—in the IPO market, or whether it is because of systematic overoptimism on the part of investors. The problem with investigating these issues using data on returns and prices only is that the researcher cannot tell if ex post realized returns for a security are low because the ex ante estimated cash flows were too high (either because of overoptimism on the part of all investors or because short sales constraints prevented the beliefs of pessimistic investors

* Rajan is from the University of Chicago and Servaes is from the University of North Carolina at Chapel Hill. Part of this research was completed when Servaes was visiting London Business School. Some of the results reported in this article were contained in a previous version of a related working paper: “The Effect of Market Conditions on Initial Public Offerings” (March 1994). We thank Mike Cooper, David Denis, Jennifer Francis, Joshua Lerner, Ernst Maug, Peter Pope, René Stulz, Sunil Wahal, Marc Zenner, an anonymous referee, and seminar participants at INSEAD, Katholieke Universiteit Leuven, London Business School, North Carolina State University, Norwegian School of Management, Stockholm School of Economics, University of Lausanne, and the University of North Carolina at Chapel Hill for helpful comments and suggestions and Jay Ritter and Michel Vetsuypens for allowing us to use their databases. IBES kindly allowed the use of their data on analyst following. This research was partially supported by the McColl Faculty Fellowship (Servaes), and NSF grant SBR 9423645 (Rajan).

from being reflected in the price) or because the expected returns were low. One possible way to disentangle the two is to look at investor expectations. To the extent that brokerage house analysts reflect or drive investor expectations, data on analyst following and forecast accuracy may throw more light on the debate.

With this in mind, we explore whether the behavior of analysts is related to the IPO anomalies. In particular, we address four questions: (i) Is analyst following related to the extent an initial public offering is underpriced? (ii) Do analysts make systematic errors in forecasting the performance of the firm undertaking the IPO? (iii) Is the number of IPOs coming to the market related to analyst (over)optimism? (iv) Is the long run performance of IPOs related to analyst (over)optimism?

We have to correct for a number of factors before we attempt to interpret the results. A growing literature has shown that analysts do not pick the firms they follow at random, nor are they unbiased in their forecasts. O'Brien and Bhushan (1990) find that analyst following increases with institutional ownership and industry growth. Pearson (1992) documents a positive relation between analyst following and beta, firm value, and the number of firms operating in an industry, and a negative relation between analyst following and the market model residual standard deviation. Several papers have documented that analysts tend to be overoptimistic (see, for example, Abarbanell (1991) and Brown, Foster, and Noreen (1985)). Dugar and Nathan (1995) and Lin and McNichols (1995) argue that part of the overoptimism may be because some analysts work for investment banks that have a relationship with the firm being analyzed, and issue optimistic forecasts for fear of jeopardizing the relationship. McNichols and O'Brien (1996) argue that the documented overoptimism may also stem from a selection bias; analysts typically start following stocks they are optimistic about. Finally, while many of these studies show that investors adjust for potential biases in analyst recommendations, investor behavior does appear to be affected by analysts. Irvine (1994) finds that trading volume and brokerage market share increase after a brokerage firm releases an investment report.

Even after correcting for previously documented influences, we obtain some interesting results. First, we find that more underpriced issues attract larger analyst following. Analysts then systematically overestimate the earnings of these companies, with forecast errors averaging 5 percent of the firm's stock price. As the forecast window (the length of time between making the forecast and the period for which the forecast is made) increases, so does the forecast error. Thus, analysts are not only overoptimistic, they are more overoptimistic about a firm's long term prospects than a firm's short term prospects. These forecast errors are lower after we make size and industry adjustments, but they remain highly significant. This indicates that the overoptimism of analysts for IPOs is only partly a reflection of their overoptimism in general. In addition, since their forecasts worsen with the forecast horizon, investors who rely on analyst forecasts to make investment decisions, are likely to purchase

these shares at inflated prices.¹ We also study long-run (five years) earnings growth forecasts and find that within six months of the IPO, analysts predict that these firms will grow approximately six percentage points faster than their industry peers. These long run growth predictions decline substantially over the following months, which suggests that analysts eventually realize that the predicted growth cannot be attained.

Second, we document a positive relation between the number of IPOs coming to market in a given industry in a given quarter and several measures of analyst long-term earnings growth projections for recent IPOs in these industries. This finding is, perhaps, not surprising, since firms in industries with higher growth projections are likely to need more funds to finance this growth and an IPO may be the best method of obtaining these funds. However, we know that these growth projections are overly optimistic. Hence, these results suggest that firms take advantage of this optimism by raising funds from the public. What lends credence to this interpretation is that the number of firms coming to market is also positively correlated with the magnitude of the (matched firm adjusted) earnings forecast errors made by analysts for recent IPOs.

Finally, we relate analyst long-term growth projections to the aftermarket stock price performance of IPOs and find dramatic results. When firms are subdivided into quartiles according to their long-term growth projections, firms with the highest projected growth substantially underperform three benchmarks, whereas firms with the lowest growth projections outperform these benchmarks. The difference in returns between the two extreme quartiles is more than 100 percent. This indicates that investors appear to believe the inflated long-term growth.

A number of other articles also attempt to document and explain IPO anomalies. Loughran and Ritter (1995) report that IPOs completed in the 1970 to 1990 period have generated average annual returns of only five percent over the five year period subsequent to the offering. They argue that firms take advantage of windows of opportunity to issue stock publicly; these are periods when investors are willing to pay high prices, relative to some historical benchmarks, for corporate assets in certain industries. Rajan and Servaes (1995) present evidence consistent with this notion: more firms conduct IPOs when seasoned firms in their industries are trading at high multiples relative to the stock market and relative to historical levels. They also find that firms coming to market during these periods have poor aftermarket stock price performance. Lerner (1994) studies a sample of 350 privately held venture-backed biotechnology firms and finds that these firms go public when equity valuations are high. Jain and Kini (1994) and Mikkelsen and Shah (1994) analyze the earnings performance of firms that conduct IPOs; these firms

¹ As indicated in the introductory paragraph, we cannot tell whether our results are because the investing public believes analyst forecasts or because analyst forecasts reflect the beliefs of the investing public. In other words, we establish correlation but not causality. However, we speculate about the likely source in the conclusion.

perform very well prior to the IPO, but very poorly afterwards. For a sample of 284 firms that went public in the 1980 to 1983 period, Mikkelson and Shah find that the median pretax operating cash flow per dollar of assets is only four cents during the first three years after the IPO. Our article differs from these in its focus on analyst data, and in its attempt to find a common link between underpricing and the other two IPO anomalies.

Finally, Teoh, Wong, and Rao (1995), find that firms with extensive discretionary accounting accruals perform poorly in the aftermarket. They argue that firms adopt these accrual adjustments to manipulate reported earnings before and soon after the IPO. Investors may not fully understand the implications of this manipulation for future earnings growth, which leads to a revaluation of share prices in the aftermarket. Our article suggests that one reason investors do not understand these implications is that they receive poor information from analysts.

