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The Performance of Initial Public Offerings in an Emerging Market: The Case of the Istanbul Stock Exchange

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ABSTRACT

This study uses the Markov chain model to examine the behavior of 189 initial public offerings on the Istanbul Stock Exchange (ISE) over the 1990-1999 periods. The non-linear estimation results suggest that Turkish IPOs do not follow a random walk but may instead follow a first-order Markov chain process. It may be possible to predict excess returns conditioned on the observation of the returns in the previous period. Furthermore, the findings are particularly interesting because, unlike what is found for most other markets; IPOs on the ISE *over perform* the market several years beyond when firms go public. The results add to our understanding of the behavior of equities in emerging markets.

JEL: G1, C5

Keywords: Markov chain; Initial public offerings

I. INTRODUCTION

A now well-known finding in finance is that initial public offerings in the U.S. tend to exhibit positive excess returns in the short term but then underperforms the market over a longer period, often for three to six years [Aggarwal and Rivoli (1990); Ritter (1991); Kang (1995)].[1] This phenomenon is not unique to the U.S. market as similar results have been found in the United Kingdom [Levis (1993)] and in several Latin American countries [Aggarwal, Leal, and Hernandez (1993)]. In fact, according to Kunz and Aggarwal (1994), the underperformance of IPOs is common to almost every equity market that has been examined. Surprisingly, while Aggarwal, Leal, and Hernandez (1993) examined the aftermarket performance of IPOs in the emerging markets of Brazil, Chile, and Mexico, the study of many other emerging markets, especially those in Europe and the Middle East has been neglected. The Istanbul Stock Exchange is a particularly interesting case to examine given its' relatively small capitalization, unique set of economic conditions, including extremely high rates of inflation, and that it is relatively new, having been created in early 1986. The purpose of this paper is to determine whether or not the excess returns of IPOs on the Istanbul Stock Exchange (ISE) are predictable. Provided that these excess returns form predictable patterns, an additional goal of the paper is to ascertain if it is possible for investors to reap financial gains based on this information.

The results of the paper will provide information as to whether or not the aftermarket performance of initial public offerings on the ISE is similar to that of other, more developed equity markets as well as the emerging markets of Latin America. The standard arguments given for why IPOs may perform differently than the rest of the market have been succinctly summarized in Ritter (1991). The first of these reasons is the "risk mis-measurement" explanation. The measurement of excess returns may be sensitive to the particular market index used. The second explanation, albeit the least scientific, is that investors in IPOs may simply have runs of "bad luck." Of course, since Ritter's (1991) study, this explanation can essentially be ruled out as the long-run underperformance of IPOs, especially in developed markets, is now well-documented. The third explanation suggests that the behavior of IPO returns is due to "fads." That is to say (naive) investors may be overly optimistic about IPO behavior and therefore bid up prices early on only to have them fall later. This last reason is particularly interesting to consider when examining IPOs in an emerging market such as that of Turkey. Since the ISE is relatively new, having begun in 1986, financial market participants may be especially eager to participate in IPO investments. It is possible that excess or pent-up demand by Turkish investors might be such that the performance of IPOs does not resemble that of the overall market.

The present paper differs from most other studies of IPO performance in that, following Hensler (1998), we use the Markov chain model to determine if IPO excess returns exhibit random walk behavior. The use of this nonlinear method has the distinct advantage of allowing the transition probabilities of the model to vary depending on the prior state (i.e., whether last period's excess returns were negative or positive). Mills (1999) describes the two-state Markov model as a type of "switching- regime" model based on an autoregressive-moving average process, capable of handling asymmetry and conditional heteroskedasticity. Thus, the assumption of normally distributed returns is not required and the Markov model does not require the linearity assumption of standard regression tests as it allows the transition probabilities to vary at each stage in a series, or chain, of states. For this reason, it is often referred to as the Markov chain model. A finding indicative of a Markov chain provides evidence against the random walk hypothesis and suggests that Turkish IPO performance may be predictable. Khan and Kiymaz (1998) and Zychowicz, Binbasioglu, and Kazancioglu (1995) suggest that the returns of many stocks listed on the ISE may not follow a random walk and that these returns are not normally distributed. We test the IPO return series used in this paper for normality and linearity before proceeding to the Markov chain examination. In order to conduct these tests we focused on a randomly selected group of 30 individual IPOs for which we had a full six years worth of data (i.e., the full sample period). Twenty-three of the thirty series exhibited non-normal returns based on the Jarque-Bera test statistic. Furthermore, we examined the issue of linearity using the method outlined in Özün (1999) and found that over one quarter of the series exhibited some form of non-linearity. Given these preliminary findings, it is appropriate to examine the random walk hypothesis using the Markov chain model.

Finally, Hensler (1998, p. 44) points out reasons for why researchers should consider the Markov chain analysis used in this paper when normality and linearity assumptions may not hold for return series under investigation. (1) The analysis provides a way to ascertain whether or not a Markovian process exists since previous states are directly incorporated into the analysis. (2) The previous states analysis may document predictability, which would contradict the random walk hypothesis, as the random walk requires that the transition probabilities do not differ across the states of the model. And, (3) the analysis can provide information regarding the stabilization or disappearance of prediction patterns by examining excess returns across time subsamples.

