The Journal of Entrepreneurial Finance

Volume 8
Issue 1 *Spring 2003*

Article 5

12-2003

Forecasting Short Run Performance of Initial Public Offerings in the Istanbul Stock Exchange

Ramazan Aktas
Turkish Military Academy

Mehmet Baha Karan
Hacettepe University

Kürsat Aydogan
Bilkent University

Recommended Citation

Aktas, Ramazan; Karan, Mehmet Baha; and Aydogan, Kürsat (2003) "Forecasting Short Run Performance of Initial Public Offerings in the Istanbul Stock Exchange," *Journal of Entrepreneurial Finance and Business Ventures*: Vol. 8: Iss. 1, pp. 69-85.
DOI: https://doi.org/10.57229/2373-1761.1211
Available at: https://digitalcommons.pepperdine.edu/jef/vol8/iss1/5

Forecasting Short Run Performance of Initial Public Offerings in the Istanbul Stock Exchange

Ramazan Aktaş[+]
Turkish Military Academy,

Mehmet Baha Karan[++]
Hacettepe University

and

Kürşat Aydoğan[+++]
Bilkent University

Previous research on IPOs has identified several factors or issue characteristics that play a role in the level of short term underpricing of initial public offerings. Some of those issue features are the firm size, market trend, size of the offer, investment banker reputation, method of intermediation, stock price range and investor type. The objective of this study is to develop a model based on these features to forecast the short term performance of IPOs in the Istanbul Stock Exchange. To this end we divided our sample period into a model building subperiod and

---

[+] **Ramazan Aktaş** received a B.S. in management from the Military Academy and an M.B.A. in general management from Middle East Technical University. He received his Ph.D. in finance at Ankara University in 1991. Currently he is an associate professor of finance at the Military Academy and has also taught at the Military Academy of Azerbaijan in spring 2001. His research interests are investments, capital markets and corporate finance.

[++] **Mehmet Baha Karan** received a Ph.D. in Finance at Gazi University in 1984. He worked in the business sector as General Director between 1985-1993 in Ankara. He taught at Girne American University-North Cyprus during 1993-1995. He joined Hacettepe University in 1995. Currently he is a professor of finance and director of the Financial Research Center of Hacettepe University. His research interests are investments and corporate finance.

[+++] **Kürşat Aydoğan** received a B.S. in management and M.B.A. in general management from Middle East Technical University . He received his Ph.D. in finance at Syracuse University in 1986. Before joining Bilkent University, he taught at Ball State University and Middle East Technical University. Currently he is a professor of finance and dean of the Faculty of Business Administration at Bilkent. He has also worked as a consultant at the Research Department of the Central Bank of Turkey between 1988-93. His research interests are investments, capital markets and corporate finance.

a testing subperiod. After identifying 9 issue features that are related to IPO short term pricing, we estimated our models using multiple regression, multiple discriminant and logit methods. The estimated models are then tested against the IPO data in the subsequent period between 1997-2000. The overall predictive ability of the forecasting models can be described as mediocre. In terms of actual abnormal returns obtained from investment strategies based on model predictions, only the logit models beat the outcome of naive strategies, albeit only marginally.

Introduction

The short term under pricing of initial public offerings (IPOs) is a well documented phenomenon. Ritter (1998) reports an average initial underpricing of 15.8% percent for the US market in the 1960-96 period. Similar magnitudes of underpricing were observed in other markets, both in developed and emerging economies. For example, Dawson (1987) and Kim and Lee (1990) find significant underpricing of unseasoned equity issues in Pacific Basin stock markets. Kıymaz (2000) shows that initial public offerings in the Turkish market between 1990-1996 provided an average abnormal return of 13.1 percent. Aggarwal, Leal and Hernandez (1993) report similar findings of underpricing for Latin American markets. Several hypotheses were put forward to explain short term underpricing of IPOs. Baron (1982), Rock (1986) and Allen and Faulhaber (1989), among others, point out asymmetric information between informed and uninformed investors as the probable cause of IPO underpricing. Market power of investment bankers (Ritter, 1984), and underwriter reputation (Tinic, 1988) provide alternative explanations for the same phenomenon.

Previous research on IPOs has also identified several factors or issue characteristics that are related with the level of short term underpricing. Some of those issue features are the firm size, market trend, size of the offer, investment banker reputation, method of intermediation, stock price range and investor type. The objective of this study is to develop a model based on these features to forecast the short term performance of IPOs in Istanbul Stock Exchange. To this end, we analyze the IPOs in the Turkish stock market in the period 1992-2000 by using 95 IPOs during 1992-96 for model building, and 95 IPOs during the subsequent 1997-2000 period for testing our models. Prior to building the forecasting models, we identify the features that can distinguish between high and low short term IPO returns. Following the leads in the literature, we come up with nine such features, or variables.