The remainder of this article is organized as follows. Section I describes the data collection process and presents some descriptive statistics. Section II contains our results and Section III concludes.

I. Data Collection and Description

We gather a sample of firm commitment IPOs completed between 1975 and the second quarter of 1987 from databases compiled by Ritter (1984, 1991), Loughran and Ritter (1995), and Barry, Muscarella, and Vetsuypens (1991). Stock price data are obtained from the Center for Research in Security Prices (CRSP) and analyst following information from Institutional Brokers Estimate System (IBES). Table I describes the sample over time and contains data on underpricing. Underpricing is computed as the difference between the first aftermarket price and the offer price, divided by the offer price. As documented previously, there is substantial variation in the number of issues coming to market over time (see Ibbotson and Jaffe (1975) and Ritter (1984)) and IPOs are underpriced, on average (see Ibbotson (1975)). Average underpricing is 10.03 percent over the sample period, and, except for 1975, IPOs are underpriced each year. There is also substantial time-series variation in underpricing, with a low of -0.88 percent in 1975 and a high of 28.99 percent in 1980.

More than half of the firms in our sample (56.3 percent) are covered on the IBES database at some point in time after the offering. However, because we are interested in the behavior of analysts shortly after the IPO, much of the ensuing analyses focus on those firms covered by IBES within one year or three years of the offering. The one-year sample consists of 935 firms, or approximately one third of the original sample. The three-year sample consists of 1410 firms, which is more than 52 percent of the original sample. Also note that IBES coverage improves over time. Except for 1975, IBES coverage within one year of going public was rather sporadic over the 1975 to 1981 period. Coverage improved substantially in 1982, and by 1986 more than half of the IPOs were covered by at least one analyst within 12 months of going public. Interestingly, there is no relation between the number of IPOs and analyst following. With

Table I

Distribution of Sample Over Time and Underpricing Information

Underpricing is computed as: (First Aftermarket Price – Offer Price)/Offer Price. Only firm commitment offers are included in the sample. Number on Institutional Brokers Estimate System (IBES) refers to the number of initial public offering (IPO) firms who are listed on the IBES database. Number on IBES < 1 (3) year(s) refers to the number of firms who are listed on the IBES database within 1 (3) years of their IPO. Fraction refers to the fraction of IPOs listed on IBES within the specified period.

Year	Number of IPOs	Average Underpricing	Number on IBES (Fraction)	Number on IBES < 1 year (Fraction)	Number on IBES < 3 years (Fraction)
75	11	-0.0088	8 (0.73)	3 (0.27)	7 (0.64)
76	28	0.0030	15 (0.54)	0 (0.00)	11 (0.39)
77	20	0.0660	6 (0.30)	0 (0.00)	3 (0.15)
78	24	0.1413	15 (0.63)	1 (0.04)	12 (0.50)
79	49	0.1351	25 (0.51)	0 (0.00)	20 (0.41)
80	125	0.2899	48 (0.38)	5 (0.04)	44 (0.35)
81	320	0.1186	131 (0.41)	24 (0.08)	107 (0.33)
82	107	0.1032	58 (0.54)	28 (0.26)	50 (0.47)
83	651	0.1100	355 (0.55)	260 (0.40)	327 (0.50)
84	336	0.0662	157 (0.47)	86 (0.26)	138 (0.41)
85	276	0.0877	177 (0.64)	110 (0.40)	171 (0.62)
86	551	0.0785	376 (0.68)	286 (0.52)	360 (0.65)
87 (6 months)	227	0.0677	164 (0.72)	132 (0.58)	160 (0.70)
Total	2725	0.1003	1535 (0.56)	935 (0.34)	1410 (0.52)

limited analyst resources (and time needed to increase trained capacity), one might expect that fewer IPOs are followed during hot issue periods, but this is not consistent with the evidence presented in Table I. Thus capacity constraints (number of available analysts) do not seem to be a problem for the period under study.

II. Results

A. Analyst Following and Underpricing

We first explore the determinants of analyst interest in a firm and, in particular, we investigate whether analyst following is related to the extent of underpricing. IBES collects all forecasts from a group of analysts who agree to provide them in return for free use of IBES products or data. Consequently, if IBES's choice of analysts is random, the data are unbiased. However, it is possible that some biases creep into IBES's choice of analysts. For instance, it may be easier for IBES to obtain forecasts from analysts of the major brokerage houses. These analysts may be more likely to ignore small firms trading on regional exchanges. If this is the case, there are two reasons why firms may not be followed: either analysts do not deem the firm worthy of following or IBES does not get forecasts from the analysts most likely to follow the firm.

To correct for a potential selection bias in the IPOs for which we have no evidence of analyst following, we employ Heckman's (1979) two stage process. In the first stage, we attempt to correct for potential selection biases in IBES's choice of analysts. In the second stage, we investigate the determinants of analyst following (including underpricing).

In the second stage, the dependent variable is the average number of analysts making earnings forecasts per forecast period during the year after the IPO. This is a measure of analyst interest in the firm. The explanatory variables are firm size (the log of market value of equity computed at the first after market price), which should be positively correlated with analyst interest. Since analysts typically specialize in particular industries, there are likely to be more analysts with the potential to follow IPOs in industries with more seasoned firms. So, we also include the number of seasoned firms (firms on COMPUSTAT for more than three years at the time of the IPO) in the two-digit Standard Industrial Classification (SIC) code of the IPO firm. Finally, we include the degree of underpricing.

The first stage explains why the dependent variable is not missing. We could report the regression only for the observations that are not missing, but we would then be losing some potential information in the data.² As argued above, the data could be missing because of a selection bias in IBES coverage or it could be missing because of a lack of analyst interest.

In the first stage regression, we include variables that ought to proxy for the potential selection bias. As Table I indicates, IBES's coverage improves over time. So clearly, the inclusion of year dummies is warranted in the first stage regression. Furthermore, IBES is more likely to have relationships with analysts in large brokerages headquartered in the financial centers than with analysts from small brokerages in remote areas. Since the clients of the latter are likely to be smaller, and not listed on a major exchange, we include firm size, and an indicator if the firm is not listed on a major exchange (i.e., not on New York Stock Exchange (NYSE), American Stock Exchange (AMEX), or National Association of Securities Dealers Automated Quotation (Nasdaq)). We also include the number of firms in the industry at the time of the IPO. Finally, since IBES's choice of analysts may be biased toward those following certain industries, we include dummies for the 13 most important two-digit SIC industries in our database.

The results are reported in the first regression model presented in Panels A and B of Table II. The average number of analysts making forecasts is strongly positively related to firm size ($\beta = 0.59$, $t = 17.8$). It is also strongly positively related to the degree of underpricing ($\beta = 0.99$, $t = 6.51$). A one standard deviation increase in underpricing (an increase by 0.26) increases the number of analysts following the firm in the first year by 0.25.³ Since there are 0.7 analysts following a firm on average in the first year, the coefficient is also

² All the results we report hold qualitatively when we confine the regression only to firms for whom we have analyst following data in the first three years.