II. A BRIEF REVIEW OF THE RELATED LITERATURE[2]

Ritter (1991) finds that U.S. IPOs underperformed the market in the three years after going public. He argues that the results are most consistent with the "fads" explanation of IPO performance as firms may go public when their industry is doing exceptionally well. Loughran (1993) suggests that the underpricing of U.S. IPOs is not limited to only three years after going public. Examining 3,656 IPOs over the period from 1967 to 1987, Loughran finds that IPOs have underperformed in the 72 months after going public. Following in the footsteps of Ritter's (1991) study, Levis (1993) analyzes short-run and long-run returns of IPOs issued in the United Kingdom. The results on long-run performance are similar to those previously documented for the U.S. market.

The performance of IPOs in emerging markets is not well documented. However, Aggarwal, Leal, and Hernandez (1993) analyzed IPO returns in three Latin American countries – Brazil, Mexico, and Chile. They find that IPOs in these markets experienced significantly negative mean market-adjusted returns after one to three years. Recently, Hensler, Herrera, and Lockwood (2000) investigated differences in the performance of bank and non-bank IPOs in the Mexican market. Their results on long-run performance (defined as 300 days after issuance) of 68 individual IPOs indicates that 54 non-bank IPOs underperformed the Mexican market by 21%, while 14 bank IPOs overperformed the market by 56%.

The results of the previous studies suggest that IPOs typically behave differently than the rest of the market. It also appears that IPOs typically underperform the market over periods of one to several years. These findings motivate the study of other emerging markets and, in particular, our examination of IPOs on the Istanbul Stock Exchange where, as in many Eastern European and Middle-Eastern countries, financial markets and investing are just now starting to gain prominence.

III. THE MARKOV CHAIN PROCESS, DATA, AND METHODOLOGY

Variants of the Markov model have been used to study a number of financial time series. Engle and Hamilton (1990) examined the relationship between the British sterling and the U.S. dollar by fitting a two-state Markov process to the data. They determined that movements in the exchange rate could be characterized by long swings. Thus, once an exchange rate is in a particular regime it is likely to remain there often for more than a year. McQueen and Thorley (1991) used a Markov chain model to test the random walk hypothesis in U.S. stock returns as an alternative to standard, linear regression-based tests. They found non-random walk behavior in the post-war period and random walk behavior in the pre-war period. Recently, Hensler (1998) employed the Markov chain model to test for random walk behavior of 1,932 U.S. initial public offerings. Hensler's results indicated that U.S. IPO excess returns do not follow a random walk process and he provides evidence on the existence of a second-order Markov chain. Our analysis closely resembles that of Hensler (1998) except that we examine IPOs on the Istanbul Stock Exchange (ISE).

The data used in this study are monthly excess returns of companies offered to the public for the first time on the ISE and cover the period from January 1990 to August 1999. The underlying stock prices are obtained from *Analiz.com*.[3] Over the 1990-1999 periods, 209 IPOs are identified based on information made available from the ISE. For twenty of the IPOs, complete price series were not available, thus, the number of IPOs included in the analysis is 189. Table 1 reports the distribution of IPOs and the number of observations per year. The fewest number of IPOs is 9 and occurred in 1992, while 1991 saw the most IPOs at 35.[4]

Daily return series (R_d) are computed for the IPOs as well as for the National 100 index, our measure of the Turkish market, in the following way:

$$R_d = \frac{P_d}{P_{d-1}} - 1 \tag{1}$$

P_d denotes the closing price on day d.[5] Compounded monthly returns (R_t) are given by:

$$R_t = \left[\prod_{d=1}^{n} \left(1 + R_d\right) \right] - 1 \tag{2}$$

where n is the number of days the return is compounded in month t. Monthly excess returns (ER_t) are the arithmetic difference between monthly returns and the market return (R^m), thus:[6]

$$ER_t = R_t - R_t^m \tag{3}$$

Table 1
Summary information for initial public offerings on the Istanbul Stock Exchange