We employed three methods to build forecasting models: These are, multiple discriminant, logit and multiple regression analyses. In each case, we built a forecasting model using the nine issue features in a stepwise manner. We tested these models to predict the performance of 95 IPOs during the 1997-2000 period. Our results indicate that multiple discriminant models have the best performance, while multiple regression displays the lowest predictive ability. In general, models can predict positive CARs much better than negative CARs. We also tested the economic significance of forecasting ability by computing average CARs from IPOs selected by the forecasting models and comparing them with the average CARs from a naïve strategy of investing in all 95 IPOs during the testing period. None of the models can outperform the naïve strategy, leading us to conclude that issue features, although statistically significant, cannot provide economic profits in selecting IPOs.

The organization of this paper is as follows. In Section I, we provide a brief description of the data and Turkish equity markets. Identification of variables related to the level of short term underpricing is presented in Section II. Section III contains the estimation of forecasting models and tests of the models and discussion of predictive ability. Section IV concludes the paper.

I. Turkish Equity Markets and IPO Data

Financial liberalization attempts during 1980s have promoted the development of capital markets in order to enhance the efficiency of the system by providing an alternative to banks for both the corporate and household sectors via the introduction of direct finance. The establishment of Istanbul Stock Exchange (ISE) in 1986 is an important milestone in this direction. The exchange has shown remarkable growth both in terms of trading volume and number of listed companies. As of the end of 2000, with 287 listed companies, annual trading volume reached $182 billion, and total market capitalization stood at $70 billion. These figures put ISE ahead of many emerging markets, and comparable to smaller Western European exchanges. While ISE is the only secondary market for trading common stock, Capital Markets Board (CMB) was set up in 1982 as the regulatory authority for capital markets. All publicly held companies must register with CMB and obtain permission for issuing debt and equity securities. In order to be listed on ISE, corporations should have at least 15% of their shares floating, their audited financial statements should display profits in the last two years and they should accept certain disclosure requirements. It is obvious that for Turkish corporations, most of which are closely held, family owned companies, going public would expose them to uncertainties in governance while at the same time presenting new financing opportunities. Another group of companies that would go public were government owned firms to be privatized.

A total of 204 companies went public in this period by selling their shares for the first time. The value of IPOs reaches $4.6 billion. We included all the IPOs that have full data on the variables of interest. Table I presents the distribution of 190 initial public offerings in our sample by years. Approximately in two thirds of the sample, majority shareholders sold their shares whereas in others companies issued new equity to the public and current shareholders did not exercise their preemptive rights. We have divided the period into two subperiods: 95 IPOs between 1992-96 are used for estimating the models, the remaining 95 IPOs that took place in 1997-2000 subperiod were employed in testing those forecasting models. The stock return data was obtained from Datastream and other information is taken from various publications of ISE.

II. Short Term Performance of IPOs

We analyze short term performance of IPOs using market adjusted daily returns with traditional event study methodology. The abnormal return on stock *i* on day *t*, AR_{it}, is defined as the difference between daily return, R_{it}, and the return on the market, M_t: $AR_{it}=R_{it}- M_t$. The return on day *t* is the percentage change in prices between two successive days: $R_{it}=(P_{it}-P_{i,t-1})/P_{i,t-1}$ where P_{it} and $P_{i,t-1}$ represent adjusted closing prices on days *t* and t-1. The market return is defined in a similar fashion as the percentage change in the levels of ISE Composite Index in two successive days. If $t=0$ denotes the event day, the average abnormal return on n stocks *t* days after the stock dividend-rights offering decision, AR_t, is given as:

$$AR_t = \sum_{i=1}^{n} \frac{AR_{it}}{n}$$

For n securities, average cumulative abnormal returns T days after the event date, CAR_T, is the sum of average abnormal returns over that period:

$$CAR_T = \sum_{t=0}^{T} AR_t$$

The t statistics for the average *CAR*s are computed as

$$t = \frac{CAR_T}{\sigma(CAR)_T}$$

where $\sigma(CAR_T) = \sigma(AR_T)*(T+1)^{½}$ and $\sigma(AR_T)$ is the variance over T days.

We focus on 1-day, 7-day and 15-day cumulative abnormal returns (*CAR*s) in order to assess short term performance. The overall results of IPO performance in the period 1992-2000 are presented in Table II. The bottom row in the Table shows *CAR*s for the entire sample. Initial underpricing is 9.17%. Although statistically significant, first day underpricing is lower in comparison to results obtained in other studies, including the only published study on the Turkish market. In that paper Kiymaz (2000) reports 13.1% market adjusted average first day return for his sample covering the period 1990-96. We have to note that the overlap between our sample and his is approximately 50%. Cumulative abnormal returns (*CAR*s) on the 7^{th} and 15^{th} days go up to 13.94% and 12.46% respectively. Both are statistically significant.