³ The marginal effect reported is for the latent variable.

Table II
Determinants of Analyst Following

Panel A presents the second stage estimates (using Heckman's (1979) two step procedure) of the determinants of analyst following. Panel B contains coefficient estimates for the first stage model, which is a maximum likelihood probit model that determines when the dependent variable in the second stage is not missing. Underpricing is computed as: (First aftermarket price–Offer price)/ Offer price. AV1 is the average number of analyst forecasts per reporting period during the first year after the initial public offering (IPO). Other explanatory variables are: (i) the logarithm of the market value of equity, computed on the first trading day; (ii) the number of firms listed on COMPUSTAT for more than three years at the time of the IPO who are also in the same two-digit industry; (iii) the number of lead managers to the IPO. The first regression is estimated using all firms with available data. The second regression is estimated for IPOs from 1985 onwards. Underpricing is subdivided into four categories in the second regression model, depending on the level of underpricing. *p* values are in parentheses.

	Full sample	1985 to 1987
Panel A: Second Stage Estimates: Dependent Variable is AV1.		
Underpricing	0.99 (0.00)	
Underpricing * Indicator if negative		2.03 (0.34)
Indicator if underpricing is zero		0.03 (0.75)
Underpricing * Indicator if positive but less than the median of positive observations		0.66 (0.64)
Underpricing * Indicator if positive but more than the median of positive observations		0.80 (0.00)
Log equity size	0.59 (0.00)	0.41 (0.00)
Number of firms in industry	0.002 (0.00)	0.002 (0.00)
Number of lead managers to the issue		0.13 (0.00)
Prob > Chi ²	0.000	0.000
Number of observations	2274	803
Panel B: First Stage Estimates (Explaining When the Dependent Variable in the Second Stage is not Missing)		
Estimated model: Analyst following is not missing if:		
$c + c_1 \dots c_n$ (Year indicators) + c_{n+1} (Log size equity) + c_{n+2} (number of firms in 2-digit industry) + $c_{n+3} \dots c_{n+15}$ (industry dummies) + c_{n+16} (Equity not traded on a major exchange) + $f > 0$		
The constant and the coefficients on industry and year indicators are not reported.		
Log equity size	0.64 (0.02)	0.67 (0.00)
Not traded on a major exchange	-0.37 (0.00)	-0.50 (0.00)
Number of firms in industry	0.002 (0.09)	0.005 (0.00)
Prob > Chi ²	0.000	0.000
Number of observations	2274	803

economically meaningful. The correlation between underpricing and following is robust to a variety of different specifications and to the inclusion of additional variables such as trading volume in the first 100 days (a proxy for the demand for analyst services), turnover (which may be a proxy for the stability of shareholdings), stock price volatility (a proxy for the risk of the stock), and past and future growth of the industry. It is also robust to changes in the dependent variable to (i) the average number of analysts making earnings forecasts per forecast period during the three years after the IPO, (ii) the total number of forecasts in the first year, or (iii) the total number of forecasts in the first three years after the IPO. These results are available on request from the authors.

IBES's coverage, as we have seen, was much better during the latter half of the sample period. Hence, the dependent variable should be less noisy if we only consider IPOs from 1985 onwards. Also, lead managers to an issue would like to sustain interest in IPOs they bring to market, and are more likely to encourage their analysts to follow them. So, we include the number of lead managers to the issue that we collected from the Investment Dealers Digest for all IPOs after 1984. Finally, we want to see if it is the absolute price movement at the open (i.e., both underpricing and overpricing) that attracts analyst interest, or whether it is significant underpricing only. We therefore partition the underpricing variable into overpricing (negative "underpricing"), underpricing if zero, underpricing if positive and less than the median of positive observations, and underpricing if positive and greater than the median of positive observations.

The coefficient estimates in the second model show that the number of lead managers is significantly positively related with analyst following, even after controlling for firm size. But underpricing is still important. However, only the coefficient for extreme underpricing is statistically different from zero ($\beta = 0.8$, $t = 3.19$). Also, it appears that analysts lose interest if an issue is overpriced, although the coefficient, while economically large, is measured very imprecisely.⁴

Overall, these results suggest that firms that underprice attract analyst interest. Clearly, there could be a common omitted variable that drives both underpricing and analyst following, but it is not obvious what it is. On the other hand, there are theories that suggest that underpricing may, in fact, drive the extent of analyst interest. Chemmanur (1993) argues (p. 286) that "insiders of high value firms are motivated to maximize outsider information production so that this information will be reflected in the secondary market price of their firm's equity, increasing its expected value. However, since information production is costly, only a lower IPO share price will induce more outsiders to produce information. The equilibrium offer price may involve some underpricing. . . ." To the extent that analysts are agents of outsiders, our finding supports Chemmanur's hypothesis. A number of articles take a less rational view of investors (see Ibbotson and Ritter (1995) for a more detailed

⁴ We also verify that these results are not caused by outliers.

review). Shiller's (1990) "impresario" hypothesis is that the market for IPOs is subject to fads and IPOs are underpriced by investment bankers (the impresarios) to create the appearance of excess demand, just as the promoter of a rock concert attempts to make it an "event." Rajan and Servaes (1995) argue that to ensure the success of an issue, investment bankers have to underprice to deal with potential "feedback" trader risk.⁵ Finally, we will shortly present evidence that analysts tend to be systematically overoptimistic. It is possible that firms underprice with the direct aim of attracting analysts, who will then keep the firm stock price high until such time as the promoters have unloaded further shares. We now turn to tests of the accuracy of analyst forecasts.

B. Earnings Forecast Errors

We focus on firms listed on IBES within one year of their IPO and examine the accuracy of analyst forecasts made over the two years after going public. Including firms listed on IBES after one year would obscure some of the results, because forecast errors would be influenced both by the addition of new firms as well as revisions in forecasts of firms already listed. Moreover, we are interested in how analysts make earnings forecasts for recent IPOs. Firms that went public more than one year before the first forecast is made are less useful for this purpose. Forecast errors are computed as: $(\text{Actual earnings} - \text{Earnings forecast}) / \text{Stock price at the time of the earnings forecast}$. Thus we gather data on the firm's stock price at the time the forecast is made and employ this as a deflator of the forecast error.

Forecasts are available on a monthly basis and made for periods up to two fiscal years in the future. Obviously, forecast accuracy improves over time. We therefore report forecast accuracy for different forecast windows, defined as the number of months between the time the forecast is made and the fiscal year end for which the forecast is made. To gauge whether forecasts become more accurate over time, we separately report forecasts made within one year of the IPO, and forecasts made between one and two years after the IPO. We also report matching firm adjusted forecast errors. A matching firm is selected by ranking, according to market value of equity, all seasoned firms in the same industry (two-digit level) for which forecasts with the same window are available. The firm closest in size to the IPO firm is selected.

