ON THE PREDICTABILITY AND MARKET SEGMENTATION OF THE MEXICAN STOCK EXCHANGE

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DOCTORAL DISSERTATION

Presented to Instituto Tecnológico y de
Estudios Superiores de Monterrey

in Partial Fulfillment
of the Requirements
for the Degree of

Doctor of Philosophy

THE UNIVERSITY OF TEXAS AT AUSTIN
February 2002

ABSTRACT

I argue that the Mexican Stock Exchange is predictable to a moderate degree and that the predictability has been decreasing over time. I use the stock return autocorrelation of first order as a measurement of predictability; in other words, I evaluate the extent to which the variation of returns (daily, weekly or monthly) of the Mexican Stock Exchange is predictable using only previous observation of the stock return. I analyze the sample period from January 2,1987, to October 29,1999. My results show that the magnitude and decay pattern of the first five return autocorrelations in the daily, weekly and monthly cases, suggests the presence of a predictable component in stock return. The level of the first-order autocorrelation return is larger for short-horizon stock returns than for long-horizon stock returns. In addition to this finding, my results indicate that for weekly returns the extent of the first-order autocorrelation stock return is inversely proportional to the level of trading activity. As for the daily and monthly return autocorrelation concerns, trading activity does not create any statistically significant difference in the first-order return autocorrelations between the least trading active stocks and the most trading active stocks. Furthermore, the level of the first-order daily return autocorrelation is larger in the past than that of current times. This tendency is also seen for first-order autocorrelation on weekly and monthly returns. I conclude that the level of predictability on the Mexican Stock Exchange is moderately low and that it is decreasing over the sample period. My results show that only 3.6% of the variation in the daily stock returns is predictable using previous daily stock return for 1989 and that this figure decreases over time to the level of 0.74% for 1999.

Ownership restrictions create market segmentation in the Mexican Stock Exchange. I analyze the sample period from January 1994 to December 1999 and find stock price premia for unrestricted series that are statistically significant. These premia vary longitudinally and across individual firms. I analyze different hypotheses to explain the determinants of the price premium by performing a panel-data model to mutually examine cross-sectional and time-series behavior of the equity premia. The results show that premia exhibits a strong mean reversion, which suggests that short-run order imbalances in the restricted and unrestricted series stock cause temporary changes in stock price premia that are eventually reversed. In addition, I find that the relative supply of **B** series inversely affects the level of the premium, which suggests that companies may intentionally limit the extent of foreign involvement, inducing market segmentation. This outcome is consistent with the Stulz and Wasserfallen (1995) hypothesis, which says that companies discriminate between investor clienteles with different demand elasticities. Additionally, I find that in times of crisis the relative supply of **B** series does not have a statistically significant effect on the level of stock premia. Furthermore, my findings are consistent with the liquidity hypothesis, since I find that premia decreases with the level of market capitalization and increases with both the relative liquidity of unrestricted shares and the level of free-float.

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CHAPTER I

INTRODUCTION AND OBJECTIVES OF THE RESEARCH

INTRODUCTION

Of the seven large equity exchanges in Latin America, the two biggest in terms of market capitalization are those of Brazil and Mexico, with sizes of $223.5 billion and $144.7 billion respectively[1]. The sector breakdowns of these capitalizations are given in Table I.1. As one can see from the table in both countries, the largest sector is the telecommunication sector, which accounts for more than 30% of the total market size. The next two largest Latin American exchanges are those of Chile and Argentina, which have sizes of $55 billion and $42 billion respectively (see Table I.2). In these two cases, the telecommunication sectors are relatively smaller with the biggest sectors being petrochemical and electric power. The next three exchanges are Peru, Venezuela and Colombia with sizes of $11.2 billion, $8.4 billion and $4.4 billion respectively, where telecommunication and energy are the sectors with the largest capitalizations (see Table I.3).

The total market capitalization of these seven exchanges aggregates to $490 billion. To have an idea of the size of these emerging economy exchanges relative to other exchanges from

[1] In the particular case of México, the Mexican Stock Exchange experienced a reduction in its size due to negative performance (-23%) for the year 2000.

developed countries--such as United States of America--General Electric and Microsoft have market capitalizations of $491 billion and $332 billion respectively[2].

The search for predictability in asset returns in both developed and emerging equity exchanges has engaged the attention of practitioners and scientists since the opening of organized financial markets. Forecasting and explaining future prices have triggered the development of mathematical models of asset prices and the respective empirical testing of those models. The fine structure of securities markets and frictions in the trading process may generate predictability, which can be viewed as a necessary reward for an investor to bear certain dynamic risks.

For investors looking for better returns, Latin American equity markets have produced high returns relative to other emerging markets during the past two decades. Another characteristic of these emerging markets is that they show very high levels of volatility. In the Mexican Stock Exchange or "Bolsa Mexicana de Valores"(BMV) for instance, a very small company in the clothing industry shows an extraordinary yield of return in five years.[3] Is it possible to identify in advance winner companies? To forecast future rates of returns using only past price changes may seem too restrictive, especially in the present in which investors have access to a vast set of financial variables; nevertheless, my research can yield rich insights into the behavior of asset prices of the BMV.

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[2] Source: Economatica as of Oct 23rd 2000.

[3] Edoardo B has grown 900% from Oct 29th 1994 to Oct 29th 1999.

TABLE I.1

THE TWO BIGGEST CAPITAL MARKETS IN LATIN AMERICA: BRASIL AND MEXICO.

MARKET CAPITALIZATION							
Thousands of Dollars							
	BRASIL				MEXICO		
SECTOR				SECTOR			
Airlines	$	4,437,206.00	2.0%	**Airlines**	$	478,857.00	0.3%
Appliances	$	755,835.00	0.3%	**Beverage**	$	16,677,185.00	11.5%
Auto Parts	$	794,032.00	0.4%	**Auto Parts**	$	148,848.00	0.1%
Banking	$	27,236,773.00	12.2%	**Cement**	$	8,366,860.00	5.8%
Beverage	$	8,487,540.00	3.8%	**Chemicals**	$	24,161.00	0.0%
Cement	$	663,218.00	0.3%	**Commerce**	$	21,318,460.00	14.7%
Commerce	$	5,176,817.00	2.3%	**Constr Mater**	$	170,367.00	0.1%
Construction	$	466,299.00	0.2%	**Construction**	$	798,634.00	0.6%
Chemicals	$	424,045.00	0.2%	**Entertain**	$	1,099,427.00	0.8%
Electronics	$	2,463,804.00	1.1%	**Finance Group**	$	17,718,103.00	12.2%
Energy	$	27,235,992.00	12.2%	**Food**	$	3,426,733.00	2.4%
Fertilizers	$	733,755.00	0.3%	**Holding**	$	7,237,835.00	5.0%
Food	$	1,444,111.00	0.6%	**Insurance**	$	1,372,436.00	0.9%
Holding	$	3,717,011.00	1.7%	**Investment**	$	88,899.00	0.1%
Investment	$	204,342.00	0.1%	**Metallurgy**	$	1,290,269.00	0.9%
Mech Indus	$	183,008.00	0.1%	**Mining**	$	2,763,587.00	1.9%
Metallurgy	$	6,477,985.00	2.9%	**Paper Pulp**	$	3,226,200.00	2.2%
Mining	$	10,198,018.00	4.6%	**Steel Plant**	$	886,699.00	0.6%
Paper Pulp	$	4,602,027.00	2.1%	**Telecomm**	$	56,690,690.00	39.2%
Petrol Chemic	$	36,141,531.00	16.2%	**Textile**	$	465,486.00	0.3%
Steel Plant	$	982,820.00	0.4%	**Tourism Hotel**	$	465,486.00	0.3%
Telecomm	$	69,852,064.00	31.3%	**Various**	$	26,562.00	0.0%
Textile	$	865,317.00	0.4%				
Timber	$	508,621.00	0.2%				
Tobacco	$	1,414,930.00	0.6%				
Toys	$	12,423.00	0.0%				
Transport	$	262,344.00	0.1%				
Various	$	7,758,870.00	3.5%				
TOTAL SIZE OF MARKET	$	223,500,738.00	100.0%	**TOTAL SIZE OF MARKET**	$	144,741,784.00	100.0%

Market Capitalization has been calculated as follows: Number of shares outstanding have been multiplied by closing price for each company and the aggregate has been allocated on each respective sector. Data was provided by ECONOMATICA as of Oct. 23rd 2000. Notice that the Telecommunication Sector has a very important share on each market, over 30% of the total market capitalization.

TABLE I.2

CHILE & ARGENTINA.

MARKET CAPITALIZATION					
Thousands of Dollars					
	CHILE			**ARGENTINA**	
SECTOR			SECTOR		
Airlines	$ 402,197.00	0.7%	**Banks**	$ 5,587,839.00	13.3%
Banks	$ 8,143,272.00	14.8%	**Beverage**	$ 13,801.00	0.0%
Beverage	$ 3,834,818.00	7.0%	**Auto Parts**	$ 144,520.00	0.3%
Commerce	$ 8,574,128.00	15.6%	**Cement**	$ 245,441.00	0.6%
Constr Mater	$ 1,407,427.00	2.6%	**Chemicals**	$ 56,800.00	0.1%
Construction	$ 50,594.00	0.1%	**Construction**	$ 167,074.00	0.4%
Elect Power	$ 10,748,087.00	19.5%	**Data Process**	$ 59,200.00	0.1%
Farm Breeding	$ 144,499.00	0.3%	**Elect Power**	$ 841,684.00	2.0%
Fishing	$ 146,123.00	0.3%	**Farm Breeding**	$ 42,741.00	0.1%
Food	$ 629,773.00	1.1%	**Food**	$ 629,464.00	1.5%
Forest	$ 554,019.00	1.0%	**Holding**	$ 28,600.00	0.1%
Investment	$ 5,925,746.00	10.8%	**Home Appliance**	$ 24,182.00	0.1%
Metallurgy	$ 716,379.00	1.3%	**Investment**	$ 346,500.00	0.8%
Mining	$ 931,878.00	1.7%	**Others**	$ 4,458,573.00	10.6%
Navigation	$ 14,426.00	0.0%	**Paper Pulp**	$ 37,507.00	0.1%
Others	$ 2,264,327.00	4.1%	**Petrol Chemic**	$ 14,756,288.00	35.0%
Paper Pulp	$ 2,248,193.00	4.1%	**Steel Plant**	$ 3,052,079.00	7.2%
Pension Fund	$ 956,839.00	1.7%	**Telecomm**	$ 10,634,890.00	25.3%
Petro Chemic	$ 346,170.00	0.6%	**Textile**	$ 3,000.00	0.0%
Telecomm	$ 5,918,680.00	10.8%	**Timber**	$ 2,880.00	0.0%
Textile	$ 7,206.00	0.0%	**Tobacco**	$ 720,580.00	1.7%
Various	$ 1,070,400.00	1.9%	**Transportation**	$ 4,132.00	0.0%
			Various	$ 255,830.00	0.6%
TOTAL SIZE OF MARKET	$ 55,035,181.00	100.0%	**TOTAL SIZE OF MARKET**	$ 42,113,605.00	100.0%

Market Capitalization has been calculated as follows: Number of shares outstanding have been multiplied by closing price for each company and the aggregate has been allocated to each sector respectively. Data was provided by ECONOMATICA as of Oct. 23rd 2000. Petro Chemical, Electric Power and Telecommunication are the sectors with largest share in terms of market capitalization on these markets.

TABLE I.3

PERU, VENEZUELA & COLOMBIA.

MARKET CAPITALIZATION					
Thousands of Dollars					
	PERU			VENEZUELA	
Banks	$ 1,586,264.00	14.1%	**Banks**	$ 2,378,768.00	28.1%
Beverage	$ 578,103.00	5.1%	**Cement**	$ 457,246.00	5.4%
Auto Parts	$ 3,153.00	0.0%	**Chemicals**	$ 22,842.00	0.3%
Cement	$ 561,272.00	5.0%	**Construction**	$ 26,431.00	0.3%
Chemicals	$ 22,742.00	0.2%	**Elect Power**	$ 1,726,259.00	20.4%
Constr Mater	$ 24,753.00	0.2%	**Food**	$ 279,280.00	3.3%
Construction	$ 4,748.00	0.0%	**Holding**	$ 38,222.00	0.5%
Elect Electron	$ 4,535.00	0.0%	**Investment**	$ 172,686.00	2.0%
Elect Power	$ 1,229,309.00	10.9%	**Navigation**	$ 12,162.00	0.1%
Farm Breeding	$ 60,885.00	0.5%	**Others**	$ 119,775.00	1.4%
Fishing	$ 11,203.00	0.1%	**Paper Pulp**	$ 100,588.00	1.2%
Food	$ 118,526.00	1.0%	**Petroleum**	$ 2,118.00	0.0%
Holding	$ 630,857.00	5.6%	**Steel Plant**	$ 100,504.00	1.2%
Insurance	$ 29,372.00	0.3%	**Telecomm**	$ 3,029,210.00	35.8%
Mechan Indus	$ 32,463.00	0.3%	**Textile**	$ 6,712.00	0.1%
Mining	$ 4,697,183.00	41.6%			
Non Met Min	$ 33,124.00	0.3%	**TOTAL SIZE OF MARKET**	$ 8,472,803.00	100.0%
Others	$ 33,320.00	0.3%			
Pension Fund	$ 86,745.00	0.8%			
Petrol Chemic	$ 162.00	0.0%		COLOMBIA	
Steel Plant	$ 20,731.00	0.2%			
Telecomm	$ 1,405,075.00	12.4%	**Banks**	$ 621,540.00	14.1%
Textile	$ 80,440.00	0.7%	**Beverage**	$ 869,101.00	19.7%
Various	$ 33,571.00	0.3%	**Cement**	$ 931,089.00	21.1%
			Commerce	$ 433,258.00	9.8%
TOTAL SIZE OF MARKET	$ 11,288,536.00	100.0%	**Entertainment**	$ 54,074.00	1.2%
			Finance Group	$ 43,703.00	1.0%
			Food	$ 335,280.00	7.6%
			Investment	$ 1,030,328.00	23.3%
			Mechanic Indus	$ 5,258.00	0.1%
			Steel Plant	$ 12,674.00	0.3%
			Textile	$ 19,718.00	0.4%
			Tobacco	$ 62,075.00	1.4%
			TOTAL SIZE OF MARKET	$ 4,418,098.00	100.0%

Market Capitalization has been calculated as follows: Number of shares outstanding have been multiplied by closing price for each company and the aggregate has been allocated to each respective sector. Data was provided by ECONOMATICA as of Oct. 23rd 2000. Mining, Telecommunications and Energy are the largest sectors.

The tremendous growth of Latin America emerging markets took place in the late 1980s due to economic reforms and financial liberalization policies as means to increase domestic saving and to attract international resources. In the present, the stocks from all listed companies are freely available to foreign investors in the markets of Brazil, Argentina and Colombia.

Dividend policy and capital gains are very liberal in these markets; nonetheless, a few restrictions on entry and repatriation of income and capital gains still exist in Chile, Venezuela and México.

The Mexican environment is very dynamic, and it has changed its policy restrictions on the so-called financial companies. Currently financial firms operate under "O" series that makes them available for both domestic and foreign investors; in the present it is possible for a foreign individual or foreign institution to take over any Mexican financial firm completely, such is the case of Banamex which was taken over entirely by Citicorp.

Particularly in the BMV, twenty-two (non-financial) stocks are actively trading with both restricted (exclusively for Mexicans) and unrestricted series. The distinctions between series are mainly institutional in nature and are dictated by government policies with the objective of placing corporate control in the hands of individual Mexican investors. Consequently, the government policies place limits on the percentage of a firm's equity that a non-domestic investor can hold. As a result of this differentiation, one observes price premium on these stocks; Therefore, the price premia induces the phenomenon of market segmentation, i.e. different prices of the same asset for different groups of investors.

OBJECTIVES AND HYPOTHESES

Two main issues analyzed in this research are predictability of the Mexican Stock Exchange and market segmentation. On the first issue, I assess the extent to which the variation of daily, weekly and monthly returns of stocks traded on the Mexican Stock Exchange is predictable using only previous observations of the stock return. My measurement of predictability is precisely the stock return autocorrelation of first order.

On the predictability I analyze individual stocks on the BMV for the sample period of January 2,1987, to October 29,1999, and I test the following hypotheses:

H1 Stocks traded on the Mexican Stock Exchange show significant first-order autocorrelation in daily, weekly and monthly stock returns.

H2 The returns on Stocks traded on the Mexican Stock Exchange are currently less predictable than in the past.

H3 The magnitude of the first-order stock return autocorrelation is inversely proportional to the level of trading activity and to the length of the horizon on the stock return.

On the second issue, market segmentation, I analyze the impact of ownership restrictions on equity prices and also I investigate the determinants of price premia on the Mexican Stock Exchange.

The sample period of my analysis is from January 1994 to December 1999, for which I test the following hypothesis:

H4 There exist market segmentation in the BMV provoked by ownership restrictions.

On the determinants of price premia, I define the subsequent hypotheses:

H5 Premium is inversely proportional to the level of relative supply of the unrestricted series.

H6 Price premia decreases with the level of market capitalization and increases with both the relative liquidity of unrestricted shares and the level of free-float.

MAIN CONTRIBUTIONS AND LIMITATIONS OF THE RESEARCH

Emerging capital markets have been the subject of analysis by scientists and practitioners. Most of the studies on the existent literature have focused on Asia-Pacific countries such as Singapore, Hong-Kong, South Korea. In México there exists a quite respectable number of scientists that investigate the Mexican Stock Exchange (BMV). One of the problems that the researchers face while studying the BMV is the relative scarcity of the data, especially in long horizon types of analysis, and the thin-trading on several stocks. Financial institutions keep data as a very valuable asset and occasionally they are reluctant to share it. I have built up a set of data for a horizon longer than 10 years of daily prices on the stocks of the BMV, with a density big enough that enables us to perform robust statistical tests. I have figured out questions on the predictability that have implications on the efficiency of the Mexican Stock Exchange and on the reliability of technical analysis methods.

I have performed an up to date study on the market segmentation of the BMV.

The market segmentation phenomenon has been widely studied in both developed and emerging markets; nevertheless, there was not current research on this issue, and therefore the study on market segmentation of the BMV should be up-dated, due mainly to recent changes in the legislation that has made the exchange less restricted and to the natural dynamic of the Market.

CHAPTER TWO

PREDICTABILITY AND RETURN AUTOCORRELATION

THE RANDOM WALK

Since Louis Bachelier published his thesis "Theory of Speculation" in 1900, the random walk hypothesis as a model for speculative prices has held considerable interest for financial economists. Early empirical studies, Cootner (1964) and Fama (1965,1970), support the random walk hypothesis that the changes on stock prices were unpredictable. More recent empirical evidence, such as that found by Lo and MacKinlay (1988), has rejected the random walk hypothesis, from a simple specification test. This finding surprised many economists due to the defining property of the random walk is the uncorrelatedness of its increments, and the contrary implies, necessarily that price changes can be forecasted to some degree.

The results on the empirical analysis documented by Jegadeesh (1990) reject the hypothesis that the stock prices follow random walks. They also provide evidence of stock return predictability, showing negative first-order serial correlation in monthly stock returns with high degrees of significance. The latter can be attributed to market inefficiency or to systematic changes in expected stock returns.

STOCK MARKET OVERREACTION

Some studies have attributed this forecastability to what is known as the "stock-market overreaction" hypothesis. According to this hypothesis, investors create "momentum," since they are subject to waves of optimism and pessimism. This phenomenon then causes the prices to temporarily move away from their fundamental values. De Bondt and Thaler (1985,1987) suggest that stock prices overreact to information and, furthermore, that contrarian strategies (buying past losers and selling past winners) achieve abnormal returns. De Bondt and Thaler (1985) show that over three to five year holding periods, stocks that performed poorly over the previous three to five years achieve higher returns than stocks that performed well over the same period. But these results are subject to debate; Chan (1988), Ball and Kothari (1989), and Zarowin (1990) argue that the De Bondt and Thaler results are a consequence of the systematic risk of their contrarian portfolios and the size effect. Furthermore, due to the fact that long-term losers outperform the long-term winners only in January of a given year, it is still vague whether their results can be accredited to overreaction.

MOMENTUM STUDIES, REVERSAL PHENOMENON, IMPLICATION FOR MARKET EFFICIENCY

The highly cited study by Jegadeesh and Titman (1993) provides important insight as to how the market reacts to announcements of success or lack thereof by business firms. In the analysis, the authors first classify stocks as winners or losers, and then measure their subsequent relative performance. Their study covers the period 1980 through 1989, and includes all firms on the New York and American stock exchanges. Winners are defined as the 10% of the stocks in their sample with the best returns over the past 6 months, and losers are defined as the 10% with the worst returns. The study observes the relative performance of the winners and losers over three-day periods within each of the 36 months of the next three years. In each of the 36 months, they measure performance for firms that report earnings in the month, and for those firms, returns are measured only during the two days preceding and the day of the announcement of quarterly earnings per share. In the first month following the ranking of the winners and losers, the authors would focus only on those that reported earnings in that month. For these firms, the study looks at the difference between the returns for winners and losers only in the three-day vicinity of the announcement dates, the two days before and the day of. Later the differences in the return between winners and losers were plotted, showing that winners of the past do better in the first month and in the next seven months. Nevertheless after the eighth month, stocks previously classified as losers showed superior returns at the earnings announcement dates. This monthly difference in the performance of the winners and losers is significant at the 5% level in months 11 through 18, and the losers outperformed the winners in every month except for 21 and 24. The conclusion of this is that firms quickly revert to the mean in terms of their relative profitability.

The evidence of initial positive and later negative relative strength returns suggests that common interpretations of return reversals as evidence of overreaction and return persistence as evidence of underreaction are overly simplistic. One interpretation of results described above is that transactions by investors who buy past winners and sell past losers move prices away from their long-run values temporarily and thereby cause prices to overreact. This interpretation is consistent with the analysis of De Long, Shleifer, Summers, and Waldman (1990) who explore the implications of what they call "positive feedback trading strategies": buy when prices rise and sell when prices fall; if rational speculators' early buying triggers positive-feedback trading, then an increase in the number of forward looking speculators can increase volatility about fundamentals. Another explanation is that the market underreacts to information about their short-term prospects of firms but overreacts to information about their long-term prospects.

On the same line of research, a very interesting study was performed by Poterba and Summers (1988). They investigated different markets, in this case Japan, Canada, U.K., France, and U.S. For all countries except Canada and the U.K., the time period covered was 1957-86. For Canada the period was 1919-86, and for the U.K., it was 1939-86. The returns are inflation-adjusted and do not include dividends. They found that, in every country, the volatility was less than expected in the absence of reversal patterns. This outcome indicated that the market overpriced the winner stocks and underpriced the loser ones. In the long term the past inflation in the market price of the stock begins to reverse, creating a long-term reversal pattern in the returns.

CONTRARIAN STRATEGIES.