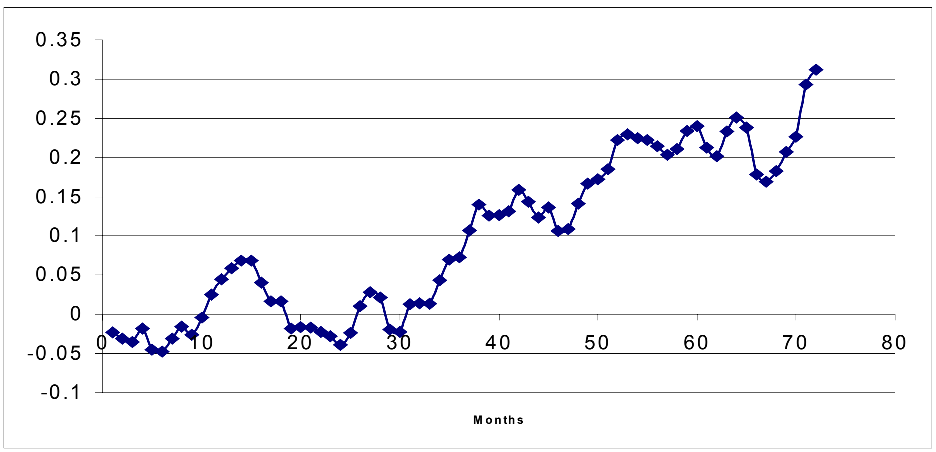
	Stage 1 Data One Previous Return		Stage 2 Data Two Previous Returns	
Year	Firms	Observations	Firms	Observations
1990	14	994	14	980
1991	35	2,485	35	2,450
1992	9	639	9	630
1993	11	775	11	764
1994	17	1,087	17	1,070
1995	34	1,717	34	1,683
1996	19	718	19	699
1997	21	498	21	477
1998	26	351	26	325
1999	3	12	2	9
Total	189	9,276	188	9,087

Notes: IPOs were issued between January 1990 and August 1999. Observation counts do not necessarily reflect a full six years of trading for all firms in the sample since more recently issued IPOs do not have a full six years of trading on the ISE.

Figure 1 plots monthly cumulative excess returns for the 189 IPOs over the six-year period.[7] First, note that short-run cumulative excess returns are negative. After 10 months, however, there is a period in which cumulative excess returns fluctuate from positive to negative, until about month 30. At that time, cumulative excess returns trend upward in positive territory well out into the 6th year and beyond. Figure 1 indicates that IPOs on the Istanbul Stock Exchange generate positive market-adjusted returns over a long-run horizon. This observation of long-run overperformance is contrary to the well-documented phenomenon of long-term IPO underperformance found in many other equity markets. The use of market returns to calibrate nominal returns could result in more positive excess return counts than what might occur from using a more risky benchmark, assuming the stocks in the National 100 index are relatively more established and less risky than a portfolio comprised of IPO stocks. Thus, the number of positive counts may be biased upward and this should be taken into account when interpreting Figure 1 and our results. However, a relatively small number of stocks on the ISE does not allow us to develop a benchmark that would appropriately control other factors such as industry, capital structure, size, etc. We choose to focus on the National 100 index as the benchmark, in part, because of these difficulties and also because, for an emerging market such as the ISE, it is not clear exactly what constitutes an appropriate benchmark for IPOs. However, for comparison purposes, we examine the behavior of excess returns using various benchmarks and report those findings in the conclusions.

Figure 1

Cumulative excess returns of IPOs on the ISE from January 1990 to August 1999



Note: The mean cumulative excess return is measured on the vertical axis.

Of interest is the determination of whether or not this longer-term overperformance of initial public offerings on the Istanbul Stock Exchange is predictable. Moreover, if the excess returns form a predictable pattern, then we are also interested in whether or not it is possible for a market participant to establish a trading strategy that will provide meaningful financial gains based on this information.

As explained by Hensler (1998), the Markov chain model has two distinct advantages over standard regression models. First, non-linearity can be handled since the transition probabilities can take different values in a stage or from one stage to another, depending on the previous stages. Second, normally distributed return behavior is not a requirement. Moreover, since non-linearity is allowed, the Markov chain model is capable of dealing with mean reverting behavior that is due to fads and/or rational speculative bubbles [McQueen and Thorley (1991)]. The ensuing discussion is based in large part on that of Hensler (1998).

The transition probabilities across the stages of the Markov chain provide information as to the predictability of the series under the assumption that the series are Markov chain stationary, which is, they have constant transition probabilities over time. Equal transition probabilities are indicative of a random walk process while transition probabilities that are not equal suggest a violation of the random walk hypothesis. To conduct the test, X_t is defined as:

$$X_t = \begin{cases} P & \text{if} \quad ER_t > 0 \\ N & \text{if} \quad ER_t < 0 \end{cases} \tag{4}$$

Excess returns are classified as either negative (N) or positive (P) and there are T excess returns. The probability of obtaining a negative return in the period after a positive return is defined as λ_P, and the probability of obtaining a negative return in the period after a negative return is defined as λ_N.[8] Formally, we have:

$$\begin{aligned} \lambda_P &= \Pr\left[X_t = N \middle| X_{t-1} = P\right] \\ \lambda_N &= \Pr\left[X_t = N \middle| X_{t-1} = N\right] \end{aligned} \tag{5}$$

The number of negative observations after a negative (positive) return is denoted by N_N (N_P). The log likelihood function employed to estimate the parameters of the model, $\Lambda_1 = [\lambda_P\ \lambda_N]$, is given by:[9]

$$L_1\left(S_{t1}, \Lambda_1^{'}, \Pi_1\right) = \log \Pi_1 + \sum_{i=N}^{P} N_i \log \lambda_i + P_i \log\left(1 - \lambda_i\right) \tag{6}$$

S_{t1} are the observed excess returns defined in X_t. The subscript 1 indicates the first order Markov chain. Thus, the maximum likelihood estimates are:

$$\lambda_i = \frac{N_i}{\left(N_i + P_i\right)} \tag{7}$$

$$SE_i = \left(\lambda_i\left(1 - \lambda_i\right)\left(N_i + P_i\right)\right)^{0.5} \tag{8}$$

where SE_i is the standard error of λ_i. The test for equality of the probabilities is equivalent to testing for random walk behavior in the excess returns. If the transition probabilities are equal, then a random walk process exists and the series does not follow a first-order Markov process.