Forecast errors are reported in Table III. Panel A contains the forecasts made within one year of the IPO. The results indicate that analysts are systematically overoptimistic with regard to the earnings of firms that recently went public (see also Ali (1996)). The forecast error as a percentage of the stock price is -3.36 percent for forecasts made for a three-month window; the error

⁵ Feedback traders are investors whose demand is based on prior returns. If they observe that the first trading price is below the offer price, they may sell the offer short, which will further depress the stock price. Rational investors, who anticipate the behavior of feedback traders, will ensure that this behavior is already reflected in the first trading price. Investment banks who stabilize the issue in the aftermarket protect themselves from this feedback trader risk by underpricing.

Table III

Analyst Earnings Forecast Errors for Initial Public Offerings (IPOs)

The sample consists of all forecasts made by analysts for earnings in the two year period following the IPO. Only forecasts made for firms listed on Institutional Brokers Estimate System (IBES) within one year of the IPO are included. The forecast error is computed as: (Actual earnings – Earnings forecast)/Stock price at the time of the earnings forecast. We report forecast errors for forecast windows of three through 21 months in three-month intervals. Window is the number of months between the time the forecast is made and the fiscal year end for which the forecast is made. Matched firm adjusted forecast errors are computed by subtracting the forecast error of the firm with the same two-digit Standard Industrial Classification (SIC) code closest in size to the IPO firm, if this firm has been listed on COMPUSTAT for at least three years. The number of observations in the matched firm adjusted sample is smaller because no matched firms can be found for certain forecast windows. *p*-values are in parentheses.

Window	Forecast Error	Number	Matched Firm Adjusted Forecast Error	Number
Panel A: Forecasts Made Within One Year of the IPO				
3 months	-0.0336 (0.00)	412	-0.0165 (0.06)	340
6 months	-0.0445 (0.00)	400	-0.0147 (0.07)	324
9 months	-0.0449 (0.00)	442	-0.0167 (0.00)	329
12 months	-0.0577 (0.00)	327	-0.0321 (0.01)	263
15 months	-0.0456 (0.00)	310	-0.0112 (0.20)	255
18 months	-0.0430 (0.00)	268	-0.0122 (0.10)	212
21 months	-0.0486 (0.00)	175	0.0033 (0.71)	118
Panel B: Forecasts Made Between One and Two Years After the IPO				
3 months	-0.0321 (0.00)	685	-0.0182 (0.01)	436
6 months	-0.0345 (0.00)	660	-0.0130 (0.03)	426
9 months	-0.0414 (0.00)	629	-0.0192 (0.00)	364
12 months	-0.0534 (0.00)	610	-0.0205 (0.00)	421
15 months	-0.0586 (0.00)	548	-0.0244 (0.00)	358
18 months	-0.0603 (0.00)	469	-0.0103 (0.20)	294
21 months	-0.0509 (0.00)	246	-0.0108 (0.41)	130

increases with the window up to 12 months when the forecast error is -5.77 percent. Note that the number of observations is smaller than the 935 firms for which IBES data are available (see Table I) because not all firms have forecasts available for all forecast windows. Matched firm adjusted forecast errors remain negative and significant for the three to 12 month period, but they are generally less than half of the raw forecast error. For example, for the 12 month window, raw forecast errors average -5.77 percent, whereas matched firm adjusted errors are -3.21 percent. These results indicate that the previously documented overoptimism on the part of analysts is about twice as severe for IPOs.

Panel B contains the errors for forecasts made between one and two years after the IPO. A comparison of Panels A and B illustrates that forecast

accuracy does not improve as the firm becomes more seasoned. The errors presented in both panels are very similar. For example, the average forecast error is -0.0449 for the nine month window in the first year after the IPO and -0.0414 in the second year after the IPO. Similarly, there is little variation over the two years in matched firm adjusted forecast errors. For instance, the average matched firm adjusted forecast error is -0.0147 for the six month window in the first year after the IPO and -0.0130 in the second year after the IPO. The t -tests indicate that none of the differences in forecast errors between Panels A and B are significant at conventional significance levels (10 percent or better).

We also estimate cross-sectional regression models of forecast errors on firm size, the number of analysts following the firm, industry dummies, and an indicator variable, set equal to one if the firm went public in the previous two years, and zero otherwise. The coefficient on the IPO dummy is significant for all windows, and close to the matched firm adjusted forecast error reported in Table III.

Clearly, one does not have to rely on irrationality to explain this finding. It could stem, for instance, from selection bias: IPOs are underwritten by investment banks who are optimistic about the underwritten firm's prospects. It is natural for analysts from these investment banks also to be optimistic. Alternatively, conflicts of interest may prevent analysts from investment banks that are associated with the firm making the offering from being objective about the firm (see Dugar and Nathan (1995), Lin and McNichols (1995), Michaely and Womack (1996)). By definition, all IPOs have recently been underwritten, so we cannot fully separate selection bias or agency explanations of the forecast errors from explanations based on irrational investors. We can, however, test whether factors correlated with agency or selection bias problems also correlate with the size of the forecast errors.

We know the number of lead underwriters to an issue. Typically, there is a quality threshold below which firms are not underwritten. If an investment bank has a positive signal about a firm that pushes it above the threshold, it agrees to be a lead underwriter. Hence, there is a selection bias in firms that are underwritten. If investment banks independently agree to be lead underwriter, then the number of lead underwriters is a measure of the number of independent positive signals on the firm. The more the positive signals, the more likely is the firm to be truly above the underwriting threshold and the less the selection bias. If forecast errors stem from selection bias, then the more lead underwriters the lower should be the forecast error.

By contrast, if forecast errors are because of agency problems, then the more lead underwriters there are to an issue, the more likely it is that forecasts of independent analysts will be swamped by forecasts of analysts who have vested interests in the success of the issue, and the greater should be the bias in forecasts. Finally, if forecast errors are due to universal overoptimism about IPOs, there should be no consistent relation between the magnitude of the forecast errors and the number of lead underwriters to the IPO. The last is indeed the case. For instance, for the three month window forecasts, overop-

timism clearly increases with the number of underwriters (from -0.004 for IPOs with one underwriter to -0.063 for IPOs with more than three) while for the 21 month window, it clearly decreases (forecast errors go from -0.012 for IPOs with one underwriter to $+0.069$ for IPOs with more than three). For other windows, there is no clear relation. The correlation between the number of lead underwriters and the forecast error is significantly negative only for the three month window, and only at the 10 percent level, suggesting that any relationship is very weak. Finally, the number of lead underwriters may proxy for size. Including size in regression models of forecast errors on the number of lead underwriters does not affect our results. Larger firms have smaller forecast errors, but the effect of the number of lead managers is only significant (and negative) for the three month window (p -value = 0.07).⁶

Overall, the results of Table III suggest that analyst earnings forecasts for firms that have recently gone public have an upward bias, and this bias is larger than the previously documented bias for seasoned firms. The bias increases with the forecast window and persists after controlling for size, industry, and the number of analysts following the firm. While we cannot rule out agency or selection bias related explanations of the forecast errors, systematic overoptimism on the part of analysts seems part of the explanation. Of course, we will obtain more support for this interpretation if we find that these errors are related to the number of IPOs coming to market (suggesting that firms time their issues to take advantage of mispricing). Before testing this conjecture, we analyze analyst predictions of firm growth.