Attempts to explain IPO underpricing have several empirical implications by pointing our certain features of the new issue as proxies for the arguments towards subsequent underpricing. First among them is the size of the firm going public (S*ize*) and the total proceeds of the IPO (*Proceeds*). Both Ritter (1984) and Brav and Gompers (1987) suggest that due to higher uncertainty new issues of smaller firms may have bigger discounts. Similarly larger issues in terms of total proceeds have less uncertainty, hence they are expected to be less underpriced. In his study of Turkish IPOs, Kiymaz (2000) reports significant effects of firm size and total IPO proceeds. As predicted, IPOs of smaller firms and IPOs with smaller total proceeds are priced lower. We use both size (*Size*) and total proceeds (*Proceeds*) as explanatory variables in our forecasting models. Firm size is measured with total market capitalization of the new issue at the offer price, total issue proceeds is found by the market value of the public offer, again computed at the offer price.

A related explanatory feature of underpricing is the percentage of total shares offered to the public (*Rate*). As in Leland and Pyle (1977) and Keasey and Short (1992), percentage of the firm offered to outside equity investors serve as a signal for firm quality. Hence the higher the percentage rate, the lower is the perceived firm quality and therefore the greater is the need for IPO underpricing. We include *Rate* as another explanatory variable in our models.

Ritter (1984) argues that IPO underpricing is bigger in certain periods which he calls “hot issue” markets. Such hot issue markets usually coincide with bull markets. We therefore include the trend in the market (*Index*) by taking the overall market return during the previous month. The monthly rate of return on ISE-100 Composite Index is employed to proxy the market trend before an IPO is made.

The risk assumed by an investment banker underwriting an IPO is a function of the method of intermediation. Smith (1986) argues that firm commitment underwriting exposes the investment banker to higher risk than best efforts method. Hence we would expect the former method to lead to larger initial day returns compared to the latter. In addition to the method of intermediation (*Method*), we also included the relationship between the investment banking firm and the issuer (*SelfIPO*). In many instances the investment bank and the issuing firm belong to the same group of companies. Various scholars argue that when informational asymmetry between the investment bank and the issuing firm disappears underpricing need not exist, e.g. Baron (1982), Muscarella and Vetsuypens (1989), and Kiymaz (2000).

Another feature related to informational asymmetry, this time between informed and uninformed investors, is the presence of a large investor among the subscribers to the issue (*BigInv*). Large investors are more likely to possess further information about the company, thus they are expected to invest in underpriced issues more often, Rock (1986). When an investor or group of investors subscribe to more than 10% of the issue we regard it as the presence of a large investor. Following a similar line of reasoning, presence of a foreign investor is another feature that may influence the pricing of a new issue (*Foreign*). Since foreign investors employ the services of reputable professional analysts, they will also subscribe to underpriced issues more often than ordinary investors.

Finally, the level of the price of the IPO (*Price*) is thought to have an impact on short term IPO performance. Following the research findings on low priced stocks earning higher returns than higher priced stocks, we hypothesize that low price IPOs will outperform IPOs priced at higher levels.

A. IPO Features and Short Term Performance

Having specified nine features that may have an impact on short term performance of IPOs, we performed some univariate tests to see if those features are related to 1, 7 and 15 day cumulative abnormal returns (*CAR*s). For each feature we divided our sample of IPOs for the whole period (1992-2000) into two groups according to some criterion. For example IPOs are divided into two equal groups with respect to feature *Size* as large and small firms, whereas grouping according to *Method* is based on whether method of intermediation is firm commitment or best efforts underwriting. In the latter case group sizes are not equal: there are 161 cases of firm commitment underwriting, and only 29 issues with best efforts underwriting. The grouping criterion for each feature is given in Table 2 together with group sizes. Table II provides *CAR*s for 1, 7 and 15 days for each group for all nine features. Two sets of t-statistics are given for these features. The first set is the t-statistics testing the null that *CAR*s are zero, the second statistic tests if *CAR*s between two groups are the same.

Among the nine issue features, univariate t-tests show that four do not have significant explanatory power towards short term performance. These four attributes are *Price, Rate, BigInv* and *Index*. Price level and offer rate of the issue seem to be totally unrelated to IPO pricing. IPO groups based on presence of a large investor (*BigInv)* and the trend in the market (*Index*) display some differences in pricing. Contrary to our expectation, presence of a large investor is associated with lower *CAR* values. Short term IPO performance is stronger in hot issue markets, a finding consistent with our hypothesis. Three of the five issue features that exhibit significant short term performance difference between groups display relationships opposite to our expectations. These are *Method, SelfIPO* and *Foreign*. In contrast to what we expected, issues with best efforts underwriting (*Method*), issues underwritten by an affiliated investment banker (*SelfIPO*) and IPOs where there are no foreign subscribers (*Foreign*) outperform their counterparts in the related classification. *Size* and *Proceeds*, on the other hand, yield results consistent to hypothesized relationships: smaller companies and smaller issues perform better.