The procedure for determining whether or not IPO excess returns are predictable proceeds by examining several key hypotheses designed to detect random walk behavior.[10] The first hypothesis tests to see if the transition probabilities are equal and is given by:

$$H1: \lambda_P = \lambda_N$$

According to Hensler (1998), failure to reject H1 is consistent with there being no Markov chain, while rejection of H1 implies that a Markov chain may exist. In our analysis, if H1 is rejected then we will proceed to the next step (i.e., stage 2) which can help to shed light as to the existence of a Markov chain. The following probabilities are defined:

$$\begin{aligned}
\lambda_{PP} &= \Pr\left[X_t = N \middle| X_{t-2} = P, X_{t-1} = P\right] \\
\lambda_{PN} &= \Pr\left[X_t = N \middle| X_{t-2} = P, X_{t-1} = N\right] \\
\lambda_{NP} &= \Pr\left[X_t = N \middle| X_{t-2} = N, X_{t-1} = P\right] \\
\lambda_{NN} &= \Pr\left[X_t = N \middle| X_{t-2} = N, X_{t-1} = N\right]
\end{aligned} \tag{9}$$

The associated log likelihood function, ML estimates for λ_{ij}, and SE_{ij} are:

$$L_2\left(S_{t2}, \Lambda'_2, \Pi_2\right) = \log \Pi_2 + \sum_{ij=NN}^{PP} N_{ij} \log \lambda_{ij} + P_{ij} \log\left(1 - \lambda_{ij}\right) \tag{10}$$

where S_{t2} are the realized positive and negative excess returns. The subscript 2 indicates the second order Markov chain.

$$\lambda_{ij} = \frac{N_{ij}}{\left(N_{ij} + P_{ij}\right)} \tag{11}$$

$$SE_{ij} = \left(\lambda_{ij}\left(1 - \lambda_{ij}\right) / \left(N_{ij} + P_{ij}\right)\right)^{0.5} \tag{12}$$

The hypothesis used to test for the presence of a second-order Markov chain is:

$$H2 : \lambda_{PP} = \lambda_{NP} \text{ and } \lambda_{PN} = \lambda_{NN}$$

If H2 is not rejected (and H1 is rejected), the presence of a first-order Markov chain will be concluded. In addition, a third hypothesis can be employed to analyze the probabilities of all four different states.

$$H3 : \lambda_{PP} = \lambda_{NP} = \lambda_{PN} = \lambda_{NN}$$

Failure to reject H3 indicates that the probability of a negative return does not depend on the past two months' excess return sequence. Hypotheses H1 through H3 are tested via the following likelihood ratio test (LR):

$$LR = 2\left[L_U - L_R\right] \sim \chi_q^2 \tag{13}$$

where L_U is the log likelihood function for the unrestricted model and L_R is the log likelihood function for the restricted model.[11]

In order to compare the results of H1-H3 and to analyze the economic significance of returns, conditional on there being a predictable pattern, four additional hypothesis tests are employed. The first of these (H4) looks to see if the average excess return following a positive return is similar to the average excess return following a negative return.

$$H4: R_P = R_N$$

where R_i (i=P, N) denotes the mean excess return conditional on observing a positive/negative excess return in the previous month. The following hypotheses investigate the average returns conditioned on the previous two excess returns:

$$H5: R_{PP} = R_{NN} = R_{PN} = R_{NP}$$
$$H6: R_{PP} = R_{NP} \text{ and}$$
$$H7: R_{PN} = R_{NN}$$

where R_{PN} is the average of the excess returns following a positive return in a month and then a negative return in the next month. R_{PP}, R_{NN}, and R_{NP} are similarly defined. Thus, H5-H7 provide insight as to the significance of the information contained about the returns in the Markov chain process and allow us to make inference about possible trading strategies.

IV. EMPIRICAL RESULTS

The first step of the analysis tests to see if the first stage transition probabilities (λ_N, λ_P) are equal.[12] Maximum likelihood (ML) estimates for λ_N and λ_P are presented in the first two columns of Panel A in Table 2 and are found to be 56% and 58%, respectively. The result of testing H1 (i.e., $\lambda_N = \lambda_P$) is shown in the first column of Panel B in Table 2. The likelihood ratio statistic indicates that the probability of encountering a negative excess return after a negative excess return (λ_N) and the probability of encountering a negative excess return after a positive excess return (λ_P) are not the same (LR = 4.04, probability level = 0.05). Thus, we reject H1 and conclude that the excess return series do not follow a random walk. This result suggests that a predictable pattern of excess returns may exist.