C. Long-Term Earnings Growth Projections

In addition to earnings forecasts, analysts also make long term earnings growth projections. While there is no formal definition of what constitutes long term, discussions with IBES suggest that a five-year horizon is representative for what analysts have in mind when these forecasts are made. The fuzziness of the horizon and the existence of firms with currently negative earnings implies that we cannot, with great confidence, adjust this measure by the actual realizations to get firm-by-firm measures of analyst overoptimism (although averages are likely to be more meaningful). Thus, a priori, the long term earnings growth forecasts should be thought of as a measure of the *relative* optimism of analysts. We will, however, provide some evidence from an analysis of ex post returns that it may also be a proxy for the degree of overoptimism by the analysts.

⁶ Another potential explanation for our results stems from the selection bias inherent in an analyst's decision to follow a firm. As McNichols and O'Brien (1996) argue, only optimistic analysts start following firms. So recommendations by analysts (e.g., buy, hold, or sell) who have just started following firms are typically positive. But they also argue that analysts have a greater incentive to collect information about newly added stocks. This explains their somewhat surprising finding that earnings forecasts made by these analysts tend to be less upward biased. Our finding that forecasts for IPOs (which are, by definition, newly followed) are more optimistic than for seasoned firms suggests, at the very least, that there is a different underlying explanation than the one proposed by McNichols and O'Brien.

Table IV
Forecasts of Long Term Earnings Growth for Initial Public Offerings (IPOs)

Time refers to the time period after the IPO that the forecast is made. Industry-adjusted long term growth rates are computed by subtracting the average of all firms with the same two-digit industry code, for all firms listed on COMPUSTAT for at least three years. Only forecasts made the last month of each quarter after the IPO are listed. The table contains forecasts for all firms listed on Institutional Brokers Estimate System (IBES) within one year of the IPO.

Time	Long Term Growth Forecast (in %)	Number	Industry-Adjusted Long Term Growth Forecast (in %) (p-Value)	Number
3 months	23.19	28	5.42 (0.07)	27
6 months	23.73	252	5.43 (0.00)	238
9 months	22.45	433	4.22 (0.00)	400
12 months	22.03	526	3.22 (0.03)	480
15 months	21.13	568	3.08 (0.00)	520
18 months	20.26	585	3.27 (0.00)	530
21 months	19.63	582	3.02 (0.00)	530
24 months	19.77	566	3.04 (0.00)	516
27 months	19.02	568	2.40 (0.00)	515
30 months	18.14	571	1.81 (0.00)	516
33 months	17.84	547	1.64 (0.00)	490
36 months	17.61	537	1.39 (0.01)	484

Table IV contains a detailed analysis of long-term growth forecasts generated over the three-year period following the IPO. We only focus on corporations listed on IBES within 12 months of their IPO and report the average of the growth forecasts for the last month of each quarter. The initial long term earnings growth forecasts are high (23–24 percent), and they fall considerably by the third year after the IPO. IPOs are expected to grow five percentage points faster than their industry in the three to six month period after the IPO. By the end of the first year, these expectations fall to approximately three percent faster than the industry and by the end of the third year, IPOs are expected to grow only 1.4 percent faster than the industry rate.⁷

One explanation for this downward drift in industry-adjusted growth rates is that analysts (and investors) are overoptimistic about the prospects of IPOs, but they adjust their expectations over time. This could account for the long run underperformance of IPOs. A more mundane explanation is that much of the growth of IPO earnings is concentrated within the first few years after the IPO. But, to account for the revision over the first year in five-year industry adjusted growth rates in Table IV, a crude calculation shows that earnings

⁷ One problem with these numbers is that more firms are added to the IBES database as we increase the time period after going public (up to one year). However, if we restrict ourselves to firms listed on the IBES database within three months of the IPO, the results are similar to those reported in Table IV.

from the average IPO should increase at a nine percent faster rate than the industry over the first three years.⁸ This seems rather high. In addition, it is inconsistent with Jain and Kini (1994) and Mikkelsen and Shah (1994) who find that firms have poor earnings growth in the year following the IPO.

These results suggest that analysts are also overoptimistic about the long-term growth opportunities of IPOs (and we support this later with evidence that the higher the long term earnings growth forecasts, the lower, on average, are returns).

Which measure—earnings forecast errors or long term earnings growth projections—should be used in our analysis? While the former is a more direct proxy for overoptimism, it has the disadvantage of being based on ex post data, and therefore it is mechanically correlated with long term returns. Furthermore, earnings forecasts do not seem to be adjusted downwards rapidly and, as illustrated in Table III, for a given forecast window, they do not improve in accuracy over time.⁹ There may also be greater selection problems associated with earnings forecasts.¹⁰ In what follows we will investigate the relationship between both measures and the number of firms coming to market. Finally, we will examine the correlation between long term earnings growth forecasts and ex post returns. We will not use forecast errors in this case because it contains ex post data.

⁸ If we assume that the expected growth is uniform over the next five years, the growth rate for the first three years should have been approximately 27 percent, which is nine percent above expected industry growth at the start of the first year and the second year, and 10 percent above expected industry growth at the start of the third year.

⁹ We check whether earnings forecasts (as compared to forecast errors) decline over time. We analyze earnings forecasts for the end of the next fiscal year (window between 13 and 24 months) and track this number over the three years following the IPO. Expected earnings per share are \$1.16 one year after the IPO (adjusted for splits), \$1.18 after two years, and \$1.16 after three years. As a fraction of the stock price, this is 0.108 one year after the IPO, 0.096 after two years, and 0.089 after three years. Thus, while analysts project high growth rates, the projected earnings are actually flat. Given the slight increase in the stock price over time, there is a decline in the forecast to price ratio.

¹⁰ McNichols and O'Brien (1996) provide evidence that analysts disproportionately tend to follow successful firms and stop following unsuccessful firms. It is possible that this bias is concentrated more in earnings forecasts than in growth forecasts. This may explain why earnings forecasts in the second year persist in being high even though growth forecasts are revised downward—earnings forecasts in the second year contain a disproportionate number of winners. We find evidence consistent with this. At the end of one year after the IPO, we have 734 firms being followed, with an average of 2.99 analysts reporting earnings forecasts per firm. The average number of analysts reporting earnings forecasts for these firms goes up to 3.75 at the end of the second year, an increase of about 25 percent. The comparable figures for the 526 firms reporting growth forecasts at the end of the first year is 1.73 and 2.06, implying growth of about 20 percent. But the distribution of analysts among good and poorly performing firms at the end of the second year is more skewed for earnings forecasts. Firms in the lowest quartile of return performance have only 72 percent of the mean number of analysts (=3.75) reporting earnings forecasts, whereas firms in the highest quartile have 123 percent of the mean number of analysts reporting earnings forecasts. The corresponding figures for growth forecasts of 77 percent and 114 percent suggests less bias.