III. Forecasting IPO Performance

In this section we develop three alternative sets of models to predict future performance of IPOs. The first set is multiple regression models for CAR1, CAR 7 and CAR15 respectively. The second and third sets employ multiple discriminant and logit models. For each model group, using the IPO features discussed above, we first build up the model and estimate its parameters using the initial half of our sample. Then we test our model during the testing period covering the second half of the data. The three methods are briefly described below, followed by the results of estimation.

A. Multiple Regression Models

The following multiple regression model is estimated for market adjusted cumulative IPO returns:

$$CAR_i = \beta_0 + \sum_{k=1}^{K} \beta_k X_{ki} + \varepsilon_i \qquad (1)$$

where CAR_i is either 1-day, 7-day or 15-day cumulative abnormal return for IPO i, X_{ki} is the value of explanatory variable *k* for IPO *i*, β_j are parameters and ε_i is the error term with usual distributional assumptions of normality with zero mean and constant variance. The model is estimated three times, for CAR1, CAR7 and CAR15.

B. Multiple Discriminant Models

The multiple discriminant and logit models are specifically developed for binary dependent variables. In this study we would like to predict the market adjusted cumulative abnormal returns (CARs) for IPOs on the first (*CAR1*), seventh (*CAR7*) and fifteenth (*CAR15*) days after the date of issuance. For the investor in IPOs, having a cumulative return that is above the market is the critical issue. Hence a positive abnormal return versus a negative return allows the definition of a binary variable suitable for the purpose at hand.

A linear discriminant function can be described as follows:

$$Z_i = \beta_0 + \sum_{k=1}^{K} \beta_{ik} X_{ik} \qquad (2)$$

where Z_i is the discriminant value for IPO *i*, X_{ik} are values of explanatory variables, and β_0 and β_k are discriminant coefficients. When forecasting group membership, i.e. whether an IPO is classified as successful (positive CAR) or not (negative CAR), the Z value of IPO *i* is compared to the minimum cutoff point, Z*. The minimum cutoff point is obtained as the midpoint of group centroids which are defined as the discriminant functions evaluated at group means.

C. Logit Models

Logit model has certain theoretical advantages over multiple discriminant analysis (MDA) which has been commonly used in financial forecasting. While MDA assumes two completely different populations, logit assumes that a discrete event takes place after the combined effect of certain economic variables reach some threshold level (Feder and Just, 1976).

Moreover, the assumptions of the logit model are more realistic as they do not call for normal distribution of the independent variables. The model does not require the equality of deviation matrices either and thus avoids the constant variance problem inherent in MDA (Ohlson, 1980: 110-113; Mensah, 1984: 380-395; Noreen, 1988: 121).

The logit function is related to Multiple Discriminant Analysis and Multiple Regression Models in the following manner. Linear discriminant and 0-1 linear cumulative functions that are said to be linear probability functions due to the similarities between themselves can be represented as follows (Maddala, 1985).

$$P_i = Z_i = \beta_0 + \sum_{j=1}^{m} \beta_j X_{ij} \tag{3}$$

Here, X_{ij} are the independent variables and β_0 and β_j are the parameters. The cumulative probability function is given by:

$$P_i = F(\beta_0 + \sum_{j=1}^{m} \beta_j X_{ij}) = F(Z_i) \tag{4}$$

As seen, if P_i equals Z_i in linear probability function and P_i equals $F(Z_i)$ in cumulative distribution probability function, then probability of a dependent variable is equal to 1. Here, F represents any cumulative probability function. Logit or "logistic regression" function considers "u" to reveal cumulative logistic distribution which is the error concept of linear probability function.

Logit function can be illustrated as:

If $F(Z_i) = P_i = Prob(y_i=1)$, for logit model

$$Log \frac{P_i}{1-P_i} = \beta_0 + \sum_{j=1}^{m} \beta_j X_{ij} \quad . \tag{5}$$

is reached. *Prob (y=1)* indicates the probability of a dependent variable which is 1. If we take the cumulative abnormal returns (*CAR*s) as binary variables, the above expression will indicate the probability of having a positive *CAR*.

D. Model Estimation and Results

In the previous section we have identified a total of nine IPO features that are thought to be related with IPO pricing. Univariate statistical analyses of these features (variables) were summarized in Table II. It is clear that some of the variables are closely related to each other and display high correlation among themselves. Barlett's test of sphericity indicates high correlation that points out a need for reduction in explanatory variables. In order to reduce the total number variables to a reasonable level, we favor stepwise estimation of our models. The analysis is confined to the 95 IPOs in the model building period of 1992 – 1996. For each one of the three forecasting methods, multiple regression, multiple discriminant analysis and logit, we estimate three models for CAR1, CAR7 and CAR15. Altogether, 9 models are estimated. The results are presented in Table III. No statistically significant multiple discriminant and logit models were found for *CAR1*.