Table 2 also summarizes information regarding the second stage transition probabilities. Columns 3-6 of Panel A present the maximum likelihood estimates for λ_{NN}, λ_{PP}, λ_{PN} and λ_{NP}. These probabilities are found to be 55%, 58%, 56%, and 58%, respectively.[13] The two likelihood ratio statistics for testing the second hypothesis (H2), $\lambda_{PP} = \lambda_{NP}$ and also that $\lambda_{PN} = \lambda_{NN}$, are insignificant (see columns 2 and 3 of Panel B where LR = 0.123 and LR = 0.187 with actual probability values of 0.726 and 0.665, respectively). These findings imply that excess returns are not predictable conditioned on the previous two excess returns. We therefore conclude that a second-order Markov chain does not exist. This finding provides information as to how returns behave over the six-year time horizon.

The last column of Panel B in Table 2 presents the result from testing the third hypothesis that the four second stage probabilities are equal, H3: $\lambda_{PP} = \lambda_{NP} = \lambda_{PN} = \lambda_{NN}$. The likelihood ratio statistic is insignificant (LR = 5.512 with a probability value of 0.138). Thus, the previous two excess returns provide no statistically useful information as to the predictability of the next excess return. Therefore, we conclude that the probability of a negative excess return is independent of the sequence of the excess returns in the previous two months.

Table 2

Stage 1 and 2 transitions probabilities and tests of hypotheses

Log likelihood function for Stage 1 is $\sum_{i=N}^{P} N_i \log\lambda_i + P_i \log(1-\lambda_i)$. A negative excess return is denoted by *N* and a positive excess return is denoted by *P*. The number of counts for negative (positive) excess returns after observing *i* in the previous stage is $N_i(P_i)$. Estimated probability of obtaining a negative excess return following *i* is λ_i. Similarly, log likelihood function for Stage 2 is $\sum_{ij=NN}^{PP} N_{ij} \log \lambda_{ij} + P_{ij} \log(1-\lambda_{ij})$. The number of counts for negative (positive) excess returns after observing *i* in two previous stages then observing *j* in one previous stage is $N_{ij}(P_{ij})$. Estimated probability of obtaining a negative excess return following associated *ij* sequence is λ_{ij}.

Panel A: Maximum likelihood estimates and standard errors of transition probabilities

λ_N	λ_P	λ_{NN}	λ_{PP}	λ_{PN}	λ_{NP}
0.5584	0.5793	0.5537	0.5835	0.5597	0.5779
(0.0068)	(0.0078)	(0.0093)	(0.0121)	(0.0104)	(0.0104)

Panel B: Hypothesis tests

H1: λ_N=λ_P	H2: λ_{PP}=λ_{NP}	H2: λ_{PN}=λ_{NN}	H3: λ_{PP}=λ_{NP}=λ_{PN}=λ_{NN}
4.037	0.123	0.187	5.512
[0.045]	[0.726]	[0.665]	[0.138]

Notes: Standard error is given in parentheses in Panel A. Panel B reports the likelihood ratio statistic (LR) for testing the null hypothesis and actual significance level for the test is given in square brackets. The LR statistic is distributed χ^2 with *q* degree of freedom.

We now turn our attention to the examination of transition probabilities over time. Table 3 reports the transition probabilities on a year-by-year basis for the first and second stages. Panel A of Table 3 presents the transition probability estimates by year. Hypothesis tests based on these estimates are shown in Panel B. Based on results from likelihood ratio tests, we find that the transition probabilities for the first stage (λ_N, λ_P) are statistically different only in the fourth year (LR = 5.36, probability value = 0.02). The results for examining the second stage probabilities over time are also reported in Panel B. We find that the second stage transition probabilities are not statistically different in any of the six years with only one exception, that is, λ_{PN} and λ_{NN} appear to statistically differ in the sixth year (LR = 5.46, probability value = 0.02). The joint hypothesis of the equality of the four second-stage probabilities is not rejected for each of the six years (see the row marked H3). Overall, we find no clear indication of a predictable pattern over time for IPO excess returns conditioned on one previous excess return, nor is there a pattern for excess returns conditioned on two previous excess returns.

The above findings regarding transition probabilities over time suggest that it may be difficult for financial market participants to reap financial gains based on trading strategies that attempt to exploit the predictable nature of IPOs. Of course, the success of such a trading strategy will depend on the size of the excess returns themselves, provided these excess returns are predictable. Here we make the distinction between statistical significance and economic significance. The latter term is meant to convey the idea that even (nearly perfect) predictable patterns in equity returns must be associated with excess returns that are large enough to be economically meaningful since, ultimately, the investor faces some transactions costs, fees, etc. In order to explore the possibility that an investor may successfully implement a trading strategy based on information extracted from the transition probabilities, we conclude our study of IPO excess returns by focusing on the average excess return (i.e., size) conditional on the type of excess return (positive/negative) observed in the previous month(s). For this purpose we conduct analysis of variance (ANOVA) tests of excess returns, the results of which are presented in Table 4.[14]