D. Analyst Optimism and Windows of Opportunity

In this section we examine whether the long term earnings growth projections and earnings forecasts are related to the frequency with which firms engage in IPOs. If analysts are systematically overoptimistic about the prospects of IPOs and if there is substantial time series variation in this overoptimism, more firms should come to the market when this overoptimism is particularly severe. This is consistent with the “window of opportunity” arguments discussed by Ritter (1991), Lerner (1994), Loughran and Ritter (1995), and Rajan and Servaes (1995), and the “investor sentiment” evidence presented by Lee, Shleifer, and Thaler (1991). Lee *et al.* find that more IPOs come to market when closed-end funds trade at a low discount compared to net asset values; they interpret the closed-end fund discount as a measure of investor sentiment. Growth forecasts are, perhaps, a more direct measure of sentiment and a finding of positive correlation will add validity to the interpretation of Lee *et al.*

The focus in this analysis is on those industries (defined at the two-digit SIC code level) with at least 50 IPOs over our sample period. Approximately 62 percent of the firms in our sample are from industries that meet this selection criterion. The reason for limiting our analysis to industries with many IPOs is that we construct measures of analyst forecasts for recent IPOs in each industry. Obviously, such measures cannot be computed for industries with only sporadic IPO activity.

Specifically, we count the number of IPOs in each quarter in each industry and relate this frequency to measures of analyst forecasts computed on a quarterly basis. Four measures of analyst forecasts are employed: (a) long term earnings growth projections for all recent (<1 year) IPOs; (b) long term earnings growth projections for all recent IPOs, computed separately for each industry; (c) industry long term earnings growth projections for all industries with recent IPOs; (d) industry-adjusted long term earnings growth projections for all recent IPOs. Firms in the industry sample have to be listed on COMPUSTAT for at least three years. We employ forecasts made during the last month of each quarter. If no forecasts are available for the last month of the quarter, we use the second month, and if no forecasts are available for the second month, we use the first month.

Table V presents the results for the four measures of analyst forecasts. Tobit models are estimated because the dependent variable is truncated at zero. Panel A includes our earnings growth forecast measure as an explanatory variable, together with 12 industry dummies defined at the two-digit level (coefficients not reported). The column heading describes the growth measure employed in the model presented in that column. Our measures of long term earnings growth forecasts are positive in all models and significant in three of the four models. Interestingly, the model in column (i) has the largest explanatory power. In that model all long term earnings growth forecasts for IPOs completed over the last year are averaged by quarter. Thus, this explanatory variable is the same for each industry. The result is also economically signif-

Table V
Tobit Regressions of the Number of Initial Public Offerings (IPOs)
Coming to Market During a Quarter on Long Term Earnings
Growth Forecasts and Control Variables

The dependent variable is the number of IPOs coming to market in a quarter in a (two-digit) industry. Only 13 industries with at least 50 IPOs over the sample period are included in the analysis. Four long term earnings growth measures are employed as explanatory variables: (i) LT IPO earnings growth is the average long term earnings growth forecast for all firms that went public in the previous 12 month period; (ii) LT IPO earnings growth by industry is the average long term earnings growth forecast for all firms in the same two-digit Standard Industrial Classification (SIC) code industry that went public in the previous 12 month period; (iii) LT industry earnings growth is the average long term earnings growth forecast for all seasoned firms (>3 years on COMPUSTAT) in the same two-digit SIC code industry; (iv) LT IPO industry-adjusted earnings growth is the long term earnings growth forecast for all firms in the same two-digit SIC code industry that went public in the previous 12 months period, minus the same forecast for all seasoned firms in that industry. Only forecasts made during the last month of each quarter are employed. Historical MB is the average equity market to book ratio for seasoned firms in the industry (listed at least three years) at the end of the previous quarter, divided by the same measure averaged over all quarters in the five surrounding years. Relative MB is the average equity market to book ratio for seasoned firms in the industry (listed at least three years) at the end of the previous quarter, divided by the market to book ratio for all seasoned firms in the market at the end of that quarter. MARKET MB is the equally weighted equity market to book ratio for all seasoned firms in the market in the previous quarter, divided by the same measure averaged over all quarters in the five years surrounding that quarter. *p*-values are in parentheses.

	Explanatory Variable			
	LT IPO Earnings Growth	LT IPO Earnings Growth by Industry	LT Industry Earnings Growth	LT IPO Industry- Adjusted Earnings Growth
Panel A: Excluding Control Variables				
Intercept	-3.845 (0.010)	0.564 (0.68)	3.402 (0.02)	3.479 (0.01)
Growth measure	0.323 (0.00)	0.125 (0.00)	0.010 (0.75)	0.062 (0.00)
Pseudo R ²	0.117	0.058	0.037	0.047
Number	299	165	165	165
Panel B: Including Control Variables				
Intercept	-32.120 (0.00)	-49.086 (0.00)	-50.607 (0.00)	-50.696 (0.00)
Growth measure	0.186 (0.00)	0.079 (0.00)	0.000 (0.99)	0.040 (0.02)
Historical MB	-2.827 (0.47)	-14.097 (0.04)	-11.238 (0.11)	-14.423 (0.04)
Relative MB	8.275 (0.00)	15.603 (0.00)	16.882 (0.00)	17.627 (0.00)
Market MB	21.456 (0.00)	41.972 (0.00)	40.756 (0.00)	42.844 (0.00)
Pseudo R ²	0.162	0.128	0.116	0.122
Number	299	165	165	165

ificant. An increase in the long term earnings growth projections of seven percentage points (= one standard deviation) increases the number of IPOs per industry per quarter by 2.4 (= one half of its standard deviation).¹¹ This result suggests that analyst optimism may not be industry specific but applies to all IPOs during a particular period. When analysts project high earnings growth for recent IPOs, regardless of their industry, the number of new IPOs increases, consistent with the conjecture that firms exploit these “windows of opportunity” to go public.