All three multiple regression models are significant, despite low R^2 values. *Size*, *Proceeds* and *Index* are the only variables selected in the stepwise algorithm. While *Size* appears in the models for *CAR1* and *CAR7* with a negative sign, a highly correlated variable, *Proceeds* replaces it in the model for *CAR15*. Significant negative sign of these two IPO features is consistent with our expectations: smaller firms and smaller issues have higher market adjusted short term returns. *Index*, on the other hand, is significant in *CAR1*, and *CAR15* models with a positive sign, again consistent with our hypothesis. Underpricing is larger in periods following the month in which the market went up.

Multiple discriminant and logit models yield similar results for *CAR7*[1]. In both cases, *Index* is the only explanatory variable for *CAR7* with the expected positive sign. In models for *CAR15*, *Index* is accompanied by *Rate* and *Size*, but with opposite signs. In the multiple discriminant model *Rate* and *Size* have positive signs, while the sign of *Index* is negative. Signs are reversed in the logit model for *CAR15*. We know that coefficients in these models should be interpreted with caution, hence we pay more attention to the models and selected variables rather than individual coefficients. It is also interesting to note the percentage of correctly classified cases in these two binary models. If the model correctly classifies an IPO's market adjusted return (CAR) as positive or negative, we consider it as "success". Overall success rate ranges between 62% and 69% for the IPOs during the testing period, 1992-1996. As seen in panels B and C of Table III, logit models have higher success rates then their multiple discriminant counterparts.[2]

Next we test the forecasting ability of the models in the testing period which covers the IPOs that took place in the second part of the sample, between 1997 – 2000. We first obtain predicted values of *CAR1*, *CAR7* and *CAR15* by substituting the values of the variables in the estimated multiple regression models of Table III, panel A. Hence for each IPO in the testing period, we come up with an estimate of *CAR1*, *CAR7* and *CAR15* based on the estimated multiple regression model. For example the model for *CAR1* has *Index* and *Size* as explanatory variables. By substituting the values of these two variables for IPO *i* in the model, a forecast for *CAR1* for IPO *i* is obtained. If the sign of the estimated value of *CAR* matches with the sign of actual *CAR* for IPO *i*, we classify this as "success". Furthermore we distinguish between success in positive *CAR*s versus negative *CARs*. This way all 95 IPOs in the testing period are evaluated. The results are presented in panel (i) of Table IV. The overall success rate of multiple regression models is around 51%[3]. The multiple regression model is most successful in predicting positive first day abnormal returns (CAR1) with a success rate of 92.73%. The model for seven day cumulative abnormal return (CAR7) has the worst overall performance: only 12.2% of negative values and 73.9% of positive values were correctly predicted. In general predictive ability of multiple regression models is much better for positive values than for negative abnormal returns in all three horizons.

[1] No significant logit or multiple discriminant models were found for *CAR1*.

[2] We have also carried out a similar appraisal for the multiple regression models. If the sign of the predicted value of CAR matches with the sign of the actual IPO, we classified it as a "success". The overall success rate is found to be 76.84% for CAR1, 70.53% for CAR7, and 69.17% for CAR15.

[3] The overall success rate is found by dividing the total success in negative and positive values by total number of IPOs in the period.

Multiple discriminant models achieve an overall success rate of 65% in predicting the sign of 7 day and 15 day cumulative abnormal returns (CAR7 and CAR15). As panel (ii) of Table IV demonstrates, prediction of negative values is not particularly worse, and it is even much better for CAR15 with a success rate of 76.8%. Logit models, on the other hand display an overall success rate of 54% in predicting the signs of CAR7 and CAR15, placing them between multiple discriminant and regression models in terms of overall predictive ability. Similar to multiple regression models, logit models are poor performers as far as negative abnormal returns are concerned. As one can observe in panel (iii) of Table IV, only 5 out of 49 (10.2%) negative cumulative abnormal returns on day 7 (CAR7) could be predicted by the logit model.

The natural question that comes to mind at this point is the economic significance of the forecasting models. To address the issue of economic significance, we performed the following experiment: We assumed that an investor would subscribe to an IPO if his model predicts a positive abnormal return (CAR). The actual outcome of this strategy will be determined by the actual CAR of the IPOs invested in. We compute the average abnormal return for each model as the average actual CAR of the IPOs that the model signals to invest in. The results are presented in Table V. For comparison we also included the average CARs of all IPOs in the testing period in the first row of the table. These figures should be interpreted as the outcome of a naïve strategy in which the investor subscribes to every IPO. A comparison of model predicted averages with the outcomes of the naïve strategy reveals that logit models achieve the best performance, followed by multiple regression and multiple discriminant models. The performance of the latter even falls short of the naïve outcome. Note that in the testing period actual CARs are lower than the figures reported in Table II, which covers all IPOs in both sub periods. If our models had picked up only the IPOs with positive CARs in the testing period, the average CAR1, CAR7 and CAR15 would be 16.14%, 24.75% and 30.97% respectively. These values correspond to the best possible outcome we could have obtained. Even the best model-based strategy seriously falls short of the best outcome. The best performer, the logit model performs only marginally better than naïve strategy for CAR7 and CAR15, but entirely fails to come up with a model for CAR1.