A contrarian stock selection strategy consists of buying stocks that have been losers and selling short stocks that have been winners. This strategy is oriented to take advantage of the market overreaction to news, so winners tend to be overvalued and losers undervalued; thus the investor exploits this inefficiency by using this strategy and gains when stock prices revert to fundamental values. Many investments strategies, such as those based on the price/earnings ratio, or on the book/market ratio, can be seen as variants of this strategy. As mentioned earlier, De Bondt and Thaler (1985) report that, on the basis of the past half century of data, large abnormal returns can be earned by the contrarian investment strategy; thus, they interpret this as support for the market-overreaction hypothesis. Kahneman and Tversky (1982), in their study in experimental psychology, find that people tend to overreact to unexpected and dramatic events. Chan (1988) offers an alternative interpretation of the evidence on the performance of the contrarian strategy. He basically proposes that the risks of winner and loser stock are not constant over time. The risk of the strategy seems to correlate with the level of expected market-risk premium. The estimation of abnormal returns may be sensitive to how the risks are estimated. The model of risk and return that he adopts is the standard Sharpe-Lintner Capital Asset Pricing Model (CAPM). Chan finds that the risk of losers and winners are not constant. The estimation of the return of this strategy is sensitive to the methods used. The loser's betas increase after a period of abnormal loss, and the winner's betas decrease after a period of abnormal gain. Therefore, betas estimated from the past should not be used.

When risk changes are controlled for, only small abnormal returns are found. If this experiment is interpreted as a test of market overreaction, Chan finds no strong evidence in support of the hypothesis. An investor who follows the contrarian strategy is likely to find that his risk exposure varies inversely with the level of economic activity and consumption. On average, the investor realizes positive abnormal returns, but that excess return is attributed to a normal compensation for the risk in the investment strategy.

Another opinion about overreaction is granted by Lo & MacKinley (1990), who show evidence against overreaction as the only cause of contrarian profits. They question that the profitability of contrarian investment strategies necessarily implies stock market overreaction. Their rationale is as follows: if returns on some stocks systematically lead or lag those of others, a portfolio strategy that sells winners and buys losers (contrarian strategies) can produce positive expected returns, even if no stock's returns are negatively autocorrelated. Using a particular contrarian strategy, they show that weekly portfolio returns are strongly positively autocorrelated, in spite of the fact that the individual stock returns were negatively autocorrelated, and reveal that the cross-sectional interaction of security returns over time is an important aspect of stock-price dynamics. Their research also implies that stock market overreaction is not the only potential explanation for profitability in contrarian portfolio strategies.

RELATIVE STRENGTH STRATEGIES

Despite the attention that contrarian strategies have received in the recent academic literature, in the past the early literature on market efficiency focused on relative strength strategies that buy past winners and sell past losers. To mention one notable work, Levy (1967) claims that a trading rule that buys stock with current prices that are substantially higher than their average prices over the past 27 weeks realizes significant abnormal returns. This trading rule was found after examining 68 different trading rules. Nevertheless, Jensen and Bennington (1970) express skepticism about Levy's conclusions. They analyze the profitability of his trading rule over a long time period that was outside Levi's original sample period for the most part. They found that, in their sample period, the rule does not outperform a buy-and-hold strategy. They therefore attribute Levy's result to a selection bias.

The academic debate has concentrated on contrarian rather than relative-strength trading strategies. Nonetheless, a number of practitioners still use relative strength as one of their stock-selection criteria. Grinblatt and Titman (1989,1991) have examined the mutual fund industry, and the majority of fund managers show a tendency to buy stocks that have increased in price over the previous quarter. Furthermore, the Value Line rankings are known to be based in large part on past relative strength. Copeland and Mayers (1982) and Stickel (1985) examine the predictive power of Value Line, along with the success of many of the mutual funds in the Grinblatt and Titman sample. They also provide evidence that the relative-strength strategies may cause abnormal returns.

The paradox between academic literature, which suggests using opposite strategy as a generator of abnormal returns, and the success of Value Line rankings and the mutual funds can be explained by the following two explanations: One possibility is that the abnormal returns realized by these practitioners are either spurious or are unrelated to their tendencies to buy past winners. A second explanation is that the disparity is caused by the difference between the time horizons used in the trading rules examined by academic researchers and those used in practice. For example, academics that are in favor of contrarian strategies as generators of abnormal returns based their trading strategies on very short-term return reversals of one week or one month, or very long-term return reversals, of three to five years. Nevertheless, according to Bernard (1984), practitioners who use relative strength rules base their selections on price movements over the past three to twelve months. Indeed, one of the inputs used by Value Line to assign a timeliness rank for each stock is a price-momentum factor based on the stock's past three to twelve month returns. Jegadeesh and Titman (1993) provides an analysis of relative strength trading strategies over 3 to 12 month horizons. The results of their test shows that the profits are not due to the systematic risk of the trading strategies. Also, the evidence supports that the profits cannot be attributed to a lead-lag effect resulting from delayed stock-price reactions to information about a common factor, as was proposed by Lo and MacKinlay (1990). Nevertheless, the evidence is consistent with delayed price reactions to firm-specific information.

The acquisition of information and its distribution to other units of the economy are central activities in all areas of finance, and especially so in capital markets. Asset-pricing models typically assume both that the diffusion of every type of publicly available information takes place instantaneously among all the investors and that they act on the information as soon as it is received. For instance, it may be reasonable to expect quick reactions in prices to the announcement through standard channels of new data (i.e. earnings or dividends announcements), which can be rapidly evaluated by investors using generally accepted models. Nevertheless, there are other opportunities in which the expected duration between the creation of this investment opportunity and its elimination by rational investor actions in the market place can be considerable.

There are a number of hypotheses concerning the above mentioned lagged information transmission between different kinds of investors, among them, herd behavior, common information, information set-up costs and legal risk faced by portfolio managers, lagged price adjustment by market makers, and the degree of institutional ownership.

HERD BEHAVIOR

John Maynard Keynes (1936) suggests that professional managers will follow the herd if they are concerned about how others will assess their ability to make sound judgments. "Worldly wisdom teaches that it is better for reputation to fail conventionally than to succeed unconventionally". The same principle can apply to corporate investment, when a number of companies are investing in similar assets. Gwynne (1986) documents problems of herd behavior in bank's lending policies toward LDCs. The manager's job is not measured by how correct his country-risk analysis is. As a result managers tend to do what hundreds of other larger international banks have done, and any blame for poor forecasting would be shared by thousands of bankers around the world. That is one of the benefits of following the herd. Morck, Shleifer and Vishny (1989) study the effectiveness of boards of directors in dealing with poorly managed firms. Their principal finding is that top management firings are primarily associated with the poor performance of a firm relative to its industry, rather than with industry-wide failures. This finding provides evidence that boards have a difficult time assigning blame to their managers for mistaken strategies, when other firms in the industry are following similar strategies. Thus, one might expect that managerial behavior would be distorted in the direction of herding.

Herd behavior by money managers could provide a partial explanation for excessive stock market volatility. By mimicking the behavior of others, buying when others are buying, and selling when others are selling, rather than only responding to private information, members of a herd will tend to amplify exogenous stock price shocks. Shiller and Pound (1986) present evidence that is consistent with the existence of herd behavior in the stock market. They survey institutional investors to determine the factors that went into their decision to buy a particular stock. Purchase of stocks that had recently had large price run-ups tended to be motivated by the advice of others. This surge can be contrasted with more stable stocks, where fundamental research played a more important role. Such disparity suggests that the comfort inherent in following common wisdom can lead professional money managers to invest in stocks where fundamentals might dictate otherwise. Although this behavior is inefficient from a social standpoint, it can be rational from the perspective of managers, who are concerned about their reputations in the labor market.

COMMON INFORMATION

The highly cited study by Lo and MacKinlay (1990) report that current returns on a portfolio of small stocks are correlated with lagged returns on a portfolio of large stocks, but not vice versa. This unidirectional trend could be the result of infrequent trading in small stocks; nevertheless, the authors demonstrate that very unlikely low-trading frequencies would be required to account for their empirical results. This evidence seems attributable to the fact that some stocks react faster than others to new information—known as common information--that has value implications across stocks.

In theory, the number of analysts may have an effect on the speed of adjustment to new information. For example, researchers like Holden and Subrahmanyam (1992) and Foster and Viswanathan (1993) made great contributions; in addition to the classic model of Kyle (1985), they have found that, as the number of informed investors increases, the share price will reflect new information more rapidly. Such a development would suggest an association between the number of analysts and the speed of adjustment, assuming that the number of analysts can be viewed as a proxy for the number of informed investors.

Brennan, Jeegadeesh and Swaminathan (1993) study the relationship between the number of analysts following a firm and its speed of adjustment to new information that has common effects across firms. In their experiment, they hold firm size constant because the results from Lo & MacKinlay show that size is related to the speed adjustment, although those authors do not offer any explanation for why size may be an important determinant of the speed of adjustment. One possibility of this is that size is positively associated with the number of individual who are interested in a firm and therefore know about it, either because they already own the stock or because they gain information about the firm in the normal course of their business [Merton (1987)]. Brennan, Jeegadeesh and Swaminathan found little effect of the number of analysts on the serial correlation of portfolio returns; nevertheless, they found (by using Granger causality regressions) that the returns on many analyst firm portfolios tend to anticipate those on few analyst firm portfolios. This relation is nonlinear, and the marginal effect of the number of analysts on the speed of price adjustment increases with the number of analysts. In fact, many analyst firms' portfolios respond more rapidly to new information contained in returns on the value-weighted and the equal-weighted market indices.

INFORMATION SET-UP COSTS AND LEGAL RESTRICTIONS

Merton (1987) argues that there is a receiver or set-up cost to information processing. The investor will want to pay this fixed cost if the value of adding the security to the portfolio is sufficiently large. Therefore, investors will follow only a small subset of traded assets. Such behavior would imply that institutional investors who perform systematic investigations would concentrate their attention, and consequently their investments, on assets for which the volume of available information is large relative to the information set-up cost. On average, these would tend to be larger firms.

The fact that professional money managers must satisfy prudence requisites affects their investment strategies. In the United States, the common-law "prudent man" rule and/or the labor department's "prudent expert" rule governs the investment behavior of institutional portfolio managers. Thus, portfolio managers in their fiduciary capacity should make prudent investments. In a court of law, prudence is evaluated not only in a portfolio context but also in the context of individual investments. If an investment is catalogued to be imprudent, the law requires the fiduciary to be personally liable for any losses. Therefore, institutional investors have the incentive to invest in only a subset of marketed assets.

Badrinath, Gay and Kale (1989) analyze the patterns of institutional ownership of common stock, within the context of the institution's fiduciary responsibility. Since managers' performance and investment choices are continually monitored and evaluated, they tend to insure their investment decisions and to create the perception among the auditors that their decisions are very reasonable, well informed and prudent. This external evaluation of investment choices becomes more significant during times of lack-luster performance. Therefore, during such times, a safety net is provided to managers if they can prove that their judgments regarding the soundness of a particular investment choice was shared by others. Badrinath, Gay & Kale's empirical tests support this hypothesis since the level of institutional holdings is an increasing function of the safety-net potential of common stock.

TOURNAMENT INTERPRETATION

The award-winning study by Brown, Harlow and Starks (1996) provides an original interpretation of the behavior of managers of investment portfolios. These authors test the hypothesis that, when mangers' compensation is connected to relative performance, those managers with portfolios likely to end up as "losers" will maneuver fund risk in a different manner than those with portfolios likely to end up as "winners". After reviewing the performance of 334 growth-oriented mutual funds during 1976 to 1991, they found that losers in the middle of the year tend to increase fund risk in the latter part of an annual evaluation phase to a greater degree than mid-year winners. They argue that, even without incentive fee contracts, the nature of the mutual fund industry can influence a manager's decision-making process. Viewing the mutual fund market as a tournament, in which all funds with similar investment objectives compete with each other, gives a helpful structure for a better understanding of manager's behavior. Sirri and Tufano (1992) explain that mutual funds that earn the highest returns during an evaluation period receive the largest rewards in terms of increased new investments in the fund, and poor return mutual funds are not penalized in an offsetting manner. Therefore, the structure of the decision-making process for a manager has the shape of a call-option payoff that is influenced by their relative performance ranking. This option-like compensation pattern is analogous in essence to the incentive fee contract discussed by Grinblatt and Titman (1987, 1989a), Kritzman (1987), and Starks (1987). They note that the convexity of such a reward system provides incentives for managers to change the risk of their portfolios. Furthermore, for those who have performed poorly, the motivation will be to augment their relative risk level given that they can only profit by improving their ranking by year end; therefore, managers who find themselves positioned at an interim assessment period as losers (performance lower than average) will need to generate a return over the rest of the "tournament" that is sufficient to make up their first period "deficit". In order to achieve such return, managers will have to alter risk fund during the rest of the competition to a degree that is larger than that expected for the interim winners. These findings are consistent with the work of Bronars (1987), McLaughlin (1988), and Ehrenberg and Bognanno (1990). For example, Bronars finds that losing sports teams will tend to take greater risks toward the end of the game than they would under less time-constrained circumstances.

CROSS-AUTOCORRELATIONS IN STOCK RETURNS

The literature related on cross-autocorrelations initiates with the study by Lo and MacKinlay (1990). They find that positive autocorrelations in portfolio returns are due to positive cross-autocorrelations among individual security returns. In particular, they find that the correlation between lagged large-firm stock returns and current small-firm returns is higher than the correlation between lagged small-firm returns and current large-firm returns.

There are many explanations to this phenomenon, and they can be classified in three different groups.

The first group of explanations claims that cross-autocorrelations are the result of time-varying expected returns, as implied by the study of Conrad and Kaul (1988).

In the same line of reasoning, another explanation is suggested by Hammed (1997), who argues that cross-autocorrelations are simply a restatement of portfolio autocorrelations and contemporaneous correlations. Once account is taken of portfolio autocorrelations, then portfolio cross-autocorrelations should disappear.

The second group of explanations suggests that portfolio autocorrelations and cross-autocorrelations are the result of market microstructure biases such as thin trading, as described on the study by Boudoukh, Richardson, and Whitelaw (1994).

Finally the third category of explanations for the lead-lag cross-autocorrelations claims that these lead-lag effects are due to the tendency of some stocks to underreact, in other words to adjust more slowly to economy-wide information than others, as it is suggested by Brennan, Jegadeesh, and Swaminathan (1993) in their work about the speed adjustment hypothesis. In the same line of thought, Mech (1993) explains that these lead-lag patterns do not get arbitraged away because of the high transaction costs that any trading strategy designed to exploit these short-horizon patterns would face.

LAGGED PRICE ADJUSTMENTS, RETURN AUTOCORRELATION AND MARKET FRICTIONS

As mentioned earlier, several studies about return autocorrelation have been done in developed markets; in one of them Starks & Sias (1997) test the hypothesis that the correlated trading patterns of institutional investors is one of the factors that drive daily returns autocorrelation. Their empirical evidence is consistent with this hypothesis. They find that both individual security and portfolio daily return autocorrelations are positively related to the degree of institutional ownership. Additionally they show that the returns on portfolios dominated by institutional investors lead the returns on portfolios dominated by individual investors; this finding is consistent with the hypothesis that institutional trading increases the speed with which prices reflect market wide information. In addition, they observe that the relation between institutional ownership and autocorrelation does not appear to be driven by time-varying risk premiums or market frictions. Furthermore, their evidence shows that the degree of daily portfolio return autocorrelation is too large to be explained by nontrading alone.

Fama and French (1988) found that a slowly mean-reverting component of stock prices tend to induce negative autocorrelation in returns. They examine autocorrelations of stock returns for increasing holding periods. Large negative autocorrelations were found, for return horizons beyond a year, and that is consistent with the hypothesis that mean-reverting price components are important in the variation of the returns. These results provide evidence that stock returns are predictable, although the autocorrelation is weak for the daily and weekly holding periods.

Market frictions (partial price adjustments) have been proposed to explain return autocorrelation in the short run. The less uniformly a portfolio reflects common information, the higher the degree of autocorrelation. Thus, portfolios composed of securities affected by greater market frictions shall exhibit greater autocorrelation.

Three sources of market frictions that have been proposed to explain return autocorrelation are nonsynchronous trading, transactions costs and correction of pricing errors by market makers.

NONSYNCHRONOUS SECURITY TRADING

An early study made by Fama (1970) found slightly positive average autocorrelations in daily security returns with a lag of one day and no empirical evidence of significant autocorrelations for higher lags. Nevertheless, daily market-index returns show a pronounced positive first-order autocorrelation. This index occurrence has been called the Fisher effect because Lawrence Fisher (1966) hypothesized its probable origin.

Additionally, observed security price changes occur at different times throughout the trading day. Reported daily returns only reflect the last trade of the day. Thus, there is often a substantial divergence between reported transaction-based returns and true returns, especially for less active stocks, resulting on the econometric problem of errors in variables.

The presence of nonsynchronous trading has been used as an explanation for autocorrelation on portfolio daily returns (Fisher 1966; Scholes and Williams, 1977; Boudoukh et al., 1994). If there is not trading on a particular stock for a given period, then any information will not be reflected in the stock's price until it trades in a later period, inducing spurious cross-autocorrelation. Cohen, Maier, Schwartz and Whitcomb (1979, 1986) show also how this nonsynchronous security trading will induce spurious auto-and cross-correlations into individual-security and market-index returns. Their models have several implications. One is that individual-security daily returns based on observed transaction prices should be slightly negatively first order autocorrelated. Another implication is that first-order cross-correlations between securities will not equal zero and should be predominantly positive. Also, market-index returns based on transaction prices should be positively first-order autocorrelated, and this induced positive autocorrelation will be more sever when more weight is given to thinly traded securities, as in an equal-weighted market index.

Cohen et al. allocate nonsynchronous trading in a broader class of market frictions, which may induce price-adjustments delays into the trading process. Therefore the nonsynchronous trading effect is one of several factors that may contribute to the presence of autocorrelation in market-index returns.

In the same line of research, Atchison, Butler and Simonds (1987) investigates the extent to which nonsynchronous trading explains observed autocorrelations in daily returns on stock market indices. They observe that, on average, daily returns on individual stocks show slightly positive first-order autocorrelations, whereas indices exhibit strong positive values. With a particular nonsynchronous trading model, they examine the source of this pronounced index autocorrelation and its level. This estimated level is found to be substantially less than that observed empirically. Thus, other factors appear to be playing the major role in generating the autocorrelations.

It seems that closing prices of different stocks need not be set simultaneously; nevertheless few empirical studies employing daily data take this into consideration. Overlooking this apparently unimportant nonsynchronicity can result in substantially biased inferences for the temporal behavior of asset returns. Suppose that the returns to stock *i* and *j* are temporally independent, but *i* trades less frequently than *j*. When news arrives near the close of the market day, it is more likely that *j*'s end-of-day price will reflect this information than *i*'s, because *i* may not trade after the news arrives. Eventually, *i* will respond to this information, but the fact that it responds with a lag induces spurious cross-autocorrelation between the closing prices of *i* and *j*. As a result, a portfolio consisting of securities *i* and *j* will show serial dependence even though the underlying data-generating process was assumed to be temporally independent. In a similar way, spurious own-autocorrelation is created. These effects have clear implications for the recent tests of the random walk and efficient-markets hypotheses.

Lo and MacKinlay (1990) develop a stochastic model of nonsynchronous asset prices based on sampling with random censoring. They build estimators to quantify the magnitude of nontrading effects in commonly used stock returns data bases, and show the extent to which this phenomenon is responsible for recent rejections of the random walk hypothesis.

Lo and MacKinlay conclude that the portfolio autocorrelation induced by the lack of trading is simply the nontrading probability of the securities in the portfolio. Thus, portfolio autocorrelation is an increasing function of the nontrading probability.

TRANSACTIONS COSTS

The relation between transaction costs and volatility contributes to portfolio return autocorrelations. Mech (1993) has developed a model and presented evidence that portfolio return autocorrelation is not caused by time-varying expected returns, nontrading, stale limit orders or market maker trading strategies. In his model, prices adjust more slowly when transaction costs are larger relative to volatility. Informed traders are not going to trade on brand new information until the differential between price and value overcome transaction costs. If the bid-ask spread is too large or the volatility is too small, then information will not be reflected in the stock's price until it trades in a later period. The implication is that markets are inefficient in that prices do not always fully reflect all available information. Mech's empirical evidence is largely consistent with his model.

PRICE ERRORS BY MARKET MAKERS

Chan (1993) provides an argument for an alternative market-friction source of portfolio autocorrelation. When market makers observe noisy signals about the value of their stocks but cannot instantaneously condition prices on the signals of other stocks, which contain marketwide information, there will be pricing errors after observing true values or previous price changes of other stocks. These price errors are then corrected, causing stock returns to become positively cross-autocorrelated. For example, assume that market makers have favorable, but noisy, signals concerning their holdings. They adjust prices upward or downward (depending on whether the signal is confirmed).

In general, market-friction models suggest that portfolios composed of securities exposed to market frictions will have greater return autocorrelation. Furthermore, these models suggest that greater market frictions slow the speed at which portfolios fully reflect marketwide information. Nevertheless, these models have found limited empirical support.

INSTITUTIONAL OWNERSHIP

It is argued that the past returns on stocks held by informed institutional traders will be positively correlated with the contemporaneous returns on stocks held by noninstitutional uninformed traders. Institutional investors have the incentive to invest in only a subset of marketed assets or institutionally favored firms (IF). Badrinath, Kale and Noe (1995) found that, when equity portfolios are formed on the basis of the level of institutional ownership in firms, the returns on the portfolio of firms with the highest levels of institutional ownership lead the returns of portfolios with lower levels of institutional ownership by as much as two months. In theory, it is expected the time taken by uninformed investors to incorporate past price data into their current demand to be reasonably short. One way to reconcile Badrinath et al. findings with theory would be to assume that investors update their information infrequently. Such behavior is the case for such institutional investors as pension funds. Furthermore, when portfolios are size-based, the lead-lag period is in general no longer than one month. The significance of the institutional ownership-based lead-lag relation persists, in monthly as well as in weekly returns, even after controlling for firm size, suggesting that the stock price performance of firms with high institutional ownership, and not the performance of large firms, is a leading indicator of subsequent equity market performance, and therefore it is likeable that the primary path for information transmission in equity markets is between returns on IF and institutional unfavored firms (UF).

RETURN AUTOCORRELATION AND IMPLICATION FOR MARKET EFFICIENCY

We can divide in three schools of thought, the views over the meaning on the existence of autocorrelation on stock returns and the consequent implication for market efficiency. Those who think that markets rationally process information compound the first school.

Large autocorrelations at short horizons are not due to fundamentals; they believe that autocorrelations arise from market frictions. Specifically, both the pattern and the magnitude of the correlations are consistent with the following: measurement error in data, e.g., nonsynchronous trading and bid-ask spread (Cohen et al. 1986; Lo and MacKinlay 1990), institutional structures, e.g. trading mechanisms (Keim 1989; Bessembinder and Hertzel 1993), or microstructure effects, e.g. systematic changes in either inventory holdings or the flow of information (Hasbrouck 1991; Admati and Pfleiderer 1989; Mech 1993).

The second school of thought believes that markets are efficient; nevertheless, even in frictionless markets, short-horizon stock returns can be autocorrelated. The correlation patterns are consistent with time-varying economic risk premiums. Intertemporal asset pricing models, such as conditional versions of the arbitrage-pricing theory or the consumption-based asset-pricing model, can explain changing risk premiums. Variation in risk factors, such as past market returns, past size returns, or interest rate spreads, can induce variation in short-horizon risk premiums. Examples on these matters are the studies of Keim and Stambaugh (1986) and Lo and MacKinlay (1992) for monthly returns that use linear factor models; Conrad and Kaul (1989) for weekly returns in univariate setting; and Connolly and Conrad (1991), Conrad, Gultekin, and Kaul (1991), Conrad, Kaul, and Nimalendran (1991), and Hammed (1992), for an analysis of weekly returns in multivariate framework.

The third school of thought takes a singular approach. This school believes that markets are not rational; thus, profitable trading strategies do exist, and psychological factors are important for pricing securities. Time series patterns in returns occur because investors either overreact or only partially adjust information arriving to the market. Several papers document excess profits form various trading rules based on positions in either individual securities or portfolios. For example, as seen before, on the analysis of contrarian strategies, Jegadeesh (1990) and Lehmann (1990). Jeegadeesh and Titman (1992) and Lo and MacKinlay (1990) have made the analysis of profits due to cross-serial correlation across stocks. Furthermore, Brock, Lakonishok, and LeBaron (1992), study in detail several technical trading strategies based on past movements in Dow Jones 30.

SHORT HORIZON RETURN AUTOCORRELATION

Conrad, Gultekin, and Kaul (1991) report remarkable evidence that seems to be at odds with existing interpretations of cross-serial correlation patterns documented by Hawawini (1980), Lo and MacKinlay (1990), and Mech (1990). They found that, in multiple regressions of small-firms portfolio returns on lagged returns, lagged large-firm returns have no predictive power beyond lagged small-firm portfolio returns. In another study, Boudoukh, Richardson and Whitelaw (1994) argue that cross-serial correlations can be explained by the portfolios' own autocorrelation patterns together with high contemporaneous correlations across portfolios. Also, given the fact that small firms exhibit the most autocorrelations, then, understanding the dynamics of short-horizon returns is very much related to explaining the magnitude of small-firm portfolio return autocorrelations. Boudoukh et al. provide an analysis of one possible explanation for the magnitude of this autocorrelation based on the risk characteristics and nontrading of small firms. They develop several specifications of nontrading, as an alternative to Lo and MacKinlay's (1990b) homogeneous model of nonsynchronous trading, and then they show that the effect of nonsynchronous trading has most probably been understated. For example, they consider portfolios with autocorrelations as low as seven percent, and then they show that those autocorrelations can be as high as twenty percent when it is taken into account the degree of heterogeneity within the portfolio in both the nontrading and the betas of individual stocks. This evidence shows that nonsynchronous trading is an important determinant of the magnitude of autocorrelations in portfolio returns.

Despite the conclusions of other researchers who defined economic risk premiums as the source of autocorrelations and cross-serial autocorrelations in size portfolio returns, Boudoukh, Richardson and Whitelaw argue that these are unlikely source. For instance, the effect on nonsynchronous trading, in a case where returns are not autocorrelated, can be eighteen percent or higher. It is not clear whether the residual autocorrelation can be credited to time-varying economic risk premiums, or more likely, some other microstructure effects. Finally, Boudoukh et al. examine the autocorrelation properties of small firm indices and future contracts written on them. They find that the spot index's autocorrelation is significantly higher than that of the futures.

DIRECTIONAL ASYMMETRY

The study by Boudoukh, Richardson and Whitelaw (1994) shows that cross-autocorrelation between large and small stock portfolio returns can be characterized by the autocorrelation of the small stock portfolio. The study by Lo & MacKinlay (1990a, 1990b) argues that such autocorrelation cannot be explained by appeals to traditional nontrading arguments. Both studies have triggered a search for more explanations of why small stock returns can be predicted by past larger stock returns.

McQueen, Pinegar and Thorley (1996), document a new empirical characteristic of the data, *directional asymmetry* in order to explain the cross-autocorrelation between large and small stock returns. They demonstrate that the cross-autocorrelation is asymmetric in up and down markets. While conditioning on months when the stock market falls, they find a high concurrent beta for the small stock portfolio and no significant lagged beta. In the other hand, while conditioning on months when the stock market rises, they find a smaller concurrent beta and a significantly positive lagged beta. Therefore, the small stock betas on both the current and lagged market proxy return exhibit directional asymmetry. This remarkable finding suggests that all stocks, large and small, react quickly to negative macroeconomic news, but that some small stocks adjust to positive news about the economy with a delay. This finding is consistent with the view of Sias and Starks (1994), who observe that herding behavior by institutional investors is related to the delay. Furthermore, McQueen et al. document current and lagged asymmetries from monthly and weekly returns that are consistent with the studies of Lamoureux and Panikkath (1994) who found that cross-sectional dispersion of daily returns is asymmetric between large up and down moves in the market; Chang, Pinegar, and Ravichandran (1994), who found that an asymmetric response to macroeconomic news helps explain day-of- the-week effects; and Grinblatt, Titman, and Wermers (1995) and Keim and Madhavan (1995), who found asymmetric trading patterns by institutional investors.

In contrast to Badrinath, Kale, and Noe (1995), McQueen, Pinegar and Thorley's cross-sectional tests suggest that the delay in small stock responses to large stock movements does not decrease with the fraction of outstanding shares held by institutions; in fact, they point out that the stocks with favored information are more susceptible to delay than those with unfavored information. This is consistent with the findings of Sias and Starks (1994) for one-day cross-autocorrelations and suggests momentum trading similar to that documented by Grinblat, Titman and Wermers (1995). Nevertheless, McQueen et al.'s finding of directional asymmetry implies a tendency to buy past winners but not to sell past losers. Their study on the time series portfolio tests and cross-sectional tests of the delay for individual securities suggests that existing explanations of the cross-autocorrelation puzzle based on data mismeasurement, minor market imperfections, or time-varying risk premiums fail to capture the directional asymmetry in the data.

INTRADAY AUTOCORRELATION OF DAILY INDEX RETURNS

Many previous researchers, Cunningham (1973), Schwartz and Whitcomb (1977), and Scholes and Williams (1977), have shown that time series of daily return indexes calculated using close-to-close returns exhibit considerable first-order autocorrelation. Nevertheless, few researchers have investigated the phenomenon concerning the autocorrelation of market indexes terminating during intraday periods. McInish and Wood (1984) show that the cross-correlation of individual minute-to-minute stock returns are high at the beginning and end of the trading day relative to the interior period. The following proposition made by Cohen et al. (1986, Proposition 3, pp. 119-120) says, *"For portfolios compounded by a large number of positive beta securities, these individual security cross-correlations will lead to positive index serial correlation".*

A study by McInish and Wood (1986) develops a precise measure of thin trading, the time from the last trade in a security to the interval close. This measure is strongly correlated with trading frequency. They argue that this measure is a good proxy for market frictions in general since, as shown by Cohen et al. (1980,1983) and Theobald (1986), actively traded securities have a greater following among security analysts and smaller bid-ask spreads. In the same line of research, Jain and Joh (1988) and McInish and Wood (1989, 1990) state that the number of shares traded and number of trades have U-shaped patterns over the trading day. Thus, thinness would be higher after the open, but prior to the close, since number of shares traded and number of trades are likely inversely correlated with thinness.

Amihud and Mendelson (1987) investigate the first-order autocorrelation of individual stock returns using open-to-open series and close-to-close series. Using and ARMA (1,1) model, these authors find that the opening autocorrelations exhibit higher residual variance and stronger dependence on past returns.

McInish and Wood (1991) examine first-order autocorrelation coefficients of daily equally weighted open-to-open returns, daily equally-weighted intraday-to-intraday returns and daily equally-weighted and value-weighted close-to-close returns. They find that there is no significant difference in the behavior of autocorrelations based on open-to-open returns and 24-hour returns terminating at 10:15 a.m.; therefore, differences in the trading mechanism between the open and the remainder of the trading day do not affect first-order autocorrelation of index returns. Cohen et al. (1986, p. 120, Proposition 4) establish the following: *"A value-weighted market index constructed from observed returns will have smaller serial correlation than a similarly constructed equally weighted market index."* McInish and Wood (1991) proportionate empirical evidence to sustain this proposition and a new corollary to Cohen proposition is developed: *"The serial correlation of an equally-weighted index constructed from observed returns for thin securities will be greater than for a similar index constructed for thicker securities"*. They present empirical evidence to support this corollary.

Another relevant result is that the plot of autocorrelation versus terminal time of the daily-index returns reveals a U-shaped pattern. McInish and Wood (1991) found that daily index autocorrelation is higher at the beginning and end of the trading day than during the interior period. Trading delays can explain only a small part of this intraday pattern in index autocorrelations. This pattern is consistent with findings by Perry (1985) and Atchinson, Butler and Simmonds (1987).

PREDICTABILITY OF SHORT HORIZON STOCK RETURNS AND TRADING VOLUME

There has always been great interest in knowing the role played by trading volume in predicting future stock returns. In a recent study, Chordia and Swaminathan (2000) find that trading volume is a significant determinant of the lead-lag patterns observed in stock returns. They conduct vector autoregressions including pairs of high and low volume portfolio returns. Holding firm size constant, they examine whether lagged high volume portfolio returns can predict current low volume portfolio returns controlling for the predictive power of lagged low volume portfolio returns. They find that high-volume portfolio returns significantly predict low volume portfolio returns. These results show that own autocorrelations and nonsynchronous trading cannot fully explain the observed lead-lag patterns in stock returns, as was implied by Fisher (1966), the study by Scholes and Williams (1977), and the research made by Boudoukh et al. (1994).

In addition to the above conclusions, Chordia and Swaminathan examine the source of these cross-autocorrelations, by conducting Dimson (1979) market model regressions. Their results show that the lead-lag effects are related to the tendency of low-volume stocks to respond more slowly to marketwide information than high-volume stocks. Furthermore, Chordia and Swaminathan use a speed of adjustment measure based on lagged betas from Dimson regressions to examine the ex-ante firms characteristics of a subset of stocks that contribute the most (or the least) to portfolio autocorrelations and cross-autocorrelations. The outcome indicates that there are prominent differences in trading volume across stocks that contribute the most and the least to portfolio autocorrelations and cross-autocorrelations. Particularly, stocks that contribute the most have 30 percent to 50 percent lower trading volume.

The main conclusions of this study are as follows: returns of stocks with high trading volume lead returns of stocks with low trading volume since the high volume stocks adjust faster to marketwide information. This pattern is consistent with the speed of adjustment hypothesis. Therefore, trading volume is a key factor to explain the dissemination of marketwide information. It is worthy to point out that thin trading can explicate some of the lead-lag effects, but it cannot explain all of them. Neither can the lead-lag effects be explained by own autocorrelations.

MAXIMIZING PREDICTABILITY

Recent studies like those of Fama and French (1990) and Ferson and Harvey (1991b) claim that the demonstrable predictability in long-horizon stock-returns indexes is due to business- cycle movements and changes in aggregate-risk premia. Others like DeBondt and Thaler (1985), Lehmann (1990), and Chopra et al. (1992) argue that such predictability is typical of inefficient markets, by which I mean markets occupied with overreacting and irrational investors. Also, there is a growing number of proponents of market timing or tactical-asset allocation, such as the studies made by Clerke et al. (1989), Droms (1989), Hardy (1990), Shilling (1992) and Wagner et al. (1992). Nevertheless, predictability is rarely maximized systematically in the literature.

Chen (1991), Ferson and Harvey (1991a,b, 1993) and Ferson and Korajczyk (1993), among other scientists, use the following two-step procedure to search for predictability in asset returns:

(1) Construct a linear factor model of returns based on cross-sectional explanatory power.
(2) Analyze the predictability of these factors.

This approach is useful when the factors are known, but it is not as informative when the factors are unknown.

Lo and MacKinlay (1997) propose a method to maximize explicitly the predictability in asset returns, by creating portfolios of assets *(Maximally Predictable Portfolio, MPP)* that are the most predictable with respect to a set of ex-ante observable economic variables. In order to disaggregate the source of predictability, they use sector portfolios, market-capitalization portfolios, and stock/bond/utility portfolios, over various holding periods, and find that the sources of maximal predictability reallocate considerably across asset classes and sectors as the horizon changes. For example, when applying a monthly return horizon, the results show that the MPP has a long position in the trade sector and a short position in the durables sector; nevertheless, at an annual return horizon, the MPP shift to a short position in the trade sector and long in the durables.

Lo and MacKinlay (1997) also test the significance of the predictability of the MPP, by using three out-of-sample measures of predictability:

(1) Forecast errors:

In a regression framework they examine the relation between the forecast error of a naïve constant-expected-excess-return model (an unconditional forecast), and a conditional forecast minus the naïve forecast. If excess returns are unpredictable, these quantities should be uncorrelated.

(2) Merton's market-timing measure (Merton 1981):

They use this method to test how predictable is MPP in the context of a simple asset allocation rule.

(3) Profitability of a simple asset allocation rule:

Based on maximizing predictability, they present a profitability calculation for this rule.

They find that the predictability of the MPP is both statistically and economically significant.

CHAPTER THREE

MARKET SEGMENTATION AND EMPIRICAL RESEARCH OF THE MEXICAN STOCK MARKET

LATIN AMERICAN EMERGING MARKETS

Emerging capital markets have been subject of analysis by scientists and practitioners from the finance community. Professional analysts and market practitioners are attracted by these promising economies to get higher-than-average rate of return on investment and diversification of portfolio. Most of the studies on the existent literature have focused on Asia-Pacific countries such as Singapore, Hong-Kong, South Korea. Recently, Eastern Europe is also capturing the attention of many academic researchers and professional investors. In Latin America, such countries as México, Chile, Brazil and Argentina have became attractive for investors who are looking for better returns. Barry and Rodriguez (1997) found that Latin American equity markets have produced high returns relative to other emerging markets during the past two decades. Also, they found high levels of volatility attached to these high returns. Other studies such as Leal and Ratner (1994), and Cabello and Ortiz (1995) have focused on the inefficiencies and on the opportunity for investing in those emerging markets.

The Region has had positive rates of growth; for example, Chile has shown 54.7, Colombia 49.9 and Brazil 27.9 percent cumulative growth from 1981 through 1994. Since 1991, GNP growth has been positive and increasing. Huge flows of capital funds from foreign sources have benefited the Region. Only in 1992, capital transfers to the area amounted to $27.4 billion; nevertheless, the external sector was in deficit and inflation rate for the Region was very high--470.0% in 1992.

In a study about the prospects and problems for an investor, Ghosh and Ortiz (1997) show macroeconomic figures that explain why the Region is far from being homogenous. For example, Argentina and Venezuela have shown paths of both crisis and economic recovery. GDP growth has been 0.82% in annual terms. GDP per capita has fallen by -1.82 % per year, a situation similar to that of Argentina. In contrast to these trends stand the case of Chile and Colombia. Chile's cumulative GNP growth increased 16.6% for the period from 1981 through 1988 period (2.07% per year), and since 1989, GNP has increased almost 7% per year, showing a cumulative increase of 49.9%. The case of Colombia is even more impressive: GNP averaged almost 4% per year (31.96% cumulative), from 1981 through 1988; and GNP per capita increases the average of 3.6% per year from 1981 through 1994.

BACKGROUND

During the post-World War II era in Latin America, different growth policies were implemented; they generally sponsored protectionism and strict controls, resulting on high rate of growth of real gross domestic product along with a decline in exports, high inflation, and a relatively low savings rate. Edwards (1995) explains that regulation created an economic structure that could not react quickly to changing economic conditions. He also points out that large public-sector budgets combined with inefficient tax systems diminished the government's ability to provide social services while producing one of the world's most unequal distributions of wealth. The latter can also be attributed to the large growth in the percentage of foreign debt to gross domestic product during the years leading up to the early 1980s.

DEBT CRISIS

The Debt crisis in Latin America commenced with the announcement by Mexican officials, on August 20, 1982, that Mexico could not meet its international obligations,[1] and drove the passage of regulation and legislation in the U.S. requiring public disclosure by banks of foreign-loan exposure. These regulations were established by both the Securities and Exchange Commission (SEC) and bank supervisory agencies and were also mandated by the International Lending Supervision Act of 1983.

[1] México's Finance Minister Jesús Silva Herzog announced México's inability to repay its foreign loans.

Cornell and Shapiro (1986) and Schoder and Vankudre (in press) examine the U.S. stock market response to the México default announcement, but neither study reports a significant relation between bank stock-market response and Mexican-lending exposure.

Examining the effect on bank valuation on U.S. at the time of the Mexican default, Smirlock and Kaufold (1987) find that, in the absence of disclosure rules, the market was able to discriminate between those banks with extensive Mexican loan portfolios, those with lower levels of exposure, and those with no Mexican exposure; these findings suggest that investors were able to discriminate among banks with different levels of exposure even in the absence of public disclosure regulations.

Barry, Peavy, and Rodriguez (1997) provide returns showing that the Mexican stock market lost about 65 percent of its value from January through July 1982, and that later in August the market had a 9 percent return. The change suggests a positive reaction to Mexico's acknowledging its problems.

The study by Barry et al. supports the notion that equity markets may have anticipated the debt crisis. During this period, Latin America faced the problems arising from a drastic reduction in new foreign loans, high real interest rates on existing foreign debt, and massive capital flying out. Despite expenditure in reducing and switching policies, trade surpluses did not cover interest payments. Some unorthodox stabilization plans were launched. Argentina's Austral Plan, Brazil's Cruzado Plan, Peru's APRA Plan, and the Mexican Pacto. These plans reduced inflation in the very short run, but after only few months, inflation returned to its original (or even higher) level (Edwards 1997). The poor results from these initiatives combined with the history of failed policies and reversals in policies may be the explanation of why we observe high volatility in these emerging markets. Bekaert and Harvey (1997) show that economies that are more open have significantly lower volatilities.

BRADY BONDS AND THE RISK OF DEFAULT

In 1989, U.S. Treasury Secretary Nicholas Brady proposed official support for a reduction in country-debt burdens. Since then, the IMF, World Bank, and other official creditors have granted financial support in the form of partial credit guarantees to nine countries--México among them--in exchange for debt relief from the commercial creditors of these countries. After the introduction of the Brady Plan in 1989, a large share of commercial bank claims were securitized by conversion into bonds. The liquidity and efficiency of the developing-country debt market were improved in a great extent due to this securitization. Trading volumes increased from $1.5 billion in 1985 to more than $200 billion in 1992. Mexican Brady bonds are now one of the most actively traded and most liquid of international bonds.

A great number of researchers have used developing country debt prices as indicators of country repayment capacity. For example Cohen, and Portes (1990) and Boehmer and Megginson (1990) identify the fundamental determinants of repayment capacity by regressing sample of debt prices on a set of variables, such as debt-to-exports ratios, reserves-to-imports ratios or inflation.

Claessens and Pennacchi (1996) point out that market prices of developing country debt incorporate investor's views of country repayment capacity. Indeed, they argue that debt prices are a concave function of repayment capacity and are also affected by the specific terms of their principal and interest payments as well as collaterals. They build a pricing model that takes these factors into account. Applying the model to Brady bonds issued by México, they find that the estimated repayment capacity often performs differently from the unadjusted bond prices.

LATIN AMERICA NEW CONSENSUS

The remarkable growth of the Latin American capital markets began to take place in late 1980s, provoked by economic reforms and financial liberalization policies. The promotion of larger and efficient capital markets as a means to increase domestic savings and attract international resources to their economies--by way of deregulation of investment restrictions and capital remittances to foreign portfolio holders--has caught the attention of global investors. In the present time, the stocks from all listed companies are freely available to foreign investors in the markets from Brazil, Argentina and Colombia. Dividend policy and capital gains is very liberal in these markets. Nevertheless, a few restrictions on entry and repatriation of income and capital gains still exist in Chile, Venezuela and México. In the Mexican case, for instance, twenty-two stocks are actively trading with both restricted series (exclusively for Mexicans) and unrestricted series, causing price premium in these particular stocks and consequently creating market segmentation on the exchange [Domowitz, Glen and Madhavan (1997)].

The success of East Asia's outward-oriented policies, the fall of the Soviet Union, the emergence of a large group of professional economists in the Latin American region, and the relative success of early reformers (Chile and México), are factors leading to the "new Latin America consensus".

The three basic elements related with the new consensus are macroeconomic stability, opening of the external sector to foreign competition, reducing of the state's role in the productive process.

MACROECONOMIC STABILITY

Different efforts were made in order to achieve macroeconomic stability. The policies that prove to be successful include reducing of massive foreign debt, implementing fiscal programs to reduce public sector deficits, establishing exchange rate policies consistent with the anti-inflationary efforts.

The Brady Plan in 1989 was designed to restructure the foreign debt based on its secondary market. In order for a country to participate, it was necessary to show evidence of serious intentions to undertake particular economic reforms. Tax reform, expenditure reduction, and credit policy efforts were implemented in order to accomplish reduction on the public sector deficit.

In the long run, a flexible exchange rate policy is superior to a rigid one. Nevertheless, during the transition to disinflation, the exchange rate may be used as a nominal anchor to guide inflation downward. This policy should be taken carefully to avoid real exchange-rate overvaluation. The December 1994 Mexican peso collapse provides clear evidence of how emerging equity markets react to the problem of exchange rate overvaluation. *Indeed, this collapse was unpredicted by participants in the Mexican stock exchange.* The main cause of the Mexican peso crisis was an unsustainable current account deficit that had been financed by very large capital inflows. This situation was known as the "tequila effects" and affected other neighboring countries (Alford, 1995). Cabello and Ortiz (1995) concluded that the Mexican crisis of 1994 was strongly linked to foreign portfolio investments in the securities markets. Market confidence did not return until after the Mexican government unveiled a tight macroeconomic program.

OPENING OF LATIN AMERICAN MARKETS TO FOREIGN COMPETITION

The debt crisis brought an immediate need to reduce imports, leading to protectionist trade policies. Import tariffs, quotas, and prohibitions increased the cost of imported goods that include intermediate materials used to produce exports. Furthermore, protectionist trade policies perpetuated the existence of inefficient industries. The reduction of nontariff barriers, reduction of import tariffs, reduction or elimination of export taxes characterize recent Latin American trade reforms. Free trade agreements were signed; in particular, the so-called North American Free Trade Agreement (NAFTA) between Canada, United States and México--signed during the Salinas administration--has been recognized as one of the key factors that has led México into higher stages of development.

Because of the integration policies, the market in México became more incorporated with global markets. Consequently, the Mexican Stock Exchange became more correlated with the Dow Jones. The stock exchanges of México and Brazil, for example, have been about to reach the level of a developed market. By late 1994, total market capitalization neared \$130 billion for México and \$189 billion for Brazil (Cabello 1997). The share in market capitalization of the world's emerging markets increased from 3.42% in 1981 to almost 7% by 1992. Their cumulative growth from 1981 to 1994 has been an impressive 318%, although it is still below the average for the emerging markets as a whole.

PRIVATIZATION, DEREGULATION AND STRATEGIC ALLIANCES

Privatization has regulated in positive fiscal impact in the case of México and produced efficiency and welfare gains in a number of cases. The elimination of the state's monopolies increased the offers made for firms being privatized due to reduced uncertainty as a result of knowledge of the environment in which firms operate. Esteban (1997) declares that privatization and merger expansion has contributed to the consolidation of new industrial and financial groups in México, many of them created as a result of higher foreign participation. Furthermore, Esteban finds that the Mexican market reacted efficiently to alliance announcements due to previous undervaluation of stocks, financial performance, and synergy coming from assets and organizational restructuring.

Deregulation and growth of the markets have led to better and more frequent corporate financial disclosures, and fierce competition in brokerage services has brought better services and lower intermediation costs. Also, deregulations of the developed capital markets have induced investors to move into emerging capital markets as an attempt to achieve higher returns. Thus, by 1992, Latin American equity markets experienced both rapid growth and fast internationalization. Market capitalization growth in Buenos Aires stock was the largest of the Region (1,793%) for the period from 1981 through 1994. Venezuela has the smallest market capitalization growth during the same period (168.4%). Ghosh and Ortiz (1997) review and confirm the outstanding growth realized by the Latin American stock markets from 1989 to 1993. They observe that during 1989 and 1990 three Latin American markets were amid the ten best performers in the global economy;

furthermore, in 1991 all six markets have been among the markets yielding the highest returns, but in 1992 only Chile and Colombia joined this top group.

RISK AND RETURN: EVIDENCE FROM THE MEXICAN MARKET

Latin American equity markets have experienced an extraordinary growth in terms of market capitalization, and they offered very attractive rate of returns for the period of 1989 to 1993. In an interesting study made by Soenen and Schrepferman (1997), one can see that based on the coefficient of variation as relative measure of volatility, the U.S. investor has done well in México, Chile, and Colombia in comparison with the domestic U.S. market for the period mentioned above. In their study, the Sharp index shows that, from the U.S. investor's perspective, all Latin American markets (with the exception of Venezuela) outperform the U.S. stock market; nevertheless, authors like Perold and Schulman (1988) and Arnott and Henriksson (1989) observe that under the unhedged basis, foreign stocks are much riskier than those of the U.S. market.

Political and currency risk are central for the investment decision, particularly for foreign investors. The Business Environment Risk Information–BERI–index has been designed to measure political risk of a specific country--the lower the index the higher the risk--Mexico's index is 46 (high-risk); Chile's index for example is 52 (medium-risk) and Argentina's index is 40 (high-risk). Political risk can have a significant impact on stock prices. Companies with significant foreign financing, foreign suppliers and customers are relatively exposed to adverse changes in laws and regulations. The probability of expropriation can differ across industries. An example is the Mexican Banking System that was nationalized in 1982.[2] The study on political risk by Smirlock and Kaufold (1987) shows the significant impact of political and regulatory events on equity values, especially for banks. Furthermore, political and economic reforms may have a negative impact on firms that enjoy monopolies and other kind of privileges. An example is the deregulation of the U.S. airline and banking industries.

If price levels and exchange rates are considerably volatile and cannot be reasonably hedged, then importing (exporting) companies are adversely (favorably) affected by depreciation in the real value of the domestic currency. Their share prices may reflect an ex-ante premium for exchange rate risk. Cervantes (1999) includes exchange rate as one of the factors that explains returns in the Mexican Stock Exchange. He finds that the returns are explained by market index, size, book-to-market equity ratio, momentum and exchange rate.

Shares of firms that are not directly involved in international business may also reflect a currency risk premium due to the impact of exchange-rate changes on foreign competitors, input costs, aggregate demand and other factors that affect cash flows. Brown and Otsuki (1990) find some evidence that exchange-rate fluctuations are a priced factor in cross-sections of national stock-index returns changed to a common currency; nevertheless, there is little evidence that these risks are priced from studies of cross-sections of stock returns

[2] The Mexican Banking System was privatized in the Salinas' administration. Later on it would experience its worst crisis ever and needed to be rescued by the "FOBAPROA" during the Zedillo's administration.

from the same country. In addition Jorion (1990, 1991) reports that some U.S. stocks respond to fluctuations in the trade-weighted value of the dollar, even though exchange rate exposure on average does not earn and ex-ante risk premium.

Bailey and Chung (1995) explore the impact of exposure to exchange rate fluctuations and political risk on stock prices of individual companies from México. They measure the extent to which exposure to these factors (exchange rate risk and political risk) explains cross-sections of returns on individual security and industrial portfolios. They work with a limited data set that is short in length, that has many missing observations, and that sometimes includes data from thinly traded or very volatile stocks. In spite of all these problems typical with all emerging markets data, they find some evidence consistent with time-varying equity-market premiums for exposure to changes in the free market dollar premium and Mexican default risk. Although they find no evidence of unconditional equity market premiums for the currency and political risks, their results suggest common factors in the Mexican Stock Exchange (BMV) and currency markets.

The findings of Bailey and Chung (1995) about premiums for currency and political risks have some practical implications for financial management. In particular, the recent emergence of the MEXDER[3] enables corporations to manage currency and political risks. Futures on the exchange currency, based on interest rate parity, significantly reduced volatility on the pesos-dollar exchange rate in 1995. Futures for December 1999 were quoted at slightly more than eleven pesos per dollar; nevertheless, the peso did not depreciate at the pace established by the interest rate parity. The peso has been fluctuating

[3] Mexican Market for Derivatives

between 9.19 to 10.17 pesos per dollar (inter-banking exchange rate) for the period of January 1999 to December 2000. As of November 2001, the peso shows a quite strong position with a very stable exchange rate of 9.26 pesos per dollar.[4]

Harvey (1995) performs a brilliant analysis of the predictability of the returns in emerging markets. He tests whether adding emerging-markets assets to the portfolio problem significantly shifts the investment opportunity set and finds that the addition of emerging-market assets considerably improves portfolio opportunities. While executing a correlation analysis among emerging markets, he discovers that the average cross-country correlation of the emerging market returns is only twelve percent, whereas another study made by the same author (Harvey 1991) reveals that the average cross-country correlation in seventeen developed markets is forty-one percent for the period of February 1970 to May 1989. Furthermore, astonishingly Brazil has a negative correlation with Argentina, Venezuela, and México.

Harvey also offers evidence that suggests that the emerging markets returns are generally more predictable than the developed market returns. Predictability in emerging markets can be induced by time varying risk exposures since it is strongly influenced by local information. He declares that over half of the predictable variance in the emerging market returns can be attributed to local information, which is consistent with the possibility that some of these countries are segmented from world capital markets.

[4] Source: Banamex.com

De la Uz (2002) finds relative evidence in favor of the martingale hypothesis on the Mexican Stock Exchange. For both indexes IPC and INMEX the martingale hypothesis cannot be rejected; thus, De la Uz concludes that the conventional valuation of contingent claims instruments is valid if the underlying is the IPC or the INMEX; nevertheless, 32% of the total number of stocks fail the martingale hypothesis test. Additionally, the stocks that fail the test show mean aversion. This outcome is very important especially for the market participants, since the level of risk could be under- estimated if volatility is obtained by multiplying the observed volatility times the number of periods.

MARKET SEGMENTATION ON THE MEXICAN STOCK EXCHANGE

Foreign investors in the Mexican market face investment barriers in the form of restrictions on foreign equity ownership. These barriers place limits on the proportion of a firm's equity that foreign investors can hold, inducing capital market segmentation, i.e. different prices for different groups. In the Mexican Stock Exchange, there are several firms that issue multiple classes of the same stock that differentiate between foreigners and domestic traders. Domowitz et al. (1997) observe price premia for unrestricted shares that vary over time and across individual firms. This variation could be the result of differences in the relative valuation of cash flows by domestic and foreign investors. Stulz and Wasserfallen (1995) suggest that the relative scarcity of such shares explain the observed premia. They argue that in order to maximize firm value, companies discriminate between domestic and foreign investors in the presence of differential demands for domestic shares. Price discrimination explains why shares available to foreign investors sell at a premium when the price-elasticity of the aggregate demand from foreign investors exceeds the price-elasticity of the aggregate demand from domestic investors.

Another explanation for the existence of price premia is the variation in market liquidity. Price premia for unrestricted "B" shares reflects the lower transaction costs and greater liquidity relative to the often inactively traded restricted "A" series. Thus, price premia is directly proportional to the relative costs of trading in the "A" and "B" markets. Bid-ask spreads reflect the risks of carrying inventory and adverse selection costs. Both factors are likely to be higher in "A" series stocks were trading is thin and then they create a positive price premium for unrestricted shares.

Domowitz et al. find that firms with stock differentiated by foreign ownership restrictions show average premium that is both statistically and economically significant, suggesting that investment hurdles to foreign ownership are a source of market segmentation. The average price premia varies over their sample period (1990 to 1993), from 4.13 percent for 1990 to 12.44 percent in 1992, before dropping to 9.90 percent in 1993.[5] This trend coincides with the massive interest in emerging markets by foreign investors and the opening of domestic market. Bailey and Jagtiani (1994) report premia for East Asian countries that are considerably higher than the premia found by Domowitz et al. in the Mexican market.

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[5] The estimated premium documented by Stulz and Wasserfallen (1995) for Switzerland is (for all shares) an average of seventy percent from January 1985 to November 1988, falling drastically to forty percent from December 1988 to December 1989. This huge disparity between Switzerland and México is possibly due to differences in risk tolerances between foreign and domestic investors.

The empirical results of Domowitz et al. support the Stulz-Wasserfallen hypothesis, giving emphasis to the relative shortage of unrestricted shares. They find that the price premium for unrestricted stocks is positively related to proxies for foreign demand and is negatively related to the relative supply of unrestricted shares defined as the ratio of unrestricted to total shares outstanding.

As far as the liquidity hypothesis concerns, Domowitz et al. use a proxy to measure relative liquidity in restricted and unrestricted series, i.e. the ratio of unrestricted to total trading volume. They find that relative liquidity cannot explain the time-series and cross-sectional patterns in observed premia. The lack of power on the test suggests that the premia are not the result of differential market liquidity. In addition to those findings, these authors show that segmentation increases with firm capitalization, suggesting that larger companies tend to be chosen by foreign investors and in periods in which foreign opinions about currency risk are optimistic.

The firms that Domowitz et al. analyze have experienced different kind of changes since 1994 due to unifications or because some of them are currently unlisted. Indeed, the so-called "financieros" (financial firms) stocks are not restricted anymore. Currently, all financial firms quote under one single type of series, the "O" series. Foreigners are entitled to own partially or entirely any financial firm; such is the case of Banamex that was totally taken over by Citycorp for twelve billions dollars.

The following is a list up to date of the firms included in DGM research that shows their current status[6]:

CEM CEMEX “A”, “B”. It quotes under one single series: “CPO”.

CIF CIFRA “A”, “B”. Currently it quotes under **WALMEX** “V”, “C”.

CER Internacional de Cerámica “A”, “B”. The series now are: “UB”, “ULD”.

COM Controladora Comercial Mexicana “A”, “B”. Now it is **COMERCI** “UB”,”UBC”.

EPN EPN “A”,”B”. Now it is written off.

FEM Fomento Económico Mexicano “A”,”B”. It is now **FEMSA** “UB”,”UBD”.

KIM Kimberly Clark de México “A”,”B”. No changes

LAT Conductores Latincasa “A”,”B”. It has been written off.

MAS Grupo Industrial Maseca “A”,”B”. Currently there is only one series: “B”.

PON Ponderosa Industrial “A”,”B”. It has been written off.

SID Grupo Sidek “A”,”B”. It is suspended,

SYN Grupo Synkro “A”,”B”. It quotes under series “A”,”C”.

LEGAL FRAMEWORK. “LEY DEL MERCADO DE VALORES”

By all means, it is practically impossible to take over completely a non-financial Mexican firm through the BMV. This is due to the fact that the free float--shares that can be traded, as a percentage of the total number of shares--in most of the cases is less than forty percent.

[6] Source: Banamex-Accival as of August 2001.

The firm that shows the maximum free float is TELMEX with seventy five percent and UNEFON shows the minimum with seven percent.[7]

There is not restriction on the level of free float that a company should have; nevertheless, as one has already seen, there are multiple series of shares in the Mexican market that differentiate between national and foreign investors, with the objective of placing corporate control in the hands of individual Mexican investors. There are six representative series and four compounded or linked series (a combination of two or more representative series). These distinctions are well defined in the so-called "Ley del Mercado de Valores" (Equity Market Law), specifically in its second chapter "Del Registro Nacional de Valores e Intermediarios (National Inscription of Equity and Intermediates), article 17, 17 Bis and 17 Bis1. The series and their characteristics are listed as follows:

REPRESENTATIVE SERIES:

A Limited exclusively to Mexican individuals or Mexican-controlled institutions. They have full voting rights. They must represent the majority of voting shares.

B Free subscriptions (for Mexicans and/or foreigners). Full voting rights, but cannot collectively represent the majority of voting shares.

C For Mexicans and/or foreigners. It has limited voting rights.

L Subscribed for Mexicans and/or foreigners. It has limited voting rights. They function like a preferred stock in the sense that they receive a constant dividend.[8]

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[7] Source: Banamex-Accival.
[8] Source: Article 17 Bis "Ley del Mercado de Valores".

D Non-restricted. They grant special rights to shareholders. They can be converted into another type of series. No voting rights.

V Non-restricted. They are very similar than B series. The “V” stands for “voting”.

COMPOUNDED SERIES:

CPO Certificados de Participacion Ordinaria. They are sets of “A” and “B” series with voting rights that depend on the proportion of “A” to the total.

UB Set of “B” series. “U” stands for units. For example four shares of “B” series compound COMERCI UB. The proportion varies across firms.

UBC Set of “B” and “C” series. Three shares of “B” and one of “C” series compound COMERCI UBC.

UDL Set of “D” and “L” series.

CHAPTER FOUR

FORECASTING MODELS

MATHEMATICAL FRAMEWORK

AUTOCORRELATION MODEL

The model to examine the serial correlation properties of returns of individual securities is developed as follows.

Let $\tilde{R}_{it}$ be the return on security i in month t, which is expressed as

$$\tilde{R}_{it} = E(R_i) + \tilde{\eta}_{it}. \qquad (1)$$

where $E(R_i)$ is the unconditional expected return on security i, and where $\tilde{\eta}_{it}$ is the unexpected return in month t, in an unconditional sense. Consider the following cross-sectional regression model:

$$\tilde{R}_{it} = a_{0t} - \sum_{j=1}^{j=J} a_{jt} R_{it-j} + \tilde{u}_{it}. \qquad (2)$$

The expression for the slope coefficients in the multivariate regression (2) is

$$\begin{bmatrix} a_{1t} \\ \cdot \\ \cdot \\ \cdot \\ a_{Jt} \end{bmatrix} = \begin{bmatrix} \mathrm{cov}_i \begin{Bmatrix} R_{it-1} \\ \\ \\ \cdot \\ R_{it-J} \end{Bmatrix} \end{bmatrix}^{-1} \begin{bmatrix} \mathrm{cov}_i(R_{it,} R_{it-1}) \\ \\ \\ \cdot \\ \mathrm{cov}_i(R_{it}, R_{it-J}) \end{bmatrix}.$$

The subscript under the covariance operator has been included to emphasize that this operation is carried out across the cross-section of stocks. Expand the components of the second term on the right-hand side using equation (1), and take expectations:

$$\mathrm{cov}_i(R_{it}, R_{it-J}) = \mathrm{cov}_i(\eta_{it}, \eta_{it-j}) + \mathrm{var}_i(E(R_i)).$$

The covariance term thus has two components. The first component is the average serial covariance of individual security returns. The second component is the cross-sectional variance of unconditionally expected returns. While the first component will be zero in the absence of serial correlation, the second component will be positive as long as the expected returns vary across the securities in the cross-section.

Consider the following cross-sectional regression:

$$\widetilde{R}_{it} - \overline{R}_i = a_{0t} + \sum_{j=1}^{j=J} a_{jt} R_{it-j} + \widetilde{u}_{it}, \tag{3}$$

here $\overline{R}_i$ is an unbiased estimate of the unconditional expected return of security i obtained from a sample period, which excludes months t - J through t . In this case, the covariance between the dependent variable and the j th independent variable is

$$\text{cov}_i(R_{it} - \overline{R}_i, R_{it-j}) = \text{cov}_i(\eta_{it}, \eta_{it-j}).$$

In equation (3), the slope coefficients will be different from zero only if the security returns are serially correlated. The particular cross-sectional regression model used by Jegadeesh (1990) in his empirical test is

$$\widetilde{R}_{it} - \overline{R}_{it} = a_{0t} + \sum_{j=1}^{j=12} a_{jt} R_{it-j} + a_{13t} R_{it-24} + a_{14t} + R_{it-36} + \widetilde{u}_{it} \tag{4}$$

Here $\overline{R}_{it}$ is the mean monthly return of security i in the sample period t + 1 to t + 60.

MEAN-REVERTING COMPONENTS OF STOCK PRICES

Consider the following model for stock prices:

$$p(t) = q(t) + z(t) \tag{5}$$

$$q(t) = q(t-1) + \mu + \eta(t). \tag{6}$$

where $p(t)$ is the natural log of a stock price at time t. Thus, $p(t)$ is the sum of a random walk, $q(t)$, and a stationary component, $z(t)$; μ is the expected drift and $\eta(t)$ is the white noise. Since $p(t)$ is the natural log of the stock price, the continuously compounded return from t to $t + T$ is

$$r(t,t+T) = p(t+T) - p(t) = [q(t+T) - q(t)] + [z(t+T) - z(t)]\,. \tag{7}$$

The random walk price component produces white noise in returns.

Now the following will show that the stationary price components $z(t)$ causes negative autocorrelation in returns. The slope in the regression of $z(t+T) - z(t)$ on $z(t) - z(t-T)$--in other words the first order autocorrelation of T- period changes in $z(t)$--is

$$\rho(T) = \frac{\operatorname{cov}[z(t+T) - z(t), z(t) - z(t-T)]}{\sigma^2[z(t+T) - z(t)]} \tag{8}$$

the numerator covariance is

$$\operatorname{cov}[z(t+T)-z(t), z(t)-z(t-T)] = -\sigma^2(z) + 2\operatorname{cov}[z(t), z(t+T)] - \operatorname{cov}[z(t), z(t+2T)]. \tag{9}$$

as T increases the covariances on the right of (9) tend to be 0.0 due to the stationarity of $z(t)$, therefore the covariance on the left approches $-\sigma^2(z)$. Indeed, the variance in the denominator of the slope,

$$\sigma^2[z(t+T)-z(t)] = 2\sigma^2(z) - 2\operatorname{cov}[z(t+T), z(t)]. \tag{10}$$

tends to be $2\sigma^2(z)$ as T increases. Therefore from (9) and (10) the slope in the regression of $z(t+T)-z(t)$ on $z(t)-z(t-T)$ on equation (8) approaches - 0.5 for large T.

If $z(t)$ is a first-order autoregression (AR1), the expected change from t to T is

$$E_t[z(t+T)-z(t)] = (\Phi^T - 1)z(t). \tag{11}$$

The covariance in the numerator of $\rho(T)$ is

$$\operatorname{cov}[z(t+T)-z(t), z(t)-z(t-T)] = (-1+2\Phi^T - \Phi^{2T})\sigma^2(z) = -(1-\Phi^T)^2\sigma^2(z). \tag{12}$$

Thus, the covariance is minus the variance of the T-period expected change, $-\sigma^2[E_t z(t+T)-z(t)]$. Therefore, when $z(t)$ is an AR1, the slope in the regression of $z(t+T)-z(t)$ on $z(t)-z(t-T)$ is (minus) the ratio of the variance of the expected change in $z(t)$ to the variance of the actual change. This interpretation of the slope is a valid approximation for any slowly decaying stationary process. Furthermore, for long return horizons, the interpretation of the slope as the proportion of the variance of the change in *z(t)* due to the expected change is valid for any stationary process. If *z(t)* is a stationary process with a zero mean, the expected change from t to T tends to be $-z(t)$ as T increases, and the variance of the expected change approaches $\sigma^2(z)$. The ratio of the long-horizon variance of the expected change in $z(t), \sigma^2(z)$, to the long-horizon variance of the actual change, $2\sigma^2(z)$, is 0.5, in other words, the negative of the long-horizon value of $\rho(T)$.

Equation (11) shows that when Φ is close to 1.0, the expected change in an AR1 slowly approaches $-z(t)$ as T increases. The slope $\rho(T)$ is close to 0.0 for short return horizons and slowly approaches –0.5. Summers (1986) points out that slow mean reversion can be missed with the short return horizon common in market efficiency tests. We will discuss more about these issues on the section: Difficulties with Long Horizon Returns Inferences.

DISCOUNTED PRESENT-VALUE MODEL AND THE LAW OF ITERATED EXPECTATIONS

The idea that efficient security returns should be random has often caused confusion. Underlying this confusion may be a belief that returns cannot be random if security prices are determined by discounting future cash flows. In fact, the discounted present-value model of a security price is entirely consistent with randomness in security returns. Let us define two information sets I_t and J_t, where $I_t \subset J_t$; in other words, the information contained in I_t is also in J_t but J_t is superior because it contains some extra information.

Now, consider expectations of a random variable X conditional on these information sets, $E[X / I_t]$ or $E[X / J_t]$, applying the Law of Iterated Expectations. Thus,

$$E[X / I_t] = E[E[X / J_t] / I_t]. \tag{13}$$

This means, if one has limited information I_t, the best-forecast one can make of a random variable X is the forecast of the forecast that one would make of X if one had superior information J_t. Equation (13) can be rewritten as

$$E[X - E[X / J_t] / I_t] = 0. \tag{14}$$

The above equation has the following interpretation: One cannot use limited information I_t to predict the forecast error that one would make if one had superior information J_t.

Samuelson (1965) showed the relevance of the Law of Iterated Expectations for security market analysis and LeRoy (1989) grants a brilliant review of the argument, which is as follows: suppose that a security price at time t, P_t, can be written as the rational expectation of some supposedly fundamental value V^*, conditional on information I_t available at time t. Thus,

$$P_t = E[V^* / I_t] = E_t V^*. \tag{15}$$

Equation (15) holds one period ahead, therefore,

$$P_{t+1} = E[V^{*} / I_{t+1}] = E_{t+1}V^{*}. \tag{16}$$

The expectation of the change in the price over the next period is

$$E_t[P_{t+1} - P_t] = E_t[E_{t+1}[V^{*}] - E_t[V^{*}]] = 0. \tag{17}$$

because $I_t \subset I_{t+1}$, thus $E_t[E_{t+1}[V^{*}]] = E_t[V^{*}]$ by the Law of Iterated Expectations. *Therefore realized changes in prices are unforecastable, given information in the set* I_t.

LINEAR PRESENT-VALUE RELATION. THE MARTINGALE MODEL OF STOCK PRICES

We say that a sequence of random variables $\{M_n : 0 \le n \le \infty\}$ is a *martingale* with respect to the sequence of random variables $\{X_n : 1 \le n \le \infty\}$, provided that the sequence $\{M_n\}$ has two basic properties. The first property is that for each $n \ge 1$ there is a function $f_n : \Re^n \to \Re$ such that $M_n = f_n(X_1, X_2, ..., X_n)$, and the second property is that the sequence $\{M_n\}$ satisfies the fundamental *martingale identity*:

$$E(M_n \mid X_1, X_2, ..., X_{n-1}) = M_{n-1} \text{ for all } n \ge 1.$$

The notion of a *fair game*, which is neither in your favor nor your opponent's, is the essence of a *martingale,* a stochastic process $\{ P_t \}$ which satisfies the following condition[1]:

$$E[P_{t+1} / P_{t,} P_{t-1},...] = P_t .$$

The martingale hypothesis states that tomorrow's price is expected to be equal to today's price, given the asset's entire price history. Alternately, the asset's expected price change is zero when conditioned on the asset's price history; therefore, its price is just as likely to rise as it is to fall. Such process can be stated as follows:

$$E\left[P_{t+1} - P_t / P_t, P_{t-1},...\right] = 0 .$$

Now assume that the expected stock return is equal to a constant R,

$$E_t[R_{t+1}] = R \ . \tag{18}$$

The definition of the return on a stock (where P = Price and D = Dividend) is

$$R_{t+1} \equiv \frac{P_{t+1} + D_{t+1}}{P_t} - 1 . \tag{19}$$

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[1] In order for the series of P_t to be considered as a Martingale, P_t should be discounted by the rate of growth of the asset.

Taking expectations of the identity (19) and combining (18), one obtains an equation relating the current stock price to the next period's expected stock price and dividend:

$$P_t = E\left[\frac{P_{t+1} + D_{t+1}}{1+R}\right]. \tag{20}$$

The equation (20) is an expectational difference equation that can be solved forward by repeatedly substituting out future prices and using the Law of Iterated Expectations on equation (13), $E_t[E_{t+1}[X]] = E_t[X]$, to eliminate future-dated expectations. Solving forward K periods on equation (20) , one obtains

$$P_t = E_t\left[\sum_{i=1}^{K}\left(\frac{1}{1+R}\right)^i D_{t+i}\right] + E_t\left[\left(\frac{1}{1+R}\right)^K P_{t+K}\right]. \tag{21}$$

The second term on the right side of equation (21) is the expected discounted value of the stock price K periods from the present. As the horizon K increases, this term tends to be zero:

$$\lim_{K\to\infty} E_t\left[\left(\frac{1}{1+R}\right)^K P_{t+K}\right] = 0. \tag{22}$$

Equation (22) will be satisfied unless stock price is expected to grow at rate R or faster. Therefore, the stock price will be a function of the expected present value of future dividends, discounted at a constant rate:

$$P_t = P_{Dt} \equiv E_t\left[\sum_{i=1}^{\infty}\left(\frac{1}{1+R}\right)^i D_{t+1}\right]. \tag{23}$$

GORDON GROWTH MODEL

When Dividends are expected to grow at a constant rate G ($G < R$ to keep the stock price finite), one arrives at this equation:

$$E_t[D_{t+i}] = (1+G)E_t[D_{t+i-1}] = (1+G)^i D_t. \tag{24}$$

Substituting (24) in (23), one obtains the Gordon growth model (Gordon, 1962) for the price of a stock with a constant discount rate R and dividend growth rate G, where $G < R$:

$$P_t = \frac{E_t[D_{t+1}]}{R-G} = \frac{(1+G)D_t}{R-G}. \tag{25}$$

Equation (20) implies that

$$E_t[P_{t+1}] = (1+R)P_t - E_t[D_{t+1}]. \tag{26}$$

One can see that the stock price is not a martingale. To obtain a martingale, one must construct a portfolio for which all dividend payments are reinvested in the stock. At time *t*, this portfolio will have N_t shares of stock, where

$$N_{t+1} = N_t\left(1 + \frac{D_{t+1}}{P_{t+1}}\right). \tag{27}$$

The value of this portfolio at time *t*, discounted to time 0 at rate R, is

$$M_t = \frac{N_t P_t}{(1+R)^t}. \tag{28}$$

where M_t is a Martingale.

Equation (23) can be transformed to a relation between stationary variables, by subtracting a multiple of the dividend from both sides of the equation; thus,

$$P_t - \frac{D_t}{R} = \left(\frac{1}{R}\right) E_t \left[\sum_{i=0}^{\infty} \left(\frac{1}{1+R}\right)^i \Delta D_{t+1+i} \right]. \tag{29}$$

In this case, even though the dividend process is nonstationary and the price process is nonstationary, there is a stationary linear combination of prices and dividends, so that prices and dividends are cointegrated. Even though P_t is not generally a martingale, it will follow a linear process with an *unit root* if the dividend D_t follows a linear process with a unit root.[2] Equation (29) has been explored by Campbell and Shiller (1987), and it seems that stock prices and dividends grow exponentially over time rather than linearly; therefore, a loglinear model is more appropriate than a linear model that allows for a unit root.

DYNAMIC GORDON MODEL. TIME-VARYING EXPECTED RETURNS CASE

The relation between prices and returns becomes nonlinear when expected stock returns are time varying. Campbell and Shiller (1988) have suggested using a loglinear approximation between prices, dividends and returns, in order to calculate asset price behavior under any model of expected returns, rather than just the model with constant expected returns.

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[2] Briefly, a variable follows a process with a unit root, (*integrated process*), if shocks have permanent effects on the level of the variable, but not on the change of the variable. In this particular case, the first difference of the variable is stationary, but the level is not. *A Martingale is a unit-root process where the immediate effect of a shock is the same as the permanent effect.*

The definition of the log stock return r_{t+1} (logs of variables are denoted by lowercase letters) is as follows:

$$r_{t+1} \equiv \log(P_{t+1} + D_{t+1}) - \log(P_t).$$
$$= p_{t+1} - p_t + \log(1 + \exp(d_{t+1} - p_{t+1})). \quad (30)$$

The last term on the right-hand side of equation (30) is a nonlinear function of the log dividend-price ratio, $f(d_{t+1} - p_{t+1})$, that can be approximated around the mean of $x_{t+1}, \bar{x}$, by using a first-order Taylor expansion:

$$f(x_{t+1}) \approx f(\bar{x}) + f'(\bar{x})(x_{t+1} - \bar{x}).$$

Substituting this approximation into (30), one comes up with

$$r_{t+1} \approx k + \rho\, p_{t+1} + (1-\rho)d_{t+1} - p_t. \quad (31)$$

where ρ and k are parameters of linearization defined by

$$\rho \equiv \frac{1}{(1 + \exp(d - p))}. \qquad \text{and} \qquad k \equiv -\log(\rho) - (1-\rho)\log(\frac{1}{\rho} - 1).$$

where *(d – p)* is the average log dividend-price ratio. When the dividend-price ratio is constant, $\rho = 1/(1 + D/P)$, the reciprocal of one plus the dividend-price ratio.

Equation (31) is a linear equation for the log stock price, similar to equation (20) that is a linear difference equation for the level of the stock price, under the assumption of constant expected returns. Solving forward (31) and imposing the following condition,

$$\lim_{j \to \infty} \rho^{j} p_{t+j} = 0 \ ,$$

one finds

$$p_t = \frac{k}{1-\rho} + \sum_{j=0}^{\infty} \rho^{j} \left[(1-\rho) d_{t+1+j} - r_{t+1+j} \right] . \tag{32}$$

Equation (32) is a dynamic accounting identity that shows that, if the stock price is high today, then there must be some combination of high dividends and low stock returns in the future. Equation (32) holds *ex-post*, but it also holds *ex-ante*. Equation (33) takes expectation of equation (32); thus,

$$p_t = \frac{k}{1-\rho} + E_t \left[\sum_{j=0}^{\infty} \rho^{j} [(1-\rho) d_{t+1+j} - r_{t+1+j}] \right] . \tag{33}$$

Note that $p_t = E_t[p_t]$, because p_t is known at time *t*. Equation (33) is a dynamic generalization of the Gordon formula for stock price with constant required returns and dividend growth. Campbell and Shiller (1988) call this equation *dynamic Gordon growth model,* or the *dividend ratio model.* This model says that stock prices are high when dividends are expected to grow rapidly, or when they are discounted at a low rate, taking into consideration how long the dividend growth is expected to be high or how long the discount rate is expected to be low.

Equation (33) can be expressed in terms of the log dividend-price ratio rather than the log stock price:

$$d_t - p_t = -\frac{k}{1-\rho} + E_t\left[\sum_{j=0}^{\infty} \rho^{j}[-\Delta d_{t+1+j} + r_{t+1+j}]\right]. \tag{34}$$

Campbell (1991) use the same approach to write asset returns as linear combinations of revisions in expected future dividends and returns. Substituting (33) in (31), we get

$$\begin{aligned} r_{t+1} - E_t[r_{t+1}] = {} & E_{t+1}\left[\sum_{j=0}^{\infty} \rho^{j} \Delta d_{t+1+j}\right] - E_t\left[\sum_{j=0}^{\infty} \rho^{j} \Delta d_{t+1+j}\right] \\ & - \left(E_{t+1}\left[\sum_{j=1}^{\infty} \rho^{j} r_{t+1+j}\right] - E_t\left[\sum_{j=1}^{\infty} \rho^{j} r_{t+1+j}\right]\right). \end{aligned} \tag{35}$$

Equation (35) shows that unexpected stock returns must be associated with changes in expectations of future dividends or real returns. An increase in expected future dividends is associated with a capital gain today, while an increase in expected future returns is associated with a capital loss today. The latter may seem to be a paradox, but the reason for this apparent contradiction is that, with a given dividend stream, higher future returns can only be generated by future price appreciation from a lower current price.

FORECASTING FUTURE PRICE CHANGES

Forecasting future price changes with the use of only past price changes is still subject of controversy and empirical investigation. To construct a forecast function based on past price changes is considered to be too restrictive; nonetheless, two of the most important ideas in probability theory and financial economics--the martingale and the random walk--both grew out of this exercise.

The martingale hypothesis for an asset's price states that tomorrow's price is expected to be equal to today's price, given the asset's entire price history. Thus,

$$E[P_{t+1} / P_t, P_{t-1}, \ldots] = P_t \ . \qquad (36)$$

Also one can write,

$$E[P_{t+1} - P_t / P_t, P_{t-1}, \ldots] = 0. \qquad (37)$$

which means that the asset's expected price change is zero when conditioned on the asset's price history. The martingale hypothesis implies that the best forecast of tomorrow's price is simply today's price. This characteristic contradicts to the fact that investors are willing to hold an asset and to bear its associated risk due to the expectation for a positive asset's price change. The martingale hypothesis places a restriction on expected returns, but it does not account for risk in any way. Leroy (1973) and Lucas (1978) have showed that the martingale property is neither a necessary nor a sufficient condition for rationally determined asset prices, despite the intuitive appeal that the fair-game interpretation may have. Nonetheless, Lucas (1978), Cox and Ross (1976), and Harrison and Kreps (1979) have pointed out that, once asset returns are properly adjusted for risk, the martingale property does hold. Furthermore, the martingale led to the development of the random walk hypothesis.

RANDOM WALK HYPOTHESIS WITH INDEPENDENT AND IDENTICAL DISTRIBUTED INCREMENTS

Consider the following random walk model with IID (independent and identical distributed) increments,

$$P_t = \mu + P_{t-1} + \varepsilon_t \,, \qquad \varepsilon_t \sim IID(0,\sigma^2)\,. \tag{38}$$

with μ equal to the expected price change or drift, and the increment term ε_t having $IID(0,\sigma^2)$ distribution, i.e. zero mean and variance σ^2. If one assumes normality on the increments, it violates the limited liability condition for prices; i.e., prices cannot be negative. In order to avoid this, let's define a random walk for the logarithm of prices, $p_t \equiv \log P_t$; thus,

$$p_t = \mu + p_{t-1} + \varepsilon_t \,, \qquad \varepsilon_t \; IID\, N(0,\sigma^2)\,. \tag{39}$$

What we have in (39) is the lognormal model of Bachelier (1900) and Einstein (1905), which suggests that continuously compounded returns are *IID* normal variates with mean μ and variance σ^2.

TEST OF RANDOM WALK WITH IID INCREMENTS

Start from the simplest case, in other words with the geometric Brownian motion for the log price p_t without drift:

$$p_t = p_{t-1} + \varepsilon_t,\ \varepsilon_t \sim IID(0, \sigma^2). \tag{40}$$

I_t is the following random variable:

$$I_t = \begin{cases} 1 & \text{if} \quad r_t \equiv p_t - p_{t-1} > 0 \\ 0 & \text{if} \quad r_t \equiv p_t - p_{t-1} \leq 0. \end{cases} \tag{41}$$

where r_t is the continuously compounded return.

Cowles and Jones (1937) proposed to compare the frequency of sequences (pairs of consecutive returns with the same sign) and reversals (pairs of consecutive returns with opposite signs) in historical returns. From a sample of $n+1$ returns $r_1,\ldots,r_{n+1}$, the number of sequences N_S and reversals N_r can be expressed as a function of I_t s:

$$N_S \equiv \sum_{t=1}^{n} Y_t, \qquad Y_t \equiv I_t I_{t+1} + (1-I_t)(1-I_{t+1}). \tag{42}$$

$$N_r \equiv n - N_S. \tag{43}$$

If one assumes that log prices follow a driftless IID random walk described on equation (40) and if one also delimits the model to restrict the increments ε_t to be symmetric, then the Cowles-Jones ratio $\hat{CJ} \equiv N_S / N_r$ should be close to one. If one calls π_S the probability of a sequence and 1-π_S the probability of a reversal, then,

$$\hat{CJ} \equiv \frac{N_S}{N_r} = \frac{N_S / n}{N_r / n} = \frac{\hat{\pi}_S}{1-\hat{\pi}_S} \xrightarrow{pr} \frac{\pi_S}{1-\pi_S} = CJ = \frac{1/2}{1/2} = 1. \tag{44}$$

where $\xrightarrow{pr}$ denotes convergence in probability.

Now consider the case of a random walk with a drift:

$$p_t = \mu + p_t + \varepsilon_t , \qquad \varepsilon_t \sim N(0,\sigma^2) . \tag{45}$$

and

$$I_t = \begin{cases} 1 & \textit{with probability } \pi \\ 0 & \textit{with probability } 1-\pi \end{cases} . \tag{46}$$

where

$$\pi \equiv \Pr(r_t > 0) = \Phi(\mu / \sigma) . \tag{47}$$

It is evident that I_t is biased in the direction of the drift. If the drift μ is positive, then $\pi > 1/2$, and if it is negative, then $\pi < 1/2$.

Under this more general specification, the ratio of π_S to $1-\pi_S$ is now

$$CJ = \frac{\pi^2 + (1-\pi)^2}{2\pi(1-\pi)} \geq 1 . \tag{48}$$

It will always be the case that sequences are more likely than reversals as long as the drift is nonzero, since probability of a sequence is $\hat{\pi}_S = \hat{\pi}^2 + (1-\hat{\pi})^2$.

To develop a sample theory for the estimator $\hat{CJ}$ I start from equation (42) and note that the estimator N_S is a binomial random variable; more specifically, it is the sum of *n Bernoulli* random variables Y_t where

$$Y_t = \begin{cases} \mathbf{1} \;\; \textit{with probability} \;\; \pi_S = \pi^2 + (1-\pi)^2; \\ \mathbf{0} \;\; \textit{with probability} \;\; 1-\pi_S \end{cases}$$

When n is large, the distribution of N_S can be approximated to a normal distribution with mean $E[N_S] = n\pi_S$ and variance $Var[N_S]$. Due to the fact that Y_t is a two-state Markov chain with probabilities-- $\Pr(Y_t = 1 / Y_{t-1} = 1) = (p^3 + (1-p)^3) / p_S$ and $\Pr(Y_t = 0 / Y_{t-1} = 0) = 1/2$ --then the variance of N_S is the following:

$$\begin{aligned} Var[N_S] &= n\pi_S(1-\pi_S) + 2\,n\,Cov[Y_t, Y_{t+1}] \\ &= n\pi_S(1-\pi_S) + 2(\pi^3 + (1-\pi)^3 - \pi_S^2). \end{aligned} \tag{49}$$

Because it is of interest, review the first-order Taylor approximation, or the delta method as it is called, which states the following: given an estimator $\hat{\theta}$, and if $\sqrt{T}\left(f(\hat{\theta}) - f(\theta)\right) \overset{a}{\sim} N(0, V_\theta)$, where $\overset{a}{\sim}$ indicates that the distribution relation is asymptotic, then a nonlinear function $f(\hat{\theta})$ has the subsequent asymptotic distribution:

$$\sqrt{T}\left(f(\hat{\theta}) - f(\theta)\right) \overset{a}{\sim} N(0, V_f), \qquad V_f \equiv \frac{\partial f}{\partial \theta'} V_\theta \frac{\partial f}{\partial \theta} \tag{50}$$

The distribution follows from a first-order Taylor-series approximation for $f(\theta)$ around θ_0. Notice that only the first term of the expansion matters for the asymptotic distribution of $f(\hat{\theta})$, because higher-order terms converge to zero faster than $1/\sqrt{T}$.

By definition $\hat{CJ} = N_S/(n - N_S)$, and when one applies a first-order Taylor approximation to $\hat{CJ}$ and uses the normal asymptotic approximation for the distribution of N_S, one arrives at

$$\hat{CJ} \overset{a}{\sim} N\left(\frac{\pi_S}{1-\pi_S}, \frac{\pi_S(1-\pi_S) + 2(\pi^3 + (1-\pi)^3 - \pi_S^2)}{n(1-\pi_S)^4}\right). \tag{51}$$

THE RANDOM WALK WITH UNCORRELATED INCREMENTS

The random walk model described in equation (39) is not a plausible one when it comes to applying it to describe the characteristics of the increments for returns on prices in the financial markets. The assumption of having the same probability law for the distribution of the increments (identical distributed) for a particular period of time stock returns is virtually impossible to achieve in reality, especially over long time spans. Therefore, we are going to relax the assumption of having identical and independent increments to include processes with dependent but uncorrelated increments. This case is the weakest form of the random walk hypothesis, and one way to test it for an individual time series is to check for serial correlation, which is the correlation between two observations of the same series at different dates, also referred as autocorrelation with different lags.

AUTOCORRELATION COEFFICIENTS.

The well-known definition of the correlation coefficient between two random variables x and y is as follows:

$$Corr[x,y] \equiv \frac{Cov[x,y]}{\sqrt{Var[x]}\sqrt{Var[y]}}. \tag{52}$$

The autocorrelation coefficient is a time-series extension of the expression (52). Given a covariance-stationary time series $\{r_t\}$, the kth order autocovariance ($\gamma(k)$) and autocorrelation ($\rho(k)$) coefficients[3] are defined as

$$\gamma(k) \equiv Cov[r_t, r_{t+k}] \tag{53}$$

$$\rho(k) \equiv \frac{Cov[r_t, r_{t+k}]}{\sqrt{Var[r_t]}\sqrt{Var[r_{t+k}]}} = \frac{Cov[r_t, r_{t+k}]}{Var[r_t]} = \frac{\gamma(k)}{\gamma(0)}. \tag{54}$$

Due to the covariance-stationarity of $\{r_t\}$, one arrives at $\sqrt{Var[r_t]}\sqrt{Var[r_{t+k}]} = Var[r_t]$.

[3] Our request for a covariance-stationary process is just for notational convenience. Otherwise $\gamma(k)$ and $\rho(k)$ may be functions of t as well as k, and may not be well defined if second moments are not finite.

The autocovariance and autocorrelation coefficient might be estimated by replacing population moments with sample counterparts. For a given sample $\{r_t\}_{t=1}^{T}$,

$$\hat{\gamma}(k) = \frac{1}{T}\sum_{t=1}^{T-k}(r_t - \bar{r}_T)(r_{t+k} - \bar{r}_T), \qquad 0 \le k < T. \tag{55}$$

$$\hat{\rho}(k) = \frac{\hat{\gamma}(k)}{\hat{\gamma}(0)} \tag{56}$$

$$\bar{r}_T \equiv \frac{1}{T}\sum_{t=1}^{T} r_t \ . \tag{57}$$

If r_t is a finite-order moving average,

$$r_t = \sum_{k=0}^{M} \alpha_k \varepsilon_{t-k} \ ,$$

Fuller (1976, Theorem 6.3.5) shows that the vector of autocovariance coefficient estimators is asymptotically multivariate normal, under the following conditions: $\{\varepsilon_t\}$ is an independent sequence with mean 0, variance σ^2, fourth moment $\eta\sigma^4$, and finite sixth moment. Thus,

$$\sqrt{T}\left[\hat{\gamma}(0) - \gamma(0) \quad \hat{\gamma}(1) - \gamma(1) \quad \ldots \quad \hat{\gamma}(m) - \gamma(m)\right]' \overset{a}{\sim} N(0, \mathbf{V}), \tag{58}$$

$$\mathbf{V} = [v_{ij}]$$

$$v_{ij} \equiv (\eta - 3)\gamma(i)\gamma(j) + \sum_{\ell=-\infty}^{\infty}\left[\gamma(\ell)\gamma(\ell - i + j) + \gamma(\ell + j)\gamma(\ell - i)\right]. \tag{59}$$

Under the same conditions established for $\{\varepsilon_t\}$, Fuller (1976, Corollary 6.3.5.1) demonstrates that the asymptotic distribution of the vector of autocorrelation coefficient estimators is also multivariate normal:

$$\sqrt{T}\left[\hat{\rho}(0)-\rho(0) \quad \hat{\rho}(1)-\rho(1) \quad \ldots \quad \hat{\rho}(m)-\rho(m)\right]' \overset{a}{\sim} N(0,\mathbf{G}), \tag{60}$$

where

$$\mathbf{G}=[g_{ij}]$$

$$g_{ij} \equiv \sum_{\ell=-\infty}^{\infty}[\rho(\ell)\rho(\ell-i+j)+\rho(\ell+j)\rho(\ell-i)-2\rho(j)\rho(\ell)\rho(\ell-i)$$
$$-2\rho(i)\rho(\ell)\rho(\ell-j)+2\rho(i)\rho(j)\rho^2(\ell)]. \tag{61}$$

If $\{r_t\}$ is a random walk with IID increments (therefore all the population autocovariances are zero); and has variance σ^2 and sixth moment proportional to σ^6, then

$$E[\hat{\rho}(k)]=-\frac{T-k}{T(T-1)}+O(T^{-2}) \tag{62}$$

$$Cov[\hat{\rho}(k),\hat{\rho}(\ell)]=\begin{cases}\dfrac{T-k}{T^2}+O(T^{-2}) & \text{if } k=\ell\neq 0\\ O(T^{-2}) & \text{otherwise.}\end{cases} \tag{63}$$

Under the random walk hypothesis with IID increments ($\rho(k)=0$ for all k>0), one can see from equation (62) that the sample autocorrelation coefficients $\hat{\rho}(k)$ are negatively biased. The explanation for this is the following: autocorrelation coefficient is a scaled sum of cross-products of deviations of r_t from its mean, which can be estimated by the sample mean (equation 57). Nonetheless, by construction, deviations from the sample mean sum zero; these positive deviations must be followed by negative deviations on average and vice versa, and therefore the expected value of cross-products of deviations is negative. Fuller (1976) proposes the following bias-corrected estimator $\tilde{\rho}(k)$:

$$\tilde{\rho}(k) = \hat{\rho}(k) + \frac{T-k}{(T-1)^2}\left(1-\hat{\rho}^2(k)\right) . \tag{64}$$

which is the expected value for the bias-corrected estimator equal to

$$E[\tilde{\rho}(k)] = O(T^{-2}) . \tag{65}$$

Furthermore, Fuller (1976) shows that if $\{r_t\}$ has uniformly bounded sixth moments, the sample autocorrelation coefficients are asymptotically independent and normally distributed, as follows

$$\sqrt{T}\hat{\rho}(k) \overset{a}{\sim} N(0,1) \tag{66}$$

$$\frac{T}{\sqrt{T-k}}\tilde{\rho}(k) \overset{a}{\sim} N(0,1) . \tag{67}$$

STATISTIC TESTS FOR AUTOCORRELATIONS

The random walk hypothesis with IID increments implies that all autocorrelations are zero. A test statistic of such hypothesis is the Q-statistic by Box and Pierce (1970):

$$Q_m \equiv T\sum_{k=1}^{m}\rho^2(k). \qquad (68)$$

With the use of expression (66) and under the random walk (with IID increments) null hypothesis, thus the estimator $\hat{Q}_m = T\sum_{k=1}^{m}\hat{\rho}(k)$ is asymptotically distributed as χ^2_m. Ljung and Box (1978) give the following finite-sample correction which yields a better fit to the χ^2_m for small sample sizes:

$$Q'_m \equiv T(T+2)\sum_{k=1}^{m}\frac{\rho^2(k)}{T-k}. \qquad (69)$$

RATIOS ON THE VARIANCE

Many studies--such as those of Campbell and Mankiw(1987), Lo and MacKinlay (1988), Poterba and Summers (1988), and Richardson (1993)--have exploited an important property of all random-walk hypotheses: the variance of random-walk increments must be a linear function of the time interval.

Consider the following example for the ratio of the variance of a two period continuously compounded return $r_t(2) \equiv r_t + r_{t-1}$ to twice the variance of a one period return r_t:

$$VR(2) = \frac{Var[r_t(2)]}{2\,Var[r_t]} = \frac{Var[r_t + r_{t-1}]}{2\,Var[r_t]}$$

$$= \frac{2\,Var[r_t] + 2\,Cov[r_t, r_{t-1}]}{2\,Var[r_t]}$$

$$VR(2) = 1 + 2\rho(1)\,, \tag{70}$$

where $\rho(1)$ is the first order autocorrelation coefficient of the returns $\{r_t\}$. If increments are IID, then the autocorrelations are zero and then VR(2) will be equal to one.

The general q-period variance ratio statistic VR(q) will be

$$VR(q) \equiv \frac{Var[r_t(q)]}{q\,.Var[r_t]} = 1 + 2\sum_{k=1}^{q-1}\left(1 - \frac{k}{q}\right)\rho(k)\,, \tag{71}$$

where $r_t(k) \equiv r_t + r_{t-1} + \,...\, + r_{t-k+1}$ and $\rho(k)$ is the kth order autocorrelation coefficient of $\{r_t\}$.

For example if q=5, then one applies equation (71) to arrive at

$$VR(5) = 1 + \frac{4}{5}\rho(1) + \frac{3}{5}\rho(2) + \frac{2}{5}\rho(3) + \frac{1}{5}\rho(4)\,.$$

which is a linear combination of the first k-1 autocorrelation coefficients of $\{r_t\}$with linearly declining weights. Indeed, for all q, $VR(q)=1$, since for IID increments, all autocorrelation coefficients must be zero.

SAMPLING DISTRIBUTION FOR THE VARIANCE RATIO ($\hat{V}R(q)$) AND VARIANCE DIFFERENCE ($\hat{V}D(q)$)

Lo and MacKinlay (1988) develop the following exposition to construct a statistical test for the case of a random walk with IID increments. Under the same notation that I have defined, p_t denotes log-price process, and $r_t \equiv p_t - p_{t-1}$ denotes continuously compounded returns. The null hypothesis is

$$H_o: \qquad r_t = \mu + \varepsilon_t, \qquad \varepsilon_t \; IID \; N(0,\sigma^2).$$

For convenience the number of observation is established to be equal to $2n+1$ i.e. the log prices set is $\{p_0, p_1,..., p_{2n}\}$. Thus, the estimators for the mean and variance are

$$\hat{\mu} \equiv \frac{1}{2n}\sum_{k=1}^{2n}(p_k - p_{k-1}) = \frac{1}{2n}(p_{2n} - p_0) \tag{72}$$

$$\hat{\sigma}_a^2 \equiv \frac{1}{2n}\sum_{k=1}^{2n}(p_k - p_{k-1} - \hat{\mu})^2 \tag{73}$$

$$\hat{\sigma}_b^2 \equiv \frac{1}{2n}\sum_{k=1}^{n}(p_{2k} - p_{2k-2} - 2\hat{\mu})^2 . \tag{74}$$

Equations (72) and (73) are the maximum-likelihood estimators of μ and σ^2. Equation (74) is also an estimator of σ^2 but exploits the fact that mean and variance of increments are linear; thus, variance can be estimated by one half the sample variance of the increments of even-numbered observations $\{p_0, p_2, p_4, \ldots, p_{2n}\}$.

Stuart and Ord (1987) show that the distribution of $\hat{\sigma}_a^2$ and $\hat{\sigma}_b^2$ have the following normal limiting distributions:

$$\sqrt{2n}\,(\hat{\sigma}_a^2 - \sigma^2) \overset{a}{\sim} N(0, 2\sigma^4) \tag{75}$$

$$\sqrt{2n}\,(\hat{\sigma}_b^2 - \sigma^2) \overset{a}{\sim} N(0, 4\sigma^4). \tag{76}$$

In order to find the limiting distribution of the ratio of the variances, one can use Hausman's (1978) conclusion that the asymptotic variance of the difference of a consistent estimator and that an asymptotically efficient estimator is the difference of the asymptotic variances. This conclusion comes from the fact that any asymptotically efficient estimator of a parameter θ--say $\hat{\theta}_e$--has the property that it is asymptotically uncorrelated with the difference $\hat{\theta}_a - \hat{\theta}_e$, with $\hat{\theta}_a$ another estimator of θ. If not, then there is a linear combination of $\hat{\theta}_e$ and $\hat{\theta}_a - \hat{\theta}_e$ that is more efficient than $\hat{\theta}_e$, contradicting the assumed efficiency of $\hat{\theta}_e$.

The latter can be explained by the following:

$$aVar[\hat{\theta}_a] = aVar[\hat{\theta}_e + \hat{\theta}_a - \hat{\theta}_e] = aVar[\hat{\theta}_e] + aVar[\hat{\theta}_a - \hat{\theta}_e]$$

$$\Rightarrow \quad aVar[\hat{\theta}_a - \hat{\theta}_e] = aVar[\hat{\theta}_a] - aVar[\hat{\theta}_e], \qquad (77)$$

where $aVar[.]$ denotes the asymptotic variance operator.

Now, I will define the variance difference estimator as $\hat{V}D(2) \equiv \hat{\sigma}_b^2 - \hat{\sigma}_a^2$, and apply equations (75), (76) and Hausman's conclusion (77); thus,

$$\sqrt{2n}\,\hat{V}D(2) \overset{a}{\sim} N(0, 2\sigma^4). \qquad (78)$$

Therefore, the null hypothesis H_0 can be tested by using (78) and a consistent estimator $2\hat{\sigma}^4$ of $2\sigma^4$ such as $2(\hat{\sigma}_a^2)^2$.

As for the variance ratio statistic concerns, its asymptotic distribution of the two period variance ratio $\hat{V}R(2) = \hat{\sigma}_b^2 / \hat{\sigma}_a^2$ comes directly from equation (78), and after applying a first-order Taylor approximation, one arrives at

$$\hat{V}R(2) \equiv \hat{\sigma}_b^2 / \hat{\sigma}_a^2, \qquad \sqrt{2n}\,(\hat{V}R(2) - 1) \overset{a}{\sim} N(0, 2). \qquad (79)$$

Similarly, as in the case for the null hypothesis tested with the variance difference, the null hypothesis H_0 can be tested with the variance ratio by using (79) standardized, i.e. $\sqrt{2n}\,(\hat{V}R(2)-1)/\sqrt{2}$ which is asymptotically standard normal. However, we have to point out that both test statistics (variance difference and variance ratio) are equivalent. For example, if $2(\hat{\sigma}_a^2)^2$ is used to estimate $2\sigma^4$, then both tests ($VD=0$ or $VR-1=0$) will yield the same inferences because

$$\frac{\hat{V}D(2)}{\sqrt{2\hat{\sigma}_a^4}} = \frac{\hat{\sigma}_b^2-\hat{\sigma}_a^2}{\sqrt{2}\hat{\sigma}_a^2} = \frac{\hat{V}R(2)-1}{\sqrt{2}} \overset{a}{\sim} N(0,1)\,. \tag{80}$$

GENERAL CASE FOR $\hat{V}R(q)$ AND $\hat{V}D(q)$ STATISTIC: MULTIPERIOD RETURNS

One can expand the sample to be compounded by $nq+1$ observations $\{p_0, p_1, \ldots, p_{nq}\}$, where q is an integer greater than one, in which case the estimators are defined as follows:

$$\hat{\mu} \equiv \frac{1}{nq}\sum_{k=1}^{nq}(p_k - p_{k-1}) = \frac{1}{nq}(p_{nq} - p_0) \tag{81}$$

$$\hat{\sigma}_a^2 \equiv \frac{1}{nq}\sum_{k=1}^{nq}(p_k - p_{k-1} - \hat{\mu})^2 \tag{82}$$

$$\hat{\sigma}_b^2(q) \equiv \frac{1}{nq}\sum_{k=1}^{n}(p_{qk} - p_{qk-q} - q\hat{\mu})^2 \tag{83}$$

$$\hat{V}D(q) \equiv \hat{\sigma}_b^2(q) - \hat{\sigma}_a^2 \tag{84}$$

$$\hat{V}R(q) \equiv \frac{\hat{\sigma}_b^2(q)}{\hat{\sigma}_a^2}. \tag{85}$$

Similarly, as in the case of *2n* + 1 observations for the case of $2q + 1$ observations, the asymptotic distributions of $\hat{V}D(q)$ and $\hat{V}R(q)$ (under the null hypothesis of random walk with IID increments) are

$$\sqrt{nq}\,\hat{V}D(q) \overset{a}{\sim} N\left(0, 2(q-1)\sigma^4\right) \tag{86}$$

$$\sqrt{nq}\,(\hat{V}R(q) - 1) \overset{q}{\sim} N\left(0, 2(q-1)\right) \tag{87}$$

REFINEMENTS ON THE STATISTICS. OVERLAPPING PERIODS AND CORRECTION FOR BIAS

If we use overlapping q-period returns, we shall have a more efficient estimator and thus a more powerful test, as the one used on Lo and MacKinlay (1989).

The following estimator contains $nq-q+1$ elements (whereas $\hat{\sigma}_b^2(q)$ contains only n terms):

$$\hat{\sigma}_c^2(q) = \frac{1}{nq^2}\sum_{k=q}^{nq}(p_k - p_{k-q} - q\hat{\mu})^2 . \tag{88}$$

Correcting the bias in the variance estimators (we denote them as $\bar{\sigma}_a^2$ and $\bar{\sigma}_c^2(q)$) before performing the division one by the other:

$$\bar{\sigma}_a^2 = \frac{1}{nq-1}\sum_{k=1}^{nq}(p_k - p_{k-1} - \hat{\mu})^2 \tag{89}$$

$$\bar{\sigma}_c^2(q) = \frac{1}{m}\sum_{k=q}^{nq}(p_k - p_{k-q} - q\hat{\mu})^2 \tag{90}$$

$$m \equiv q(nq-q+1)\left(1-\frac{q}{nq}\right). \tag{91}$$

The refined statistics are[4]

$$\overline{VD}(q) \equiv \bar{\sigma}_c^2(q) - \bar{\sigma}_a^2 , \tag{92}$$

$$\overline{VR}(q) \equiv \frac{\bar{\sigma}_c^2(q)}{\bar{\sigma}_a^2}. \tag{93}$$

[4] Simulation experiments in Lo and MacKinlay (1989) report that finite-sample properties of $\overline{VR(q)}$ are closer to their asymptotic limits than $\hat{V}R(q)$.

The asymptotic distributions of the variance difference and variance ratio are the following:

$$\overline{VD}(q) \overset{a}{\sim} N\left(0, \frac{2(2q-1)(q-1)}{3q}\sigma^4\right) \tag{94}$$

$$\sqrt{nq}\left(\overline{VR}(q)-1\right) \overset{a}{\sim} N\left(0, \frac{2(2q-1)(q-1)}{3q}\right). \tag{95}$$

Similarly as in equation (80), the above statistics can be standardized to yield asymptotically standard normal test statistics. Let σ^4 be estimated by $\overline{\sigma}_a^4$:

$$\psi(q) \equiv \sqrt{nq}(\overline{VR}(q)-1)\left(\frac{2(2q-1)(q-1)}{3q}\right)^{-1/2}$$

$$= \frac{\sqrt{nq}\,\overline{VD}(q)}{\sqrt{\overline{\sigma}_a^4}}\left(\frac{2(2q-1)(q-1)}{3q}\right)^{-1/2} \overset{a}{\sim} N(0,1). \tag{96}$$

HETEROSKEDASTICITY-CONSISTENT ESTIMATOR UNDER UNCORRELATED INCREMENTS

Since volatility changes over time (heteroskedasticity), we should change our statement of the null hypothesis to account for general forms of heteroskedasticity. Following Lo and MacKinlay (1988), let $r_t = \mu + \varepsilon_t$, and define the following null hypothesis H_0^*:

(H1) For all t, $E[\varepsilon_t] = 0$, and $E[\varepsilon_t \varepsilon_{t-\tau}] = 0$ for any $\tau \neq 0$.

This condition is the uncorrelated increments property of the random walk.

(H2) $\{\varepsilon_t\}$is φ-mixing with coefficients $\varphi(m)$ of size $r/(2r-1)$ or is α-mixing with coefficients $\alpha(m)$ of size $r/(r-1)$, where $r>1$. In this case, for all t and for any $\tau \geq 0$, there exists some $\delta > 0$ for which $E[|\varepsilon_t \varepsilon_{t-\tau}|^{2(r+\delta)}] < \Delta < \infty$.

(H3) $\lim\limits_{nq \to \infty} \dfrac{1}{nq} \sum\limits_{t=1}^{nq} E[\varepsilon_t^2] = \sigma^2 < \infty$.

Condition H1 and H3 are restrictions on the maximum degree of dependence and heterogeneity, while still permitting some form of the Law of Large Numbers and the Central Limit Theorem, (White 1984).

(H4) For all t, $E[\varepsilon_t \varepsilon_{t-j} \varepsilon_t \varepsilon_{t-k}] = 0$ for any nonzero j and k where $j \neq k$.

The above condition implies that the sample autocorrelations of $\varepsilon_t$are asymptotically uncorrelated.

The assumption over log prices p_t now is that they have uncorrelated increments but still allow for general forms of heteroskedasticity--i.e. deterministic changes in the variance and Engel's (1982) autoregressive conditionally heteroskedastic process (ARCH)--which means that the conditional variance depends on past information.

Lo and MacKinlay (1988) show that:

$$\overline{VR}(q) \stackrel{a}{=} 1+2\sum_{k=1}^{q-1}\left(1-\frac{k}{q}\right)\hat{\rho}(k). \tag{97}$$

The above expression holds asymptotically under quite general conditions, and the autocorrelation coefficient estimators $\hat{\rho}(k)$ are asymptotically uncorrelated under the null hypothesis condition H4, then the statistics $\overline{VD}(q)$, and $\overline{VR}(q)-1$ converge almost surely to zero for all q as n increases without bound.

Defined by Lo and MacKinlay (1988), the heteroskedasticity-consistent estimator of δ_k is

$$\hat{\delta}_k = \frac{nq\sum_{j=k+1}^{nq}(p_j - p_{j-1} - \hat{\mu})^2(p_{j-k} - p_{j-k-1} - \hat{\mu})^2}{\left[\sum_{j=1}^{nq}(p_j - p_{j-1} - \hat{\mu})^2\right]^2}. \tag{98}$$

and the heteroskedasticity-consistent estimator of $\theta(q)$ will be equal to

$$\hat{\theta}(q) \equiv 4\sum_{k=1}^{q-1}\left(1-\frac{k}{q}\right)^2 \hat{\delta}_k. \tag{99}$$

The standardized test statistic $\psi^*(q)$ can be used to test H_0^*, in spite of the presence of general heteroskedasticity:

$$\psi^*(q) = \frac{\sqrt{nq}\ (\overline{VR}(q)-1)}{\sqrt{\hat{\theta}}} \overset{a}{\sim} N(0,1). \tag{100}$$

DIFFICULTIES WITH LONG HORIZON RETURNS INFERENCES

We have defined in equation (5) and (6) (in section, Mean-Reverting component of Stock Prices) the model proposed by Muth (1960) about the composition of log prices. The first part is a random walk that describes the fundamental component of the price (the efficient market price) and the other part is a zero-mean stationary component that reflects transitory deviation from its fundamentals. The model is as follows:

$$\begin{aligned} p_t &= w_t + y_t \\ w_t &= \mu + w_{t-1} + \varepsilon_t, \qquad\qquad \varepsilon_t \sim IID(0,\sigma^2) \\ y_t &= \text{any zero - mean stationary process.} \end{aligned} \tag{101}$$

being $\{w_t\}$ and $\{y_t\}$ mutually independent.

One problem that may arise from this model is about the definition of y_t. Since y_t is stationary, it is therefore mean-reverting by definition and reverts to its mean of zero in the long run. This construction may affect the behavior of $VR(q)$, for small q. Nevertheless as q increases the behavior of $VR(q)$ becomes less arbitrary. Observe the following:

$$r_t \equiv p_t - p_{t-1} = \mu + \varepsilon_t + y_t - y_{t-1} \tag{102}$$

$$r_t(q) \equiv \sum_{j=0}^{q-1} r_{t-j} = q\mu + \sum_{k=0}^{q-1} \varepsilon_{t-k} + y_t - y_{t-q} \tag{103}$$

$$Var[r_t(q)] = q\sigma^2 + 2\gamma_y(0) - 2\gamma_y(q), \tag{104}$$

where $\gamma_y(q) \equiv Cov[y_t, y_{t+q}]$ the autocovariance function of y_t.

For this particular case, the population value of the variance ratio is now

$$VR(q) = \frac{Var[r_t(q)]}{qVar[r_t} = \frac{q\sigma^2 + 2\gamma_y(0) - 2\gamma_y(q)}{q(\sigma^2 + 2\gamma_y(0) - 2\gamma_y(1))} \tag{105}$$

$$\rightarrow \frac{\sigma^2}{\sigma^2 + 2\gamma_y(0) - 2\gamma_y(1)} \text{ as } q \rightarrow \infty \tag{106}$$

$$= 1 - \frac{2\gamma_y(0) - 2\gamma_y(1)}{\sigma^2 + 2\gamma_y(0) - 2\gamma_y(1)}$$

$$= 1 - \frac{Var[\Delta_y]}{Var[\Delta_y] + Var[\Delta_w]}$$

$$VR(q) \rightarrow 1 - \frac{Var[\Delta_y]}{Var[\Delta_p]}, \tag{107}$$

In equation (106), I make the plausible assumption that $\gamma_y(q) \to 0$ as $q \to \infty$, which is an asymptotic independence condition implied by ergodicity.

However, when q is large relative to the total time span T = nq, the asymptotic approximation don't hold. An illustration about this may be obtained by performing an alternate asymptotic analysis, one in which q grows with T so that $q(T)/T$ approaches some limit δ strictly between zero and one. Richardson and Stock (1989) show that the unnormalized variance ratio $\hat{V}R(q)$ converges in distribution to

$$\hat{V}R(q) \xrightarrow{d} \frac{1}{\delta} \int_{\delta}^{1} X_{\delta}^{2}(\tau)\, d\tau \tag{108}$$

$$X_{\delta}(\tau) \equiv B(\tau) - B(\tau - \delta) - \delta\, B(1), \tag{109}$$

where $B(.)$ means standard Brownian motion defined on the unit interval. The expected value of (108) is

$$E\left[\frac{1}{\delta} \int_{\delta}^{1} X_{\delta}^{2}(\tau)\, d\,\tau\right] = \frac{1}{\delta} \int_{\delta}^{1} E[X_{\delta}^{2}(\tau)]\, d\,\tau = (1-\delta)^{2}\,. \tag{110}$$

Nevertheless, equation (108) offers an estimator, which is biased. But these biases are not unexpected. In spectral analysis, this will be the same as estimating the spectral-density function near frequency zero that corresponds to extremely long periods, making extraordinarily difficult to formulate inferences about periodicities that exceed the span of the data.

MAXIMALLY PREDICTABLE PORTFOLIO (MPP)

The common approach when investigating predictability in asset returns is to follow a two-step procedure: (1) Construct a linear-factor model of returns based on cross-sectional explanatory power; (2) Analyze the predictability of these factors. Several research studies have followed this two-step procedure (Chen 1991; Ferson and Harvey 1991a, 1991b, 1993; Ferson and Korajczyk 1993). This approach is useful when the factors are known, but it may not be as informative when the factors are unknown. It is possible that the set of factors that best explains the cross-sectional variation in expected returns is relatively unpredictable.

Consider two assets, A and B, which satisfy a linear two-factor model. In particular, let $\mathbf{R}_t$ denote the (2×1) vector of de-meaned asset returns $[R_{at} \;\; R_{bt}]'$ and suppose that:

$$\mathbf{R}_t = \boldsymbol{\delta}_1 F_{1t} + \boldsymbol{\delta}_2 F_{2t} + \boldsymbol{\varepsilon}_t \;, \tag{111}$$

where $\boldsymbol{\delta}_1 \equiv [\delta_{a1} \;\; \delta_{b1}]'$, $\boldsymbol{\delta}_2 \equiv [\delta_{a2} \;\; \delta_{b2}]'$, $\boldsymbol{\varepsilon}_t \equiv [\varepsilon_{at} \;\; \varepsilon_{bt}]'$ is white noise with covariance matrix $\sigma_\varepsilon^2 \boldsymbol{I}$, and F_{1t} and F_{2t} are the two factors that drive expected returns of A and B. Without loss of generality, we assume:

$$E[F_{1t}] = E[F_{2t}] = 0, \qquad Var[F_{1t}] = Var[F_{2t}] = 1, \tag{112}$$

$$Cov[F_{1s} \;\; F_{2t}] = 0 \quad \forall s,t. \tag{113}$$

Suppose that F_{1t} is unpredictable through time, while F_{2t} is predictable:

$$F_{it} \sim \text{White Noise}, \qquad F_{2t} = \beta\, F_{2t-1} + \eta_t, \quad |\beta| \in [0,1), \tag{114}$$

where $\{\eta_t\}$ is a white-noise process with variance $1-\beta^2$ and independent of $\{\varepsilon_t\}$ and $\{F_{1t}\}$. For this linear two-factor model, the contemporaneous covariance matrix and the first-order autocovariance matrix of $\boldsymbol{R}_t$ are given by

$$\boldsymbol{\Gamma_0} = Var[\boldsymbol{R}_t] = \boldsymbol{\delta_1}\boldsymbol{\delta}_1^{'} + \boldsymbol{\delta_2}\boldsymbol{\delta}_2^{'} + \sigma_\varepsilon^2 \boldsymbol{I} \tag{115}$$

$$\boldsymbol{\Gamma_1} = Cov[\boldsymbol{R}_t, \boldsymbol{R}_{t-1}] = \boldsymbol{\delta_2}\boldsymbol{\delta}_2^{'}\,\beta. \tag{116}$$

When the true factors F_{1t} and F_{2t} are unobserved, the most common approach to estimating (111) is to perform some type of factor analysis or principal-components decomposition, like the analysis made by Roll and Ross (1980), Brown and Weinstein (1983), Chamberlain (1983), Chamberlain and Rothschild (1983), Lehmann and Modest (1988), and Connor and Korajczyk (1986, 1988).

The first principal component in the two-factor model (111) is a portfolio ω_{PC1}, which corresponds to the normalized eigenvector of the largest eigenvalue of the contemporaneous covariance matrix Γ_0. Thus, the portfolio return is

$$R_{PC1,t} \equiv \omega_{PC1}' R_t, \tag{117}$$

where $R_{PC1,t}$ is the most important cross-sectional factor. In order to know the degree of predictability of $R_{PC1,t}$, we calculate the R^2 of a regression of $R_{PC1,t}$ on the lagged factors F_{1t-1} and F_{2t-1} :

$$R^2[\, R_{PC1,t}\,] = \frac{(\omega_{PC1}' \delta_2 \beta)^2}{\omega_{PC1}' \Gamma_0 \omega_{PC1}}. \tag{118}$$

Since factor 1 is white noise, it does not contribute to the predictability of $R_{PC1,t}$; nevertheless, δ_1 appear implicitly in the denominator of (118) since it affects the variance of $R_{PC1,t}$ [see (115)].

A second measure of the predictability is the squared first-order autocorrelation coefficient of $R_{PC1,t}$:

$$\rho_1^2[\, R_{PC1,t}\,] = \frac{[(\omega_{PC1}' \delta_2)^2 \beta]^2}{(\omega_{PC1}' \Gamma_0 \omega_{PC1})^2}. \tag{119}$$

Once again, an important cross-sectional factor need not reflect much predictability.

MPP GENERAL CASE

Consider a collection of n assets with returns $\boldsymbol{R}_t \equiv [R_{1t}\ R_{2t}\ \dots R_{nt}]'$, and assume the following:

Assumption A: R_t is a jointly stationary and ergodic stochastic process with finite expectation $E[\boldsymbol{R}_t] = \boldsymbol{\mu} \equiv [\mu_1\ \mu_2\ \dots \mu_n]'$ and finite autocovariance matrices $E[(\boldsymbol{R}_{t-k} - \boldsymbol{\mu})(\boldsymbol{R}_t - \boldsymbol{\mu})'] = \boldsymbol{\Gamma}_k$, for $k \geq 0$ since $\boldsymbol{\Gamma}_k = \boldsymbol{\Gamma}'_{-k}$. The n assets will be denoted as *primary* assets. $\boldsymbol{Z}_t$ will be defined as a $(n \times 1)$ vector of de-meaned primary asset returns, so that $\boldsymbol{Z}_t \equiv \boldsymbol{R}_t - \boldsymbol{\mu}$. Thus, the conditional expectation of $\boldsymbol{Z}_t$ with respect on information available at time t-1 is

$$\tilde{\boldsymbol{Z}}_t = E[\boldsymbol{Z}_t / \Omega_{t-1}], \tag{120}$$

then,

$$\boldsymbol{Z}_t = E[\boldsymbol{Z}_t / \Omega_{t-1}] + \boldsymbol{\varepsilon}_t = \tilde{\boldsymbol{Z}}_t + \boldsymbol{\varepsilon}_t, \tag{121}$$

$$E[\boldsymbol{\varepsilon}_t / \Omega_{t-1}] = 0, \qquad Var[\boldsymbol{\varepsilon}_t / \Omega_{t-1}] = \boldsymbol{\Sigma}. \tag{122}$$

In equations [(120) to (122)] is assumed that $\boldsymbol{\varepsilon}_t$'s are conditionally homoskedastic and that the information structure $\{\Omega_t\}$ is well behaved enough to ensure that $\tilde{\boldsymbol{Z}}_t$ is also a stationary and ergodic stochastic process.

Because γ will denote a linear combination of the primary assets in $\boldsymbol{Z}_t$, so the coefficient of determination is

$$R^2(\gamma) \equiv 1 - \frac{Var[\gamma' \varepsilon_t]}{Var[\gamma' \boldsymbol{Z}_t]} = \frac{Var[\gamma' \widetilde{\boldsymbol{Z}}_t]}{Var[\gamma' \boldsymbol{Z}_t]} = \frac{\gamma' \widetilde{\Gamma}_0 \gamma}{\gamma' \Gamma_0 \gamma}, \tag{123}$$

where

$$\widetilde{\Gamma}_0 \equiv Var[\widetilde{\boldsymbol{Z}}_t] = E[\widetilde{\boldsymbol{Z}}_t \widetilde{\boldsymbol{Z}}_t'], \tag{124}$$

$$\widetilde{\Gamma}_0 \equiv Var[\boldsymbol{Z}_t] = E[\boldsymbol{Z}_t \boldsymbol{Z}_t']. \tag{125}$$

Maximizing the predictability of a portfolio $\boldsymbol{Z}_t$ is equivalent to maximizing R^2 over all γ. From the analysis by Gantmacher (1959) and Box and Tiao (1977), this is given by the largest eigenvalue λ^* of the matrix $\boldsymbol{B} \equiv \Gamma_0^{-1} \widetilde{\Gamma}_0$, and is attained by the eigenvector γ^* associated with the largest eigenvalue of $\boldsymbol{B}$. Therefore γ^* is the **MPP**.

LIQUIDITY MODEL OF STOCK PRICE PREMIA

An explanation for the existence of stock price premia is the *liquidity hypothesis*. Price premia for unrestricted **B** shares reflects the lower transaction costs and greater liquidity relative to the often inactively traded restricted **A** series. Consider the marginal domestic investor who can buy **A** or **B** series shares. Let $2\varphi_A$ and $2\varphi_B$ denote the percentage bid-ask spread in **A** and **B** respectively. Thus, a buyer with value estimate **v** pays the ask price of $p(1+\varphi)$ and receives v(1-φ) upon selling in the final period. The returns net of costs to buying **B** or **A** should be identical for the investor to be indifferent between the two markets. This rationale implies that

$$\left(\frac{v(1-\varphi_B)}{p_B(1+\varphi_B)}\right)=\left(\frac{v(1-\varphi_A)}{p_A(1+\varphi_A)}\right) \tag{126}$$

where p_A and p_B denote the prices of **A** and **B** shares respectively. Rearranging (126), one comes up with

$$\frac{p_B}{p_A}=\left(\frac{1+\varphi_A}{1+\varphi_B}\right)\left(\frac{1-\varphi_B}{1-\varphi_A}\right). \tag{127}$$

The above equation shows that the price premium is an increasing function of the relative costs of trading in the **A** and **B** markets. Bid-ask spreads reflect the risks of carrying inventory and adverse selection costs. Both factors are likely to be higher in **A** series stocks were trading is thin, and thus, one can see a positive price premium for unrestricted **B** shares.

CHAPTER FIVE

ANALYSIS OF RESULTS

PREDICTABILITY AND MARKET SEGMENTATION OF THE MEXICAN STOCK EXCHANGE

ON THE PREDICTABILITY OF THE MEXICAN STOCK EXCHANGE

INTRODUCTION

The motivation of the following experiment has different dimensions. From the standpoint of science, I want to contribute with a study that is the first one to use daily data in a horizon longer than 10 years to find out the level of autocorrelation on the daily, weekly and monthly returns of stock prices on the Mexican Stock Exchange (BMV) and its implications on the predictability of the BMV. Additionally, I am also interested in defining the relationship between trading activity and first order daily, weekly and monthly return autocorrelation, and the impact that the length of the horizon of returns has on the level of the return autocorrelation.

Forecasting future prices that use only past price changes may seem too restrictive, especially in recent periods in which investors have access to a huge set of financial variables. Nonetheless, this study can yield rich insights into the behavior of asset prices. In the next few pages, I describe the way the prices have been adjusted in the data set. Later, I shall explain in detail the experiment, from the way I managed the data set, the methodology, the empirical evidence, and the interpretation of the results.

DATA DESCRIPTION

An effort to fully understand the behavior of the Mexican Stock Exchange starts from the collection of the data. Using the electronic information provided by Economatica, I have built up a set of data for two hundred and fifty four stocks that covers the period from January 2, 1987 to Oct 29, 1999. Daily closing prices are adjusted for any corporate actions that artificially affect stock prices. These corporate actions include such actions as paying-off of dividends either in cash or with more stocks, issuing of shares of stock (subscription) and finally, splitting the price in order to have a more marketable stock price. See the appendix for a detail description of the algorithm to adjust prices.

It is important to mention that the number of stocks increases over the sample period. In 1987, only 54 stocks traded at least one day during the year. The exhibit A shows the number of stocks that traded at least one day for each year of the sample. To be included in the analysis, the stock must have traded in the examined interval at least fifty times over the sample period. Since there are more observations in daily returns than those of the weekly or monthly returns, then the number of stocks analyzed for daily returns is larger (250 stocks) than that of weekly (235 stocks) or monthly (187 stocks) return intervals.

In the period from January 1987 to Oct 1999, forty-seven stocks either were removed from the exchange or were quoted under a different code name. The market capitalization of the stocks that were removed from the exchange is something in the neighborhood of $6.6 billion[1]. As seen in Table I.1, the size of the BMV as of Oct 23, 1999 was $144.7 billion; thus, the removed stocks account for only 4.5% of the total size of the market.

EXHIBIT A

Number of stocks that traded at least one day for a particular year in the data set of the Mexican Stock Exchange[2].

END OF YEAR	NUMBER OF STOCKS
1987	54
1988	59
1989	59
1990	69
1991	92
1992	123
1993	156
1994	183
1995	174
1996	181
1997	204
1998	204
1999	192

[1] Source: Banamex-Accival.
[2] In 1999 there were less stocks than those of the previous two years indicating lower trading activity. The market started to shrink, and eventually in the year of 2000, it experienced a loss in returns of –23%.

METHODOLOGY AND EMPIRICAL EVIDENCE

I am interested in finding the level of significant autocorrelation in the daily, weekly and monthly returns on the time series of each stock traded on the BMV. The returns are calculated by taking the natural logarithm of the ratio $\frac{P_t}{P_{t-1}}$ between prices on our data set; in other words, I assume the returns to be continuously compounded.

For weekly returns, I take observation of prices on Wednesday; if a particular Wednesday's price is missing, then I use the price on the next available day. For monthly returns I observe the first trading day price of each month to build up the series. The Vector Autorregression model for daily and weekly returns is defined as follows:

$$\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}. \qquad (1)$$

where $\widetilde{R}_{it}$ is the return on stock i in day or week t, and where R_{it-j} is the return on stock i in day or week t-j. Notice that for this particular case, I work with twenty-five lags. The term ρ_{jt} is the autocorrelation coefficient for each lagged return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term.

For monthly returns, I took a VAR with twelve lags (to account for one year) in the following way:

$$\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=12} \rho_{jt} R_{it-j} + \widetilde{u}_{it} . \tag{2}$$

Since I am interested in the autocorrelation coefficient ρ, it is necessary to establish whether or not autocorrelation is likely to exist. The null hypothesis $H_0 : \rho = 0$ can be tested against the alternative $H_1 : \rho \neq 0$.

If one assumes that the errors $\widetilde{u}_{it}$ are independent $(0, \sigma^2)$ random variables with defined fourth moment $\eta\sigma^4$ and sixth moment ξ, then it can be shown that $\hat{\rho}$ will be approximately normal with mean ρ and variance $(1-\rho^2)/T$. Therefore, the figure

$$z = \frac{\hat{\rho} - \rho}{\sqrt{(1-\rho^2)/T}} \tag{3}$$

will have an approximate standard normal distribution. If the null hypothesis is true, this statistic becomes

$$z = \sqrt{T}\hat{\rho} . \tag{4}$$

Consequently, at the 5% significance level, in a two-sided test, one can reject H_0 if

$$\left|\sqrt{T}\hat{\rho}\right| \geq 1.96 . \tag{5}$$

After testing for significance, I organize the results on a daily, weekly and monthly basis. Per each case, I am interested in knowing the proportion of the number of stocks with autocorrelation that show at least 95% level of significance, related with the total number of stocks. I performed the analysis for each quartile of trading activity as well as for the aggregate. The results are printed on Table A.1 to Table A.15 (See Appendix).

Examining the daily return autocorrelation, one can see that in the aggregate (Table A.1) the proportion of stocks with significant autocorrelation on the first lag is extremely high (more than 50%), indicating that positive autocorrelation is dominant in comparison with negative autocorrelation. One can also see that the proportion of stocks with positive autocorrelation diminishes rapidly with the number of lags. For the aggregate case of weekly return autocorrelation (Table A.6), the proportion of stocks with significant autocorrelation on the first lag is lower, 27.7%, and as for the case of daily returns, the positive autocorrelation is very dominant in comparison with the negative autocorrelation. Similar results are found for monthly return autocorrelation of first lag (Table A.11). The magnitude and decay pattern of the first five return autocorrelations for daily, weekly and monthly returns, and the statistical significance of the t-test, together suggest the presence of a high-frequency predictable component in stock return.

Summary of the ratio of significant autocorrelation on the first lag over the number of stock analyzed is made on Table V.1. Notice how the percentage of significant daily ρ_1 is in the aggregate greater than that of the weekly and monthly returns. This pattern suggests that daily returns are more predictable than weekly or monthly returns.

TABLE V.1

STOCK RETURN AUTOCORRELATION OF FIRST LAG. SUMMARY

Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on security i in day (week) t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily (or weekly) return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). For monthly returns the same model has been used but with twelve lags. Q1 shows the least active stocks (first quartile) whereas Q4 shows the most active stocks. I use the number of price changes as a proxy for activity. Below is the ratio of the first lag autocorrelation coefficients that show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$, over the number of stocks analyzed, aggregate daily, weekly and monthly for each of the four activity groups. This table is constructed by using the first lagged return autocorrelation from table A.1 to A.15 (See Appendix).

	Number of stocks analyzed.	% of stocks that show ρ_1 with at least 95% of significance	% of stocks with positive Autocorrelation	% of stocks with negative Autocorrelation
Daily				
Aggregate	250	53.2	48.0	5.2
Q1	97	50.5	43.2	7.3
Q2	47	53.2	46.8	6.4
Q3	25	52.0	52.0	0.0
Q4	81	56.8	53.1	3.7
Weekly				
Aggregate	235	27.7	25.1	2.6
Q1	52	40.4	38.5	1.9
Q2	45	24.4	17.8	6.6
Q3	35	31.4	28.6	2.8
Q4	103	21.4	20.4	1.0
Monthly				
Aggregate	187	23.0	19.3	3.7
Q1	15	13.3	13.3	0.0
Q2	20	55.0	45.0	10.0
Q3	17	29.4	29.4	0.0
Q4	135	18.5	14.8	3.7

Tables A.16 to A.26 (See Appendix) report the autocorrelations across all years of the sample. One can also examine the autocorrelations on an annual basis. Table V.2 reports daily, weekly and monthly return autocorrelation (ρ_1) of the first lag for each year from 1989 to 1999. Standard errors and Box-Pierce Q-statistics are also reported.

The daily ρ_1 reported in Table V.2 ranges from a value of 19.2% for 1989 to a value of 8.6% for 1999. Fuller (1976) shows that the sample autocorrelation coefficients are asymptotically independent and normally distributed[3]. The asymptotic sampling distribution of ρ_1 is normal with mean ρ and variance $(1-\rho^2)/T$. One can see from table V.2 that daily ρ_1 is statistically significant for all years. Moreover, the Box-Pierce Q-statistic with five autocorrelation has a value of 27.364 which makes ρ_1 significant at all the conventional significance levels; Box-Pierce Q-statistic with five autocorrelation is distributed asymptotically as a χ_5^2 (five degrees of freedom) for which the 99.5 and 95.0-percentile is 16.7 and 11.1 respectively.

That the level of daily ρ_1 diminishes through time suggests that the BMV is currently less predictable than it was in the past. To develop a sense of the economic significance of the autocorrelations in Table V.2,[4] observe that the R^2 of a regression of returns on a constant and its first lag is the square of the slope coefficient, which is our daily ρ_1--first order autocorrelation--then, an autocorrelation of 19.2% implies that, in 1989, 3.6% of the variation in the daily returns of the stock of the Mexican Stock Exchange was predictable by

[3] See Appendix for the demonstration of a theorem that investigates the large sample properties of the estimated autocovariances and autocorrelations.
[4] In Table V.2 years 1987 & 1988 are dropped because of 3-year lag for monthly autocorrelation.

TABLE V.2

SUMMARY OF DAILY, WEEKLY AND MONTHLY RETURN AUTOCORRELATION OF THE FIRST LAG FOR THE PERIOD JANUARY 1989 TO OCTOBER 1999 ON THE MEXICAN STOCK EXCHANGE

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in day (week) t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily (weekly) return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term, for the period 89:01:02 - 99:10:29 in the Mexican Stock Exchange (BMV). For the monthly returns I use the same model with twelve lags. For daily and weekly returns, I use periods of one year, whereas for monthly returns the periods are 89:01:02-92:12:01, 93:01:02-96:12:02 and 97:02:03-99:10:01. The table below describes the Mean and Std. Error of daily, weekly and monthly returns autocorrelation ρ_1 (first lag) respectively, as well as the Box-Pierce statistic (Q5). This table is constructed by using tables A.16 to A.26 (see Appendix)

Year	ρ1 daily	Std. Error ρ1 daily	Q5 ρ1 daily	ρ1 weekly	Std. Error ρ1 weekly	Q5 ρ1 weekly	ρ1 monthly	Std. Error ρ1 monthly	Q5 ρ1 monthly
89	0.192	0.034	27.364	0.164	0.032	6.588	0.119	0.036	33.014
90	0.178	0.019	19.079	0.116	0.039	7.442			
91	0.184	0.022	21.586	0.078	0.037	9.472			
92	0.156	0.022	23.578	0.084	0.038	13.852			
93	0.146	0.018	19.438	0.083	0.021	11.660	0.003	0.029	9.993
94	0.105	0.015	18.252	-0.003	0.024	13.406			
95	0.145	0.016	16.891	0.066	0.019	6.264			
96	0.106	0.012	14.870	-0.055	0.023	9.318			
97	0.069	0.016	17.020	-0.008	0.019	8.000	-0.040	0.020	6.640
98	0.039	0.011	12.675	0.055	0.020	8.860			
99	0.086	0.012	10.300	0.020	0.019	7.050			

using the previous day-stock return. By 1999, the daily stock return autocorrelation of 8.6% had reduced this predictability to 0.74 %.

The autocorrelations shown in Table V.2 can be compared to those found for other markets. For example, Campbell et al. (1997) find for the CRSP Equal-Weighted Index (for daily returns) a first order autocorrelation equal to 35.0% for the time span from July 3, 1962, to December 30, 1994. Furthermore, for the same time span, they find for the CRSP Equal-Weighted Index for weekly and monthly stock returns a first order autocorrelation equal to 20.3% and 17.1% respectively. Additionally, Harvey (1995) reports a first-order autocorrelation for daily returns in Chile to be equal to 18% for the time span from February 1, 1976, to June 30, 1992.

The weekly and monthly returns autocorrelation are also reported in Table V.2 for each year from 1989 to 1999, where they exhibit patterns similar to those of the daily autocorrelations. In all cases, the magnitude of the weekly and monthly autocorrelation is smaller than that of the daily. This type of outcome is also seen in the experiment reported by Campbell et al. (1997) that demonstrates that, the longer the horizon on returns, the less predictable [using prior weekly (monthly) return] is the variation in the weekly (monthly) stock return. This trend is consistent also with Boudoukh et al. (1994), in which they show that short horizon returns are significantly autocorrelated to a larger extent than long horizon returns. Finally, the first-order autocorrelation weekly return shows sign changes in years of political turmoil, a development that suggests that political events have a greater effect in longer horizon returns by creating a phenomenon of mean-reversion on the weekly returns. One of the most important political events in México during the sample period was the uprising initiated by the Zapatista guerrillas on January 1, 1994, a struggle that won worldwide attention during the Salinas Administration, and which created nervousness among investors. The same year, the Candidate for President of the Revolutionary and Institutional Party (PRI) Luis Donaldo Colosio was assassinated in Tijuana; few months later, Ruiz Massieu, General Secretary of the PRI was also killed. At the end of 1994, the events known as "December's Errors" created the worst devaluation in the last ten years. In 1997, the crisis in Asia (Hong-Kong and Singapore) clearly had an impact on the Mexican Market.

The Relationship between Trading Activity and the level of Autocorrelation

In order to determine the relationship (if any) between trading activity and the level of the first order stock return autocorrelation, I separated the data set into four trading activity groups, from the least active (quartile 1) to the most active (quartile 4). As the proxy for trading activity, I observed changes in prices, so the more changes in closing prices, the more active the asset is.

Table V.3 reports the analysis of autocorrelation structured by the level of trading activity during the period from January 1987 to October 1999. First quartile represents the least active stocks, while the fourth quartile represents the most active stocks. In all cases--daily, weekly and monthly--the least active stocks (quartiles one and/or two) show greater first-order return autocorrelation than the most active stocks (quartiles three and/or four). This result suggests that the magnitude of the first-order return autocorrelation is inversely proportional to the level of activity. The presence of thin trading may generate a return time-series, which will be either time invariant or will show small variability, generating consequently higher autocorrelation. In contrast, stocks that are highly traded will generate a pattern of returns less susceptible to be predicted by using the previous firm's return. Furthermore, market frictions tend to be lower in highly traded stocks, and these frictions have less impact on the magnitude of the first-order autocorrelation on active stocks.

I test the hypothesis that the first-order return autocorrelation is inversely proportional to the level of activity by estimating the difference between the first order autocorrelation of the least active trading active quartile (Q1) and the most active quartile (Q4) for daily, weekly and monthly stock returns, and then by comparing this difference with zero. The null hypothesis therefore is $\rho_{Q1} - \rho_{Q4} = 0$, and p-values are estimated to recognize the level of statistical significance for each test performed. Additionally, I perform an F-test for the null hypothesis $\rho_{Q1} = \rho_{Q2} = \rho_{Q3} = \rho_{Q4}$, for daily, weekly and monthly stock returns to determine if the first order autocorrelations for each level of trading activity are different. Table V.4 shows the result of the experiment, and I find that, for the weekly stock return autocorrelation, there is significant difference (7.77%) between the least active quartile (Q1) and the most active

TABLE V.3

RETURN AUTOCORRELATION FIRST LAG STRUCTURED BY STOCK ACTIVITY

Daily, weekly, and monthly stock returns.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in day (week) t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily (or weekly) return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). For monthly returns I used the same model with 12 lags. Q1 is the least active stocks (first quartile) and Q4 is the quartile for the most active stocks. I use the number of price changes as proxy for activity. The tables below show the mean and Std. Error of ρ_{1t} as well as the 10, 50 and 90 percentiles.

Daily autocorrelation first lag

	Sample Size	10%	50%	90%	Mean	Std. Error
Q1	97	-0.0469	0.0527	0.2801	0.0785	0.0158
Q2	47	-0.0181	0.0578	0.1406	0.0609	0.0110
Q3	25	0.0041	0.0738	0.1549	0.0751	0.0124
Q4	81	-0.0131	0.0824	0.1567	0.0698	0.0086
Total	250	-0.0281	0.0655	0.1861	0.0721	0.0071

Weekly autocorrelation first lag

	Sample Size	10%	50%	90%	Mean	Std. Error
Q1	52	-0.0190	0.0464	0.4254	0.1260	0.0251
Q2	45	-0.0978	0.0534	0.1890	0.0461	0.0145
Q3	35	-0.0807	0.0302	0.2130	0.0586	0.0192
Q4	103	-0.0491	0.0423	0.1421	0.0483	0.0076
Total	235	-0.0534	0.0450	0.2118	0.0666	0.0078

Monthly autocorrelation first lag

	Sample Size	10%	50%	90%	Mean	Std. Error
Q1	15	-0.0551	-0.0035	0.2942	0.0529	0.0381
Q2	20	-0.1756	0.0900	0.4001	0.1342	0.0300
Q3	17	-0.0841	0.0799	0.2013	0.0877	0.0349
Q4	135	-0.1236	0.0472	0.2172	0.0494	0.0106
Total	187	-0.1133	0.0472	0.2610	0.0622	0.0107

TABLE V.4

TEST OF THE DIFFERENCE BETWEEN RETURN AUTOCORRELATIONS

The following Table shows tests on the difference (in percentage) between $\rho_{Q1} - \rho_{Q4}$, i. e. first order return autocorrelation on quartile 1 (least trading active quartile) minus first order return autocorrelation on quartile 4 (most trading active quartile), for daily, weekly and monthly stock returns, for the sample period of January 2nd 1987 to October 29th 1999 in the Mexican Stock Exchange. Specifically the null hypothesis is $\rho_{Q1} - \rho_{Q4} = 0$ and p-values are displayed. Furthermore, F-test is performed to test the difference for daily, weekly and monthly stock-return autocorrelations between the four quartiles of trading activity. For the F-test, I use three degrees of freedom in the numerator (four quartiles minus one) and infinite degrees of freedom in the denominator. Specifically, the null hypothesis is $\rho_{Q1} = \rho_{Q2} = \rho_{Q3} = \rho_{Q4}$; values of the F as well as $F_{.01}$ are displayed.

DAILY

	Difference	p-value	F value	$F_{.01}$
$\rho_{Q1} - \rho_{Q4}$	**0.87%**	**0.4317**		
$\rho_{Q1} = \rho_{Q2} = \rho_{Q3} = \rho_{Q4}$			**0.6993**	**4.61**

WEEKLY

	Difference	p-value	F value	$F_{.01}$
$\rho_{Q1} - \rho_{Q4}$	**7.77%**	**0.0116**		
$\rho_{Q1} = \rho_{Q2} = \rho_{Q3} = \rho_{Q4}$			**8.2635**	**4.61**

MONTHLY

	Difference	p-value	F value	$F_{.01}$
$\rho_{Q1} - \rho_{Q4}$	**0.35%**	**0.4865**		
$\rho_{Q2} - \rho_{Q4}$	**8.48%**	**0.0165**		
$\rho_{Q1} = \rho_{Q2} = \rho_{Q3} = \rho_{Q4}$			**9.2917**	**4.61**

quartile (Q4) return autocorrelation. Also, the F-test shows that all the weekly return autocorrelations are statistically different. In the monthly case, the difference between quartile one and quartile four is 0.35% and is not statistically significant. The difference between quartile two and quartile four is 8.48% and it is statistically significant; then, it is not clear whether the level of activity for monthly stock returns has any relationship with the degree of first-order autocorrelation of monthly returns.

Interesting is to see that for the daily case there is not statistical difference between the first order autocorrelation of the least active stocks and the most active stocks. In fact, while performing the F-test, one can observe that all four quartiles have basically the same level of return autocorrelation of first order. I conclude that the level of first order return autocorrelation is inversely proportional to the level of trading activity for the weekly stock returns. For the daily and monthly return autocorrelation, trading activity does not create any statistically significant difference in the first order return autocorrelations between the least-trading active stocks and the most-trading active stocks.

ON THE MARKET SEGMENTATION OF THE MEXICAN STOCK EXCHANGE

INTRODUCTION

The Mexican equity market has distinct classes of shares that differentiate between national and foreign investors. This differentiation possibly induces market segmentation (i.e., different prices of the same stock for different groups) because it places limits on the percentage of a firm's equity that a non-domestic investor can hold. I will examine the impact of ownership restrictions on equity prices and trading, and also the determinants of price premia on the BMV, for the period from January 1994 to December 1999.

In the Mexican Stock Exchange (BMV), there are a number of firms that issue multiple classes of the same stock that differentiate between foreigners and domestic traders. Table V.5 shows the sample of stocks that I use in my analysis. In order to measure the level of price premia, I have a list of companies that operate in a wide variety of sectors, which issue predominantly series "A", "B", "C", "L". Notice that I am not including any kind of financial firm, since they operate under the "O" series that is available for both domestic and foreign investors that makes possible for a foreign institution to take over any Mexican financial firm.[5]

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[5] Such is the case of BANAMEX, which was completely taken over by Citycorp.

TABLE V.5

Stock Series by Company and Industry

This table contains stock series abbreviations, company names, industry classifications, and series by company for a sample of stocks actively traded on the Mexican Stock Exchange that have more than one class of shares.

Abbreviation	Company	Industry	Series
ARISTOS	Consorcio Aristos	Leasing, Hotels	A, B
CAMPUS	Campus	Beverage	A, B
CEMEX	Cemex	Cement	A, B
DESC	DESC	Holding Company	A, B, C
DIANA	DIANA	Printing	A, B
DINA	DINA	Machinery & Equipment	A, L
ELEKTRA	ELEKTRA	Commerce	A,B,CPO,L
IEM	IEM	Appliances & Electronics	A, B
KIMBER	Kimberly-Clark	Paper & Cellulose	A, B
MEDICA	Médica Sur	Health Services	A, B, L
POSADAS	Posadas	Construction & Hotels	A, L
QBINDUS	Q.B. Industrias	Petrol-Chemical	A, B
SANLUIS	San Luis Corporacion	Holding Company	A, CPO
SIDEK	Grupo SIDEK	Holding Company	A, B
SITUR	Grupo SIDEK-SITUR	Services	A, B
SYNKRO	SYNKRO	Holding Company	A, C
TELMEX	TELMEX	Communications	A, L
TMM	Transportación Marítima Mexicana	Transport	A, L
TLEVISA	Grupo Televisa	Communications	A,CPO,D,L

DATA DESCRIPTION

The distinctions between the classes of stock are mainly institutional in nature and are dictated by government policy with the objective of placing corporate control in the hands of individual Mexican investors; specifically they are described in *"Ley del Mercado de Valores"* (Equity Market Law), in its second chapter *"Del Registro Nacional de Valores e Intermediarios"* (National Registrar of Equity and Intermediates), article 17, 17 Bis and 17 Bis1. The classification of the series as well as the type of voting rights are described briefly as follows:

REPRESENTATIVE SERIES

A Limited exclusively to Mexican individuals or Mexican-controlled institutions. They have full voting rights. They must represent the majority of voting shares.

B Free subscriptions (for Mexicans and/or foreigners). Full voting rights, but cannot collectively represent the majority of voting shares.

C For Mexicans and/or foreigners. It has limited voting rights.

L Subscribed for Mexicans and/or foreigners. It has limited voting rights. They function like a preferred stock in the sense that they receive a constant dividend[6].

D Non-restricted. They grant special rights to shareholders. They can be converted into another type of series. No voting rights.

V Non-restricted. They are very similar to the B series. The "V" stands for "voting".

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[6] Source: Article 17 Bis "Ley del Mercado de Valores".

COMPOUNDED SERIES

These classes of series are characterized by the combination of two or more representative series.

CPO Certificados de Participacion Ordinaria. They are sets of "A" and other unrestricted series with voting rights that depend on the proportion of "A" to the total. The combination and proportion depends on each firm. For example, Televisa CPO consists of one A share, one L share, and one D share.

UB Set of "B" series. "U" stands for units. For example, four shares of "B" series compound COMERCI UB. The proportion varies across firms.

UBC Set of "B" and "C" series. Three shares of "B" and one of "C" series compound COMERCI UBC.

UDL Set of "D" and "L" series.

EMPIRICAL EVIDENCE

The Level of Stock Price Premia

In order to evaluate the effectiveness of ownership restrictions, I calculate the average stock price premium between the unrestricted and restricted shares: the price premium between "unrestricted" [i.e. B, C, L, D, V and the compounded CPO, UB, UBC, UDL] shares and "restricted" [i.e. A series] based on weekly observations. In other words, the premium is

TABLE V.6

STOCK PREMIUM AND TRADING VOLUMES ACROSS THE MEXICAN STOCK EXCHANGE.

The following table contains a summary of statistics on stock price premia due to restrictions on foreign ownership rights, for 19 companies (44 series in total) listed on the Mexican Stock Exchange by year. All statistics are computed based on weekly observations. Premium is calculated as ratio between price of unrestricted series stock and price of restricted series stock, the restricted being the "A" series and the unrestricted "B", "C", "L", "D", "V", and the compounded unrestricted: "CPO", "UB", "UBC", "UDL". Volume is average weekly trading volume in dollar terms, in million per firm, and reported returns are average weekly returns expressed in percentage terms. For both, volume and returns, the same conventions governing "restricted" and "unrestricted" categories apply.

	1994	1995	1996	1997	1998	1999
Average Premium	1.24	1.25	1.17	1.23	1.22	1.27
Median Premium	1.04	1.05	1.01	1.03	1.07	1.03
Standard deviation of the premium	0.57	0.60	0.58	0.57	0.42	0.67
Unrestricted Volume	10.46	4.63	3.69	4.65	3.03	4.13
Restricted Volume	1.79	1.00	0.89	2.13	1.53	1.63
Ratio of unrestricted to restricted volume	5.84	4.63	4.15	2.18	1.98	2.53
Restricted Returns	0.13	-0.31	0.14	0.26	-1.01	0.01
Unrestricted Returns	0.08	-0.44	0.31	0.53	-1.16	0.00
Observations	498	472	490	458	427	420

calculated as the ratio between the price of the unrestricted-series stock and the price of the restricted-series stock. Table V.6 includes summary statistics on the annual average stock-price premium for 1994 to 1999; the table also provides data on the dollar volume in restricted and unrestricted shares and on the returns in the two series.

The average premium of the unrestricted shares over the restricted shares is relatively constant over the sample period ranging from twenty-four percent in 1994 to twenty-seven percent in 1999, with the lowest average premium of seventeen percent occurring in 1996. The premia is relatively low in comparison of that reported by Stulz and Wasserfallen (1995) for the Swiss equity market. They show that the Swiss premia is, on average, seventy percent for the period from January 1985 to November 1988, before the premia drops to the level of forty percent for the period from December 1988 to December 1989. Regarding premia in other emerging markets, Bailey and Jagtiani (1994) report premia in East Asian countries (for some firms) to be higher than the premia I reported in Table V.6. For example, in Singapore, Singapore International Airlines in 1992 has a premia close to fifty percent. For Malaysia, Malaysian International Shipping in January 1992 shows a premia of thirty percent. Also in Philippines, San Miguel has a premia of thirty percent for 1992. An exceptional case is China where the prices of shares restricted to Chinese citizens trade at a substantial premium over the prices of identical shares restricted to foreign investors (the contrary case); for example, the restricted series for domestic investors for Shanghai Vacuum Electron (Shanghai, China) and Southern Glass (Shenzen, China) in December 1992 quote 60% and 70% (respectively) higher than the unrestricted shares.

The data on volume from Table V.6 also suggests that the unrestricted shares volume is apparently decreasing. Domowitz et al. (1997) examine an earlier period and report volume for unrestricted shares to be 9.45 for 1992 and 11.11 for 1993.[7] I found that the volume for unrestricted shares in 1994 is 10.46 and it went down drastically since then to the neighborhood of 4.0. This apparently huge decrease in the demand for unrestricted series could be related with the devaluation due to the notorious "errores de Diciembre" (December's errors) committed in December 1994. In Exhibit "B", one can see the level of foreign investment in million of pesos in the BMV from the period of March 1994 to July 1995. One should bear in mind that the devaluation of the peso was from 3.44 pesos per U.S. dollar in November 1994 to 5.00 pesos per U.S. dollar in December 1994. By July 1995, the exchange rate was 6.20 pesos per U.S. dollar, and in December 1995 it was 7.69 pesos per U.S. dollar. Thus, the decrease in the demand for unrestricted series in 1995 (since demand is evaluated in dollars) seems to be very high, whereas in reality the average weekly trading volume for these series remains quite similar (in terms of number of shares) as it used to be in the previous year (1994). The volume invested by foreigners in the BMV are in dollars, and the apparent decrease is not due to an outflow of foreign capital but mainly due to the devaluation of December 1994, in conjunction with the negative return (-29.3%) on the IPC index for the period from November 1994 to March 1995.

The level on the volume of unrestricted series remains quite similar in spite of the depreciation of the peso in the following years (By December 1997 and December 1998 the exchange rate was 8.06 and 9.90 pesos per U.S. dollar respectively). As for the volume on the restricted-shares concerns, there is an apparent reduction in this level from 1.79 to 1.00

[7] Volume is average weekly trading volume in dollar terms, in million per firm.

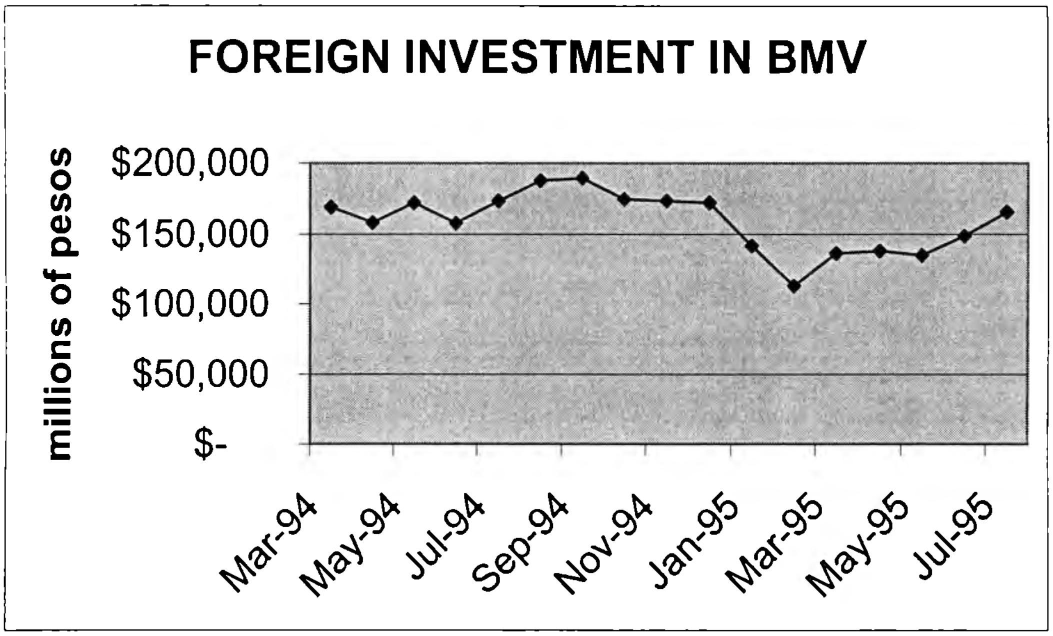

EXHIBIT B.
Level of Foreign Investment in the Mexican Stock Exchange. March 1994 to July 1995.

but it is mainly due to the devaluation of the peso and not due to an actual contraction on the demand. In contrast with those unrestricted shares, the demand for restricted shares increases, and as a consequence of this, the ratio between volume of unrestricted shares and volume of restricted shares is around two.[8]

The companies—included in Table V.5--that issue ADR's in the NYSE and Nasdaq are, CEMEX CPO NYSE, DESC C NYSE, ELEKTRA A Nasdaq, TELMEX A Nasdaq, TELMEX L NYSE, TMM A NYSE, TMM L Nasdaq, TLEVISA A NYSE.

[8] Domowitz et al. (1997) report a ratio slightly higher than one, for the period of 1991 to 1993.

The phenomenon of market segmentation should be analyzed for each market, i.e. NYSE or Nasdaq or BMV. In the case of NYSE or Nasdaq, one cannot see a single Mexican company that issues an ADR for both restricted and unrestricted series on the same exchange. TELMEX issues ADR for restricted—A—and unrestricted—L—series but they are allocated in Nasdaq and NYSE respectively. A similar case can be seen for TMM.

Empirical Determinants of Premium

Four types of hypotheses that involve the premium of unrestricted to restricted share price: the Liquidity Hypothesis, the Price Discrimination Hypothesis, the Stulz-Wasserfallen Hypothesis, and the Information Hypothesis; these hypotheses are not mutually exclusive in that they could each explain a portion of the premium.

Liquidity Hypothesis

An explanation for the existence of stock price premia is provided by the liquidity hypothesis. The premium across different stocks is an increasing function of the liquidity of the unrestricted shares relative to that of the restricted shares, in other words, price premia for unrestricted **B**[9] shares reflects the lower transaction costs and greater liquidity relative to the often inactively traded restricted **A** series. Let $2\varphi_A$ and $2\varphi_B$ denote the percentage bid-ask spread in **A** and **B** respectively. Thus, a buyer with value estimate **v** pays the ask price of $p(1+\varphi)$ and receives $v(1\text{-}\varphi)$ upon selling in the final period. The returns net of costs to buying **B** or **A** should be identical for the investor to be indifferent between the two markets.

[9] Hereafter, when I refer to unrestricted **B** series I am referring to all kind of unrestricted series that the Mexican Stock Exchange i.e. B, C, L, D, V and the compounded CPO, UB, UBC, UDL.

One can thus conclude that

$$\left(\frac{v(1-\varphi_B)}{p_B(1+\varphi_B)}\right)=\left(\frac{v(1-\varphi_A)}{p_A(1+\varphi_A)}\right) \tag{1}$$

where p_A and p_B denote the prices of **A** and **B** shares respectively.

Rearranging the above equation, one obtains the next expression:

$$\frac{p_B}{p_A}=\left(\frac{1+\varphi_A}{1+\varphi_B}\right)\left(\frac{1-\varphi_B}{1-\varphi_A}\right). \tag{2}$$

Equation (2) shows that the price premium is an increasing function of the relative costs of trading in the **A** and **B** markets. Bid-ask spreads reflect the risks of carrying inventory and adverse selection costs. Both factors are likely to be higher in **A** series stocks where trading is thin. This implies a positive price premium for unrestricted **B** shares.

The ratio of volume in the unrestricted shares to total volume is a proxy for the relative liquidity measure across firms; changes in the ratio volume in the unrestricted series to total volume will cause changes in the premium in the same direction. Furthermore, smaller companies tend to be closely held, thus spreads in the restricted series will be high relative to spreads in the unrestricted series, and thus we will observe larger premia. In contrast, larger companies may show sufficient trading activity for both **A** and **B** series and then the transaction cost differential, and hence premium, are small. Then one can conclude that transaction cost differentials between **A** and **B** series could be inversely related to market capitalization.

Price Discrimination Hypothesis

In order for firms to achieve an equilibrium price ratio based on the relative valuation earnings of foreign and domestic investors, they adjust the availability of series **A** and **B** through equity offering or repurchasing. Variation in the level of premium for **B** series across firms at any point in time will reflect differences in the demands of foreign and domestic investors relative to the shares outstanding. Also for a given firm, changes in the price premium over time will reflect adjustment to the equilibrium price ratio or changes in this equilibrium level, suggesting that unrestricted series will trade at a premium for those companies where foreign demand is higher.

Stulz-Wasserfallen (1995) Hypothesis

In the short-run the number of shares outstanding can be considered to be time invariant, and stock price premia is defined by the ratio of B to A prices as follows:

$$\frac{p_B}{p_A} = \left(\frac{v_f - \beta^{-1} S_B}{v_d - \alpha^{-1} S_A} \right). \tag{3}$$

where the valuation placed on the company's expected dividends adjusted for their value in portfolio diversification is, $v_d = \mathbf{E}_d[\tilde{\theta}] - 2A_d\sigma_d$, A_d being the coefficient of absolute risk aversion for domestic investors, and σ_d denoting the covariance of the stochastic dividend $\tilde{\theta}$ with the asset income of domestic investors, $\tilde{y}_d$. S_A and S_B are the supply of restricted and unrestricted shares respectively. Similarly, one can write $v_f = \mathbf{E}_f[\tilde{\theta}] - 2A_f\sigma_f$ for foreign investors. The demand functions take the linear form $d_A = \alpha(v_d - p_A)$ and $d_B = \beta(v_d - p_B)$; furthermore, $\alpha = N_d / 2A_d\sigma^2_{d,\theta}$ and $\beta = N_f / 2A_f\sigma^2_{f,\theta}$ where N_d (N_f) is the number of domestic (foreign) investors, and $\sigma^2_{d,\theta}$ ($\sigma^2_{f,\theta}$) is the (conditional) variance of the asset's payoff from the viewpoint of domestic (foreign) investors. Thus, the demand coefficients α and β increase with the number of investors and decrease with risk aversion and perceptions of the variance of the asset's price. Therefore from equation (3), one can establish that premium will increase with the number of foreign investors, i.e. an increase in β (for a particular ratio of shares outstanding). Similarly an increase in the perceived volatility of the asset or an increase in foreign risk aversion will reduce β and lower the stock premia.

Optimization Process

In this case, the domestic entrepreneur optimally selects the degree of market segmentation. The equilibrium prices of A and B series shares are given by the solutions to $d_A(p_A) = \Delta S_A$ and $d_B(p_B) = \Delta S_B$. It is assumed that an investment of μ yields an expected one-period payoff of $\mathbf{E}[\tilde{\theta}] > \mu$. The inverse demand functions for A and B shares are defined by $p_A(\Delta S_A)$ and $p_B(\Delta S_B)$ respectively as functions of the new issues. The optimization problem is to choose ΔS_A and ΔS_B to maximize:

$$p_A(\Delta S_A)\Delta S_A + p_B(\Delta S_B)\Delta S_B - \mu(\Delta S_A + \Delta S_B)$$

Subject to:

a) Ownership constraint imposed by the government: $S'_A + \Delta S_A \geq \Delta S_B$, where S'_A denote the existing number of A shares, ΔS_A denotes the new A shares and ΔS_B

denotes issuing of B series. For simplicity the model assumes that there are not preexisting B shares.

b) Control constraint: $S'_A \geq c(S'_A + \Delta S_A + \Delta S_B)$, where c is the minimum fraction of shares needed for control.

The Kuhn-Tucker conditions to this constrained optimization problem yield $p'_A(\Delta S_A)\Delta S_A + p_A(\Delta S_A) + \lambda = \mu$, and $p'_B(\Delta S_B)\Delta S_B + p_B(\Delta S_B) + \kappa\lambda = \mu$. λ is the Lagrange multiplier on the constraint. If the constraint imposed by the government that the **A** shares control the firm is binding, then the Lagrange multiplier λ is strictly positive. In this case, the firm would like to issue more B shares. On the other hand, when the inequality constraint is not binding, the first-order conditions imply that $\Delta S_A = \alpha(v_d - \mu)/2$ and $\Delta S_B = \beta(v_f - \mu)/2$. Substituting these expressions into the inverse-demand function yields the price premium on unrestricted shares,

$$\frac{p_B}{p_A} = \left(\frac{1 + r_f}{1 + r_d}\right). \tag{4}$$

where $r_f \equiv v_f / \mu$ and $r_d \equiv v_d / \mu$.

According to equation (4) the equilibrium price ratio is a function of the foreign to domestic valuations of the returns per share. A positive premium for the **B** shares implies that international investors have higher valuations of returns than domestic investors.

Information Hypothesis. Foreign investors choose to invest in larger companies where there is greater financial disclosure and better information, thus inducing larger premia in high market capitalization firms (Bailey and Jagtiani 1994). An increase in market capitalization over time for a particular firm may induce greater foreign participation and therefore, a larger premium (ceteris paribus). Notice how this hypothesis contradicts the liquidity hypothesis.

Methodology and Empirical Evidence

In order to find out the empirical determinants of premium, I use a panel model of the unrestricted / restricted ownership premium. The use of this type of model is due to the fact that our hypotheses are related with factors that vary both longitudinally and across firms. Panel-data methods can improve the precision of estimates of model dynamics in short time series (Hsiao 1986); this technique will also increase degrees of freedom and will reduce the collinearity among explanatory factors. Indeed, this model offers the ability to control for unobservable firm-specific effects.

The model has the following form:

$$y_{it} = \beta \, x_{it} + \alpha_i + \varepsilon_{it} \qquad (i = 1,\dots,N; t = t_i,\dots,T_i)$$

where y_{it} symbolizes the equity premium, i.e. our measure of market segmentation, for firm i in period t, and β is a k-dimensional vector of coefficients associated with observable explanatory variables, x_{it}, which may include lags of both dependent and independent variables. The error term ε_{it} has zero mean and is uncorrelated with the explanatory variables and with firm specific fixed effect α_i. The effect α_i is supposed to be a time-invariant random variable, distributed independently across firms. This coefficient α_i could be interpreted as a proxy for the effects of the unobservable control considerations on the