Two other long-term growth forecast measures also yield significant results: (i) long-term earnings growth forecasts for recent IPOs, computed by industry; and (ii) industry-adjusted long-term earnings growth forecasts for recent IPOs. Note that the number of observations in these models is smaller because we lack forecasts for recent IPOs in some industries in some quarters.¹²

Arguably, finding a relation between long term earnings growth forecasts and the number of firms engaging in an IPO is not that surprising. Firms with high future growth projections need funds to finance this growth, and selling shares to the public is one method of obtaining new financing. There are at least two reasons, however, why this argument is not entirely convincing. First, evidence presented in the previous section suggests that analyst growth projections are biased upwards; hence, the forecasts employed in the regression models presented in Table V are poor predictors of actual firm growth, and the resulting need for funds. Second, the third model presented in Table V indicates that the frequency of new IPOs is not related to industry growth projections. The coefficient on industry growth is small, and not significantly different from zero. Firms engage in an IPO when recent IPOs in that industry (and IPOs in general) are expected to grow quickly, but not when the seasoned firms in their industry are expected to grow quickly. These results are more consistent with the argument that firms go public when analysts (and, coincidentally or consequently, the public) are optimistic than with the argument that firms go public because they need to finance future growth.

In Panel B of Table V, we add a number of control variables to the estimated regression models to verify the robustness of our results. Historical MB is the average ratio of the market value of equity and the book value of equity for all seasoned firms in the industry (listed at least three years) at the end of the quarter prior to the IPO, divided by the same measure averaged over all quarters in the five years surrounding that quarter. Relative MB is the average equity market-to-book ratio for seasoned firms in the industry at the end of the previous quarter, divided by the market-to-book ratio for all seasoned firms in the market at the end of that quarter. These measures capture whether firms in the industry are trading at high multiples relative to their

¹¹ Note that this interpretation is based on an uncensored model, while the estimated model is actually censored.

¹² There are two reasons for the lack of forecasts: (i) in some years there are no IPOs in some industries, which implies that no forecasts are made; and (ii) as noted previously, IBES coverage is sporadic during the early years of the sample period.

historical levels (historical MB) or relative to the other firms in the market (relative MB). Both measures can be interpreted as proxies for growth opportunities in the industry or as proxies for investor sentiment (Rajan and Servaes (1995)). In the regression models, the coefficient on relative MB is always positive and significant; but, contrary to expectations, historical MB is always negative and it is significant in some specifications. This negative coefficient is caused by multicollinearity, however. When relative MB is not included in the regression models, the coefficient on historical MB is always positive and significant at the 10 percent level or better in three of the four models.

We also include market MB, which is the market-to-book ratio of all seasoned firms in the market, divided by the same measure averaged over all quarters in the five surrounding years. This variable measures whether the stock market is peaking and is included in the model to capture Loughran and Ritter's (1995) argument that IPOs come to market near market peaks. Its coefficient is always positive and significant. More importantly, for our purpose, however, is that the coefficients on the long term earnings growth forecast measures remain significant in the relevant three specifications.

In unreported models, we also find no qualitative differences in the significance or the magnitude of the reported coefficients when we include the following control variables: (i) the feedback risk measure proposed by Rajan and Servaes (1995), computed as the abnormal trading volume on the second trading day following the IPO;¹³ (ii) a measure of future investment growth for each industry, computed as the average ratio of investment to sales for the three following years, divided by this ratio for the past year; (iii) three measures of general business conditions, proposed by Fama and French (1989) and Choe, Masulis, and Nanda (1993): the dividend yield for the S&P 500, the default spread, and the term spread.¹⁴

Finally, instead of growth forecasts, we use earnings forecast errors and adjust them as in (a), (b), (c), and (d) above, except that we use matched firm data when adjustments are made, and not industry data. (i.e., for all recent IPOs, we employ (a) raw forecast errors, (b) raw forecast errors, computed by industry, (c) matched firm forecast errors, (d) matched firm adjusted forecast errors). This analysis examines whether analyst overoptimism leads to more IPOs. We generally find a positive relation between forecast errors and IPO frequency (not reported). The relation is only significant for one measure, however, and that is the average matched firm adjusted earnings forecast error. Arguably, this measure best reflects IPO optimism, because it adjusts for both the general bias in earnings forecasts and any industry-specific idiosyncracies in earnings. This measure remains significant when the control variables are included in the regressions.

¹³ Feedback trading leads to increased trading volume on the second day following the IPO, after one price change has been observed.

¹⁴ The default spread is computed as the difference between the yield on Baa and Aaa bonds, and the term spread is computed as the difference between the yield on ten year treasury bonds and treasury bills. Both measures, together with the dividend yield on the S&P 500, are obtained from Citibase.

In sum, the results are consistent with a scenario where firms take advantage of windows of opportunity, as suggested by Ritter (1991) and others. The evidence indicates that these windows are at least partially related to analyst overoptimism about recent IPOs.

E. Analyst Optimism and Long-Run Stock Price Performance

The previous findings indicate that firms come to market when analysts are optimistic, and that analysts overestimate the earnings and growth potential of these firms once they complete their IPO. If analyst expectations influence, or represent, market expectations, we expect firms to perform poorly in the long run as earnings materialize below analyst predictions. Furthermore, the poor performance should be correlated with analyst optimism. We provide a detailed examination of this conjecture in this subsection.

To determine the long run performance of IPOs, we compare the five year returns of the firms in our sample to three benchmarks: (i) the NYSE/AMEX value weighted index; (ii) the smallest decile of the NYSE/AMEX firms; (iii) a matching sample. The matched firm meets the following criteria: (i) it has been listed on COMPUSTAT for at least three years; (ii) it operates in the same two-digit SIC code industry as the IPO firm; (iii) it is closest in size (market value of equity) to the IPO firm. The market value of the IPO firm's equity is computed on the first day of trading, thereby taking into account the stock price change on that day.¹⁵

Table VI verifies that the IPOs in our sample perform poorly in the long run. Over the five year period following their IPO, companies have raw returns of only 23.8 percent. Adjusting for either of the three benchmarks yields negative returns, ranging from -17.0 percent (smallest NYSE/AMEX decile) to -47.1 percent (NYSE/AMEX adjusted). Also note that there is substantial variation in the long run performance of IPOs over time. This is what would be expected if there is substantial time series variation in analyst overoptimism.

For our tests, we divide firms into quartiles according to their industry-adjusted long term growth forecasts and compare the benchmark adjusted stock returns for the IPOs in the different quartiles. We employ the first long term earnings growth forecast made in the year after the IPO. We exclude returns computed over the first 252 trading days (approximately one year) from our analysis, because not all growth forecasts are available during this period. The results presented in Table VII are striking. The firms with the lowest industry-adjusted growth forecasts (less than -0.0478) outperform the NYSE/AMEX index by 35.6 percent, the smallest NYSE/AMEX decile by 78.1 percent, and the matched sample by 74.1 percent. The firms with the highest industry-adjusted growth forecasts underperform the NYSE/AMEX index by

¹⁵ Our matching procedure is similar to the procedure followed by Ritter (1991) with the following differences: (i) Ritter matches at the three-digit level, if possible; we match at the two-digit level; (ii) if a two-digit match cannot be found, Ritter employs a firm from a similar industry, whereas we do not assign a matching firm in that case; (iii) Ritter's matching firms can only be used once every three years, while we do not impose that restriction.