The apparent inconsistency between model performance measures in terms of classification between positive and negative CARs and predicted average CARs demands some explanation. In Table IV, we concluded that multiple discriminant models have the highest overall success rate while logit models came in a distant second. Yet in Table V, performance rankings are reversed. This time logit models perform best, multiple discriminant models display a rather poor performance. A careful examination of Table IV reveals the underlying explanation for this inconsistency. Logit models have the highest success rate in identifying positive CARs. Since average CARs of all IPOs are positive, higher success rate in positive CARs becomes more important. In other words, if a model misses IPOs with positive CARs its outcome is hurt more compared to the avoidance of a loss by correctly picking an IPO with a negative CAR. The logit model for CAR7, for example, can predict 44 out of 46 positive values, while it picks up only 5 out of 44 negative CAR7s. The investor subscribes to 44 IPOs with positive CAR7 which are correctly estimated by the model, whereas he/she also invests in 44 negative IPOs incorrectly specified by the model as positive. Since average value of actual CAR7 is positive and most are being invested in, avoiding only 5 negative values is enough to beat the naïve strategy. Multiple discriminant models, on the other hand, are equally successful in identifying negative and positive values. Yet, because of the asymmetry in negative and positive values, they are penalized more by missing positive IPOs.

IV. Concluding Remarks

In this study we attempt to forecast short term IPO performance in the Turkish stock market via three econometric models, namely multiple regression, multiple discriminant and logit models. To this end we divided our sample period into a model building subperiod and a testing subperiod. After identifying 9 issue features that are related with IPO short term pricing, we estimate our models in a stepwise manner with the IPO data in the model building period between 1992 and 1996. The cumulative abnormal returns for 1 day, 7 days and 15 days are the dependent variables used in the estimation. Hence a total of 9 models are estimated: three models for each one of three independent variables. No model for day one abnormal returns was found using logit and multiple discriminant analysis. These estimated models are then tested against the IPO data in the subsequent period between 1997-2000. The overall predictive ability of the forecasting models can be described as mediocre. The best performer, multiple discriminant analysis can correctly classify positive and negative abnormal returns 65% of the time. For the other methods, overall predictive ability is slightly over 50%. In terms of actual abnormal returns obtained from investment strategies based on model predictions, logit models for 7 day and15 day abnormal returns beat the outcome of naive strategies, albeit only marginally. Multiple regression models provide returns slightly above the naïve benchmarks, while multiple discriminant models fail to catch naïve strategy outcomes.

In univariate analysis of the issue features that affect IPO abnormal returns, most of them were found to be statistically significant in differentiating between high and low returns. Similarly we were able to build multivariate models of IPO abnormal returns with significant explanatory power using those issue features. However, the performance of these statistically significant models during the testing period can easily be described as dismal. Overall success rates are low and realized returns over a naïve strategy is only marginally better in some cases while it is much worse in others. These findings agree with Roll's (1994) statement on his own experience as a portfolio manager. He argues that in his practice, economic profits from investment strategies based on anomalies reported in finance literature never exist. We can talk about two possible explanations on lack of significant economic profits. First, the market may have already captured the profit opportunities and eliminated the anomalies. Alternatively, one can argue that the observed patterns were nothing but statistical artifacts, which were discovered as mere chance events. Both explanations have significant implications in favor of market efficiency.

References

Aggarwal, R., R. Leal ve L. Hernandez, 1993, The after market performance of initial public offerings in Latin America, Financial Management, 22, 42-53.

Allen, F. and G. Faulhaber, 1989, Signaling by underpricing in the IPO market, Journal of Financial Economics, 23, 303-323.

Baron, David. P. 1982, A model of the demand for investment banking advising and distribution services for new issues, Journal of Finance, 37, 955-1067.

Brav, A. and P. A. Gompers, 1997, Myth or reality? The long-run underperformance of initial public offerings: Evidence from venture and nonventure capital-backed companies, Journal of Finance, 52, 1791-1821.

Dawson, Steven M., 1987, Secondary stock market performance of initial public offers: Hong Kong, Singapore and Malaysia: 1978-1984, Journal of Business Finance and Accounting, 14:1, 65-76.

Feder Gershon and R. E. Just, 1977, A study of debt servicing capacity applying logit analysis, Journal of Development Economics 4, 25-38.

Keasey, K. and H. Short, 1992, The underpricing of initial public offerings: Some UK evidence, International Journal of Management Science, 20, 457-466.