The result reported in the first row of Panel A, Table 4 shows that excess returns conditioned on one period of previous excess return do not differ statistically (t = -0.611, probability value = 0.541). Thus, there appears to be no difference in the size of these excess returns. The findings in Panel A also indicate that we cannot reject H5 nor H7. Thus, R_{ij} do not differ for any of the *ij* combinations (F = 1.44, probability value = 0.229). Furthermore, the means of R_{NN} and R_{PN} are not found to be statistically different (F = 0.57, probability value = 0.449). However, we reject the null hypothesis that R_{NP} and R_{PP} are equal only at the 10% level (F = 3.22, probability value = 0.07). The latter finding provides weak evidence that the size of excess returns conditional on two previous returns may differ, provided a particular pattern has been observed.

Panel B of Table 4 shows the ANOVA results for looking at average returns on a year-by-year basis, both for the first stage and the second stage. Generally speaking, these results are consistent with those presented in the first row of Panel B in Table 3 for the first stage transition probabilities, and show that excess returns conditioned on one previous return do not statistically differ in any of the six years.

Table 3
Year-by-year analysis of transition probabilities

A negative excess return is denoted by *N* and a positive excess return is denoted by *P*. For Stage 1, estimated probability of obtaining a negative excess return following *i* is λ_i. For Stage 2, estimated probability of obtaining a negative excess return after observing *i* in two previous stage then observing *j* in one previous stage is λ_{ij}.

Panel A: Maximum likelihood estimates of transition probabilities by year

	Year					
	1	2	3	4	5	6
λ_N	0.556	0.564	0.567	0.540	0.555	0.570
	(0.015)	(0.015)	(0.016)	(0.017)	(0.019)	(0.022)
λ_P	0.546	0.581	0.589	0.600	0.602	0.573
	(0.017)	(0.017)	(0.018)	(0.019)	(0.022)	(0.025)
λ_{NN}	0.561	0.560	0.565	0.539	0.555	0.527
	(0.020)	(0.021)	(0.021)	(0.023)	(0.026)	(0.029)
λ_{PP}	0.557	0.585	0.577	0.602	0.624	0.579
	(0.024)	(0.027)	(0.029)	(0.031)	(0.033)	(0.039)
λ_{PN}	0.526	0.572	0.569	0.540	0.556	0.628
	(0.022)	(0.023)	(0.024)	(0.025)	(0.029)	(0.032)
λ_{NP}	0.534	0.590	0.597	0.598	0.587	0.570
	(0.022)	(0.023)	(0.024)	(0.025)	(0.029)	(0.033)

Panel B: Hypothesis tests

	Year					
	1	2	3	4	5	6
H1: $\lambda_N=\lambda_P$	0.225	0.603	0.814	5.359	2.560	0.008
	[0.635]	[0.437]	[0.367]	[0.021]	[0.110]	[0.929]
# of stage 1 observations	2049	1980	1691	1496	1152	908
H2: $\lambda_{PP}=\lambda_{NP}$	0.472	0.021	0.294	0.013	0.699	0.031
	[0.492]	[0.884]	[0.588]	[0.911]	[0.403]	[0.859]
H2: $\lambda_{PN}=\lambda_{NN}$	1.315	0.145	0.020	0.001	0.002	5.461
	[0.252]	[0.703]	[0.887]	[0.974]	[0.966]	[0.019]
H3: $\lambda_{PP}=\lambda_{NP}=\lambda_{PN}=\lambda_{NN}$	1.788	1.074	1.128	5.373	3.261	5.501
	[0.618]	[0.783]	[0.770]	[0.146]	[0.353]	[0.139]
# of stage 2 observations	2035	1805	1691	1496	1152	908

Notes: In Panel A the standard errors of ML estimates are in parentheses. In Panel B the actual probability values associated with the LR test statistics are in square brackets.

Table 4

ANOVA of average excess returns

A negative excess return is denoted by *N* and a positive excess return is denoted by *P*. For Stage 1, estimated mean excess return conditional on observing *i* in the previous month is R_i. For Stage 2, estimated mean excess return conditional on observing *i* in two previous stage then observing *j* in one previous stage is R_{ij}.

Panel A: Average excess returns

	Test statistic
H4: R_N=R_P	-0.611 [0.541]
H5: R_{PP}=R_{NN}=R_{PN}=R_{NP}	1.440 [0.229]
H6: R_{NP}=R_{PP}	3.220 [0.073]
H7: R_{NN}=R_{PN}	0.573 [0.449]

Panel B: Average excess returns on a year-by-year basis

	Year					
	1	2	3	4	5	6
H4: R_N=R_P	-0.662 [0.508]	0.066 [0.948]	0.145 [0.885]	-0.666 [0.505]	-0.104 [0.918]	-0.280 [0.779]
# of stage 1 observations	2049	1980	1691	1496	1152	908
H5: R_{PP}=R_{NN}=R_{PN}=R_{NP}	0.470 [0.701]	0.070 [0.977]	0.070 [0.974]	0.770 [0.511]	0.730 [0.537]	3.060 [0.028]
H6: R_{NP}=R_{PP}	0.973 [0.324]	0.078 [0.779]	0.180 [0.672]	1.863 [0.172]	2.154 [0.142]	1.382 [0.240]
H7: R_{NN}=R_{PN}	0.059 [0.808]	0.052 [0.820]	0.023 [0.879]	0.002 [0.963]	0.010 [0.919]	7.708 [0.006]
# of stage 2 observations	2035	1805	1691	1496	1152	908

Notes: The test statistic for H4 is a t-statistic, all others are F statistics. The test statistics for the hypothesis tests are based on ANOVA. Actual probability value is given in square brackets.

Finally, Panel B, Table 4 also provides the associated F-statistics for testing H5, H6, and H7. These (second stage) hypotheses are not rejected for each of the six years, with the exceptions of H5 and H7 where R_{NN} and R_{PN} are found to statistically differ in the sixth year (F = 3.06 with p-value = 0.028 and F = 7.71 with p-value = 0.006, respectively). Thus, even if a predictable pattern can be detected, the differences in excess returns are probably not large enough for an investor to successfully profit on.

V. CONCLUSION

The results reported in this paper provide some evidence that excess returns of initial public offerings on the Istanbul Stock Exchange may be predictable conditioned on one previous return, although this is not generally supported by the analysis of transition probabilities over time. Specifically, we use a non-linear estimation technique and find weak evidence to suggest that these excess returns follow a first-order Markov chain. However, there is no strong indication that a second-order Markov chain exists, although the analyses suggested the presence of predictable patterns in excess returns for some specific years following issuance.

In all but one of the cases examined we are unable to detect both a predictable pattern and statistically different excess returns. For instance, the likelihood ratio test of the first hypothesis (H1: $\lambda_N=\lambda_P$) for the fourth year after issuance indicates a predictable pattern based on transition probabilities; however, the associated excess returns, R_N and R_P, are not statistically different in that same year. Thus, while initial public offerings on the Istanbul Stock Exchange overperformed the market during the six years after the issuance date, an investor may not realize financial gains from the predictable nature of IPO excess returns since any differences in excess returns appear to be minor.

For comparison purposes, we repeated the tests presented in this paper using two different benchmarks. First, we employed a narrowly defined portfolio that is likely to exhibit the general return characteristics of IPOs in our sample. Second, we employed a broadly defined benchmark to overcome the (possible) independence issues that may be present since the National 100 index may include a number of IPO firms in the sample over time. The narrowly defined benchmark was constructed using the average returns of nineteen IPOs that had been traded before 1991. With regards to both the first-order and second-order Markov chain, no predictable pattern emerged. To construct the broadly defined benchmark, we used the Morgan Stanley MSCI Europe and Middle East Emerging Market Index, the use of which should remove any independencies that may be present when the National 100 index is used as a benchmark. In testing for the first-order Markov chain, the returns were not predictable at the 5% level of significance; however, consistent with the results presented in the paper there is predictable return behavior in the overall sample at the 10% level of significance. Furthermore, the results suggested the possible presence of a second-order Markov chain.

As a further test of the predictability hypotheses, we also investigated privatization IPOs. In particular, we re-ran the analyses for 19 privatization IPOs on the ISE. The results provided no evidence of a first-order Markov chain and there was no indication of the presence of a second-order Markov chain. We then conducted the analyses on the entire sample excluding the 19 privatization IPOs. The results of the tests were the same as the results presented in the paper.[15] Thus, this provides evidence that our previously reported conclusions regarding the first-order Markov chain are robust and are not affected by privatization IPOs.

One interpretation of the lack of any overriding indication that monthly excess returns are predictable is that the ISE is a small market in which a few large investors may be able to significantly influence return behavior. In fact, according to the Capital Market Board of Turkey, the average daily traded value did not exceed $100 million (U.S. dollars) until 1995. It is possible that private information on the part of large investors may be responsible for unpredictable return behavior. It is interesting to note; however, that Özün (1999) suggests that the ISE has experienced significant improvements in very recent years towards efficiency. Finally, it may be the case that market deepening has affected the market. For example, the daily average traded value in US dollars on the ISE more than doubled between 1994 and 1995 going from $92 million to $209 million. The effect of market deepening can be analyzed by examining plots of the probabilities corresponding to H1 and H2 over (calendar) time. Doing so for the first-order Markov chain, we found that there are only three years in which IPO returns were predictable at the 5% probability value (1990, 1998, and 1999). No predictable behavior is present in the other years. This finding does not suggest that market deepening was a major factor for IPO returns. With regards to the second-order Markov chain, the results were consistent with the results already presented. Thus, further research on the Turkish IPO market may be directed at determining if the return behavior detected in this paper holds into the future.

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NOTES

1. Aggarwal and Rivoli (1990) attribute some of the initial overpricing of initial public offerings to fads and the overly optimistic behavior of investors.
2. The research on IPOs is immense and too many important papers have been published to list them all here. Recent work on IPOs includes papers by Brav and Gompers (1997), Rajan and Servaes (1997), Carter, Dark, and Singh (1998), Houge and Loughran (1999), Kandel, Sarig, and Wohl (1999), Krigman, Shaw, and Womack (1999), and Lee, Taylor, and Walter (1999), to name just a few. However, in this section we report only the papers that are most related to the present study.
3. The price series reported by *Analiz.com* are adjusted for past stock splits and dividends so as to obtain consistent and comparable price series.

4. Three IPOs were actually offered in 1998 but are listed on ISE for the first time in 1999, and are thus counted as 1999 IPOs.
5. Since P_d incorporates stock splits and dividends, no additional adjustments are required.
6. The empirical analysis begins with the second full month of trading as this helps to ensure more stable series and also avoids any possible effects of underwriter efforts. See Hensler (1998) for a more detailed explanation.
7. The definition of excess returns, as used here, may not fully capture the measurement of risk given that IPOs lack a history. However, the measure does show how IPO returns compare to the return on the National 100 index and this is likely to be important to financial market participants. The distribution of de-listings by type, e.g., between firm failure or acquisition, may affect the (average cumulative) excess returns and Figure 1 may suffer from survivorship bias. Given the absence of information available on type and number of de-listings, these effects are not addressed in this paper.
8. The focus on conditional probabilities of negative excess returns follows that of Hensler (1998). One could choose to instead focus on conditional probabilities of positive excess returns without loss of generality; however, the interpretation would change accordingly.
9. McQueen and Thorley (1991) note that, in practice, $\prod_1$ may be ignored since its effect on the transition probabilities is negligible.
10. For a detailed explanation of these hypotheses see Hensler (1998).
11. The LR statistic is distributed asymptotically as χ_q^2 with q degrees of freedom (i.e., there are q restrictions).
12. The transition counts for both the first and second stages are shown in the Appendix 1.
13. Given these probabilities, an explanation for positive cumulative excess returns over time (see Figure 1) is that the relative size of positive excess returns exceeds that of negative excess returns. This conclusion is consistent with the evidence presented in Appendix 2 as most of the average excess returns appear to be positive regardless of the previous state(s).
14. Summary statistics for excess returns, including on a year-by-year basis, are presented in Appendix 2.
15. In the interest of brevity, we do not report tables of these additional results. However, the results of the analyses are available upon request.

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APPENDIX 1
Transition count matrix

A negative monthly excess return is denoted by *N* and a positive monthly excess return is denoted by *P*. Stage 1 transition counts in first two rows for negative (positive) excess returns after observing *i* in the previous stage are $N_i(P_i)$. Stage 2 transition counts in last four rows for negative (positive) excess returns after observing *i* in two previous stages then observing *j* in one previous stage are $N_{ij}(P_{ij})$.

	Next State	
Previous State	N	P
P	2313	1680
N	2950	2333
PP	968	691
PN	1280	1007
NP	1302	951
NN	1599	1289

APPENDIX 2
Average excess returns

A negative excess return is denoted by *N* and a positive excess return is denoted by *P*. For Stage 1, estimated mean excess return conditional on observing *i* in the previous month is R_i. For Stage 2, estimated mean excess return conditional on observing *i* in two previous stage then observing *j* in one previous stage is R_{ij}.

Panel A: Summary statistics for excess returns

	Stage 1 unconditional	Stage 2 unconditional	R_N	R_P	R_{NN}	R_{NP}	R_{PP}	R_{PN}
Mean	0.004	0.004	0.005	0.002	0.008	0.008	-0.006	0.003
Standard deviation	0.238	0.238	0.226	0.254	0.220	0.247	0.263	0.230
# of obs.	9276	9087	5283	3993	2888	2253	1659	2287

Panel B: Average excess returns on a year-by-year basis

	Year					
	1	2	3	4	5	6
R_N	0.009	-0.007	0.009	0.009	0.009	0.006
	(0.250)	(0.217)	(0.230)	(0.222)	(0.214)	(0.196)
R_P	0.002	-0.006	0.011	0.001	0.008	0.002
	(0.234)	(0.254)	(0.290)	(0.252)	(0.251)	(0.238)
R_{NN}	0.013	-0.009	0.008	0.009	0.010	0.029
	(0.219)	(0.215)	(0.231)	(0.227)	(0.228)	(0.220)
R_{PP}	-0.004	-0.013	0.015	-0.014	-0.010	-0.013
	(0.256)	(0.261)	(0.322)	(0.242)	(0.235)	(0.234)
R_{PN}	0.009	-0.006	0.010	0.010	0.008	-0.023
	(0.273)	(0.228)	(0.230)	(0.217)	(0.195)	(0.196)
R_{NP}	0.012	-0.009	0.007	0.011	0.021	0.013
	(0.231)	(0.230)	(0.266)	(0.259)	(0.262)	(0.241)

Notes: The first column in Panel A presents information regarding the unconditional mean and standard deviation, the remaining columns are conditional means and standard deviations. Standard deviations of the year-by-year returns are in parentheses.