Table VI
Average Five Year Performance According to Several Benchmarks
by Year of Going Public

Returns are computed for 1260 trading days starting from the second trading day. The adjusted returns are computed by subtracting the five-year return on New York Stock Exchange/American Stock Exchange (NYSE/AMEX) (value weighted), the smallest decile of NYSE/AMEX, and a matched firm from the five-year raw return. The firm closest in size (traded on NYSE, AMEX, or Nasdaq) to the Initial Public Offering (IPO) firm from the same two-digit Standard Industrial Classification (SIC) industry is used as a matching firm if it has been listed for at least three years. If firms are delisted, returns are only computed until the delisting.

Year	Raw Return	NYSE/AMEX		
		Adjusted Return	Smallest Decile Adjusted Return	Matched Firm Adjusted Return
75	1.1123	0.3868	-1.0964	-0.2260
76	2.1569	1.6706	0.6405	0.0036
77	2.2194	1.6968	0.7113	0.9836
78	2.0037	1.2153	0.3611	-0.1752
79	0.7239	-0.0253	-1.0217	-0.6812
80	-0.0416	-0.6859	-1.2514	-1.7097
81	0.1900	-0.6977	-1.1047	-1.7027
82	0.8568	-0.4530	-0.6384	-0.6583
83	0.0564	-0.6210	-0.1373	-0.2859
84	0.4361	-0.4895	0.1761	-0.0806
85	0.1577	-0.5781	-0.0284	-0.1008
86	0.0956	-0.4751	0.1040	0.0207
87 (6 months)	0.2017	-0.2552	0.1764	-0.1804
	0.2383	-0.4714	-0.1703	-0.4064

62.8 percent, the smallest 10 percent of the NYSE/AMEX stocks by 19.5 percent, and the matched firm sample by 35.9 percent. Thus, the difference in performance between the high and low growth forecast quartiles is close to 100 percent. Note that the return differences between the high and low growth quartiles are significant at the one percent level for all three benchmarks. In addition, many of the differences between the other quartiles are also highly significant. These results support our conjecture that analyst optimism is also reflected in the stock price performance of these firms.

We also verify whether the size effects and market to book effects reported by Fama and French (1992) can explain some of the patterns reported in Table VII. However, we do not find systematic differences in market-to-book ratios and sizes for the firms in the four quartiles.

The results presented in Table VII indicate an economically significant inverse relation between the long run performance of IPOs and analyst forecasts of their long term growth potential. This suggests that investors bid up the prices of firms above their fundamentals when analysts predict high growth rates and drive down the prices of firms below their fundamentals

Table VII

Long Term Returns on Initial Public Offerings (IPOs) by Forecasted Industry Adjusted Growth Quartiles

The first long term growth forecast reported for a firm after the IPO is employed in this analysis. Industry-adjusted long term growth forecasts are computed by subtracting the average long term growth forecast for all seasoned firms in the industry. Industry is defined at the two-digit Standard Industrial Classification (SIC) code level. Seasoned firms have to be listed on COMPUSTAT for at least three years. Returns are computed over the 1008 trading day (approximately four years) period starting 252 days after the IPO. New York Stock Exchange/American Stock Exchange (NYSE/AMEX) adjusted returns are computed as: raw return for IPO firm – return on Center for Research in Security Prices (CRSP) NYSE/AMEX index over the same period. NYSE/AMEX smallest decile adjusted returns are computed as: raw return for the IPO firm – return on smallest decile of NYSE/AMEX firms over the same period. Matching firm adjusted returns are computed as: raw return for the IPO firm – return on the seasoned firm in the industry which is closest in size.

Industry-Adjusted Long Term Growth Forecast Quartiles	NYSE/AMEX Adjusted 4-Year Return ^a	NYSE/AMEX Smallest Decile Adjusted 4-Year Return ^b	Matched Firm Adjusted 4-Year Return ^c
Less than -0.0478	0.3561 (123)	0.7813 (123)	0.7413 (122)
-0.0478 to 0.0152	-0.2305 (125)	0.1656 (125)	0.0333 (125)
0.0152 to 0.0960	-0.5665 (122)	-0.1404 (122)	-0.3228 (119)
Greater than 0.0960	-0.6282 (126)	-0.1948 (126)	-0.3586 (122)

^a All the returns in this column are significantly different from each other at the one percent level, based on pairwise t-tests.

^b All the returns in this column are significantly different from each other at the one percent level, based on pairwise t-tests, except for the returns in the second and third quartiles, which are significantly different from each other at the five percent level.

^c The return in the first quartile is significantly different from the return in all other quartiles at the one percent level; the return in the second quartile is significantly different from the return in the fourth quartile at the 10 percent level; the returns in the third and fourth quartiles are not significantly different from each other; the returns in the second and third quartiles are not significantly different from each other.

when analysts predict low growth rate. LaPorta (1996) provides related evidence. He examines all stocks listed on CRSP, COMPUSTAT, and IBES over the 1982 to 1991 period and finds a significant negative relation between these predicted growth rates and future returns. He also finds that analysts subsequently reduce earnings forecasts and earnings growth forecasts for those firms that were previously predicted to grow quickly. Our results indicate, however, that the growth forecasts remain above the industry average for at least three years. In addition, returns continue to be negative for high growth stocks for several years after the initial forecast is made.¹⁶

¹⁶ For example, the NYSE adjusted returns for firms in the highest industry-adjusted growth forecast quartile are -20 percent in the two-year period starting three years after the IPO.

III. Conclusion

This article presents four major results. First, analyst following is positively related to IPO underpricing. Second, analysts are overoptimistic about the earnings and growth performance of IPOs, and this overoptimism is not a reflection of their overoptimism in general: the upward bias in earnings forecasts is more substantial for IPOs than for matched firms in their industries. Third, analyst growth forecasts and the magnitude of earnings forecast errors for recent IPOs are positively related to the number of IPOs coming to market. Fourth, firms perform poorly in the long run when analysts are more optimistic about their long run growth projections.

While there is a substantial literature on both initial public offerings and analyst forecasts, this article, we believe, is the first to study both. Underpricing seems, at least in part, an effort to attract interest. The windows of opportunity that open up for IPOs in the “hot-issue” periods appear to be driven by inflated expectations that eventually lead to poor long run returns. The most important question raised by this article is whether analysts reflect, or influence, the market’s expectations. Most of the work on analysts thus far (see Dugar and Nathan (1995), for example), and information producers in general (see Kroszner and Rajan (1997)), suggests that the market is typically aware of any agency or selection biases influencing their behavior and adjusts for it. If this is so, our finding that analyst misperceptions are correlated over time with the frequency of new issues while they are cross-sectionally correlated with excess returns suggests that these misperceptions are not solely driven by agency or selection bias, but also partially reflect beliefs already widely held by the market. If this conjecture can be better established, it would suggest that analyst forecasts provide information about investor expectations for cash flows, and can be used in tests of market efficiency.

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