Kim, H. E. and Y. Ki Lee, 1990, Issuing stocks in Korea, Pacific-Basin Capital Markets Research, 243-253.

Kıymaz, Halil, 2000, The initial and aftermarket performance of IPOs in an emerging market: Evidence from Istanbul Stock Exchange, Journal of Multinational Financial Management, 10, 213-227.

Leland H. E. and Pyle D. H., 1977, Information asymmetries, financial structure and financial intermediaries, Journal of Finance, 32, 125-135.

Maddala. G.S, 1988. Introduction to Econometrics. (McMillan Publishing Company, New York).

Mensah. Y.M., 1984, An examination of the stationary of multivariate bankruptcy prediction models: A methodological study, Journal of Accounting Research. 22:1, 380-395.

Muscarella C. J. and Vetsuypens M.R., 1989, A simple test of Barron’s model of IPO underpricing, Journal of Financial Economics, 24, 12-135.

Noreen. E., 1988, An empirical comparison of probit and OLS regression hypothesis tests, Journal of Accounting Research. 26, 119-133.

Ohlson. J.A., 1980, Financial ratios and the probabilistic prediction of bankruptcy, Journal of Accounting Research, 109-131.

Ritter, Ray J., 1984, The hot issue market of 1980, The Journal of Business, 57, 215-240.

Ritter, Ray J., 1998, Initial public offerings, Contemporary Finance Digest, 2:1, 5-30.

Rock, Kevin, 1986, Why new issues are underpriced, Journal of Financial Economics, 15, 187-212.

Roll, Richard, 1994, What every CFO should know about scientific progress in financial economics: What is known and what remains to be resolved, Financial Management, 23, 69-75.

Smith, Clifford W., 1986, Investment banking and the capital acquisition process, Journal of Financial Economics, 15, 23-24.

Tiniç, Seha M., 1988, Anatomy of initial public offerings of common stock, The Journal of Finance, .43, 789-822.

Table I

Initial Public Offerings

Year	**Number of IPOs**	**Proceeds** (million US $)
1992	8	47,914
1993	16	152,447
1994	22	253,459
1995	27	230,603
1996	27	167,922
1997	28	415,768
1998	20	383,348
1999	8	85,295
2000	34	2,795,886
Total	190	4,532,732

Table II

Short Term IPO Performance

Numbers in the body of the table denote cumulative abnormal returns (CARs) on days 1, 7 and 15 for the group of IPOs defined according to the feature on the left column. Figures in parentheses indicate the t statistic that the CAR is different from zero. ***, ** and * denote significance at 0.01, 0.05 and 0.10 levels respectively. The numbers in between rows representing groups are the t statistics for group difference. The leftmost column contains the grouping variable in boldface. Below the variable name, the basis for grouping is indicated. For example, grouping w.r.t. *Size, Proceeds, Price* and *Rate* are made by ranking the observations according to the related criteria and dividing the sample equally as large-small, or low-high. Grouping w.r.t. other features is done based on the presence of a particular characteristic.

Variable (feature)	**CAR 1**		**CAR 7**		**CAR 15**	
Size Small, Large	0.1329 (3.06)^{xxx}	1.76*	0.2477 (4.14)^{xxx}	3.24***	0.2335 (3.74)^{xxx}	3.00***
	0.0506 (2.92)^{xxx}		0.0311 (1.05)		0.015 (0.43)	
Proceeds Small, Large	0.1396 (3.27)***	2.05**	0.2524 (4.21)***	3.39***	0.2471 (3.91)***	3.39***
	0.0438 (2.31)**		0.0264 (0.91)		0.0022 (0.06)	
Price Low, High	0.0975 (2.32)**	0.24	0.1456 (2.77)**	0.18	0.1231 (2.29)**	-0.04
	0.0860 (3.99)***		0.1332 (3.01)***		0.1262 (2.46)**	
Rate Low, High	0.0806 (3.66)***	-0.47	0.1390 (3.15)***	-0.01	0.1381 (2.66)**	0.36
	0.1029 (2.47)**		0.1398 (2.66)**		0.1112 (2.09)**	
Method Best(29) Firm(161)	0.2268 (3.37)***	2.22**	0.3350 (3.44)***	2.22**	0.3523 (3.14)***	2.26**
	0.0674 (2.74)**		0.1042 (2.91)***		0.0836 (2.20)**	
SelfIPO Self(135) Other(55)	01218 (4.07)***	2.33**	0.1779 (4.19)***	1.93*	0.1679 (3.72)***	1.93*
	0.0179 (0.54)		0.0448 (0.82)		0.0186 (0.30)	
Foreign Yes(71) No(119)	0.1557 (2.68)**	1.71*	0.2928 (3.75)***	2.98***	0.2986 (3.67)***	3.20***
	0.0535 (3.84)***		0.0479 (1.88)		0.0209 (0.68)	
BigInv None(120) Pres(70)	0.1184 (3.38)***	1.78*	0.1647 (3.72)***	0.99	0.1627 (3.34)***	1.39
	0.0460 (2.21)**		0.0960 (1.79)*		0.0594 (1.06)	
Index -ve(71) +ve(119)	0.0712 (1.39)	-0.59	0.1243 (1.84)	-0.31	0.1125 (1.59)	-0.24
	0.1039 (4.76)***		0.1484 (4.00)***		0.1319 (3.15)***	
All Combined	0.0917 (3.90)***		0.1394 (4.07)***		0.1246 (3.36)***	

Table III

Estimation Results

Panel A. Multiple Regression Models

Note: F-Stat stands for the F statistic. The numbers in parentheses represent t statistics for regression coefficient estimates.

Cumulative Abnormal Return	**F Stat**	**Adj. R^2**	**Multiple Regression Model**
CAR1	5.37	0.107	0.589 + 0.372 ***Index*** -0.067 ***Size*** (2.61) (2.43) (-2.21)
CAR7	11.28	0.099	1.856 – 0.225 ***Size*** (3.74) (-3.36)
CAR15	10.74	0.172	2.654 – 0.378 ***Proceeds*** + 0.968 ***Index*** (4.07) (-3.90) (2.68)

Panel B. Multiple Discriminant Models

Note: The numbers in parentheses represent significance levels. Prediction power indicates the percentage of correctly classified positive and negative CARs in the original sample 1992-1996.

Cumulative Abnormal Return	**Wilk's Lambda***	**Prediction Power (%)**	**Discriminant Function**
CAR1	-	-	-
CAR7	0.960 (0.017)	62.71%	Z = -484 + 7.60 ***Index***
CAR15	0.862 (0.004)	65.26%	Z = -9.253 + 0.044 ***Rate*** – 1.158 ***Size*** – 4.988 ***Index***

Panel C. Logit Models

Note: The numbers in parentheses represent significance levels. Prediction power indicates the percentage of correctly classified positive and negative CARs in the original sample 1992-1996.

Cumulative Abnormal Return	**Chi Square***	**Prediction Power (%)**	**Logit Function**
CAR1	-	-	-
CAR7	5.97 (0.015)	68.41%	Z = 0.51 + 4.244 ***Index***
CAR15	15.65 (0.001)	69.47%	Z = 11.546 – 0.042 ***Rate*** – 1.357 ***Size*** + 4.692 ***Index***

Table IV

Performance of Forecasting Models

In each box of every panel, actual positive and negative values are indicated in the column labeled “total”. Predicted positive and negative counts are specified in the cells under the labels “-ve” and “+ve”. Percentages under the count figure in diagonal cells denote the success rate. For example, in multiple regression model for CAR1, actual number of negative CAR1s is 40; the model was able to predict only 6 of them, with a success rate of 15%.

Panel (i) Multiple Regression Models

	CAR1 Predicted			CAR7 Predicted			CAR15 Predicted		
Actual	**-ve**	**+ve**	**total**	**-ve**	**+ve**	**total**	**-ve**	**+ve**	**total**
-ve	6 (15.0%)	34	40	6 (12.2%)	43	49	24 (42.9%)	32	56
+ve	4	51 (92.7%)	55	12	34 (73.9%)	46	14	25 (64.1%)	39

Panel (ii) Multiple Discriminant Models

	CAR1 Predicted			CAR7 Predicted			CAR15 Predicted		
Actual	**-ve**	**+ve**	**total**	**-ve**	**+ve**	**total**	**-ve**	**+ve**	**total**
-ve	-	-	40	31 (63.3%)	18	49	43 (76.8%)	13	56
+ve	-	-	55	15	31 (67.4%)	46	21	18 (46.2%)	39

Panel (iii) Logit Models

	CAR1 Predicted			CAR7 Predicted			CAR15 Predicted		
Actual	**-ve**	**+ve**	**total**	**-ve**	**+ve**	**total**	**-ve**	**+ve**	**total**
-ve	-	-	40	5 (10.2%)	44	49	25 (44.7%)	31	56
+ve	-	-	55	2	44 (95.7%)	46	10	29 (74.4%)	39

Table V

Economic Performance of Forecasting Models

Actual return is the average cumulative abnormal return (CAR) of all 95 IPOs in the testing period. Best possible outcome refers to the average CAR of the IPOs with positive values only. Other rows contain the average CARs from an investment strategy based on the prediction of the aforementioned model. The investment strategy calls for subscribing to an IPO if the relevant model signals a positive CAR.

	Average Cumulative Abnormal Return		
	CAR1	**CAR7**	**CAR15**
Actual Return (Naïve Strategy)	6.67%	8.36%	6.78%
Best Possible Outcome	16.14%	24.75%	30.97%
Multiple Regression	7.91%	9.41%	7.47%
Multiple Discriminant	-	5.33%	2.69%
Logit	-	10.11%	11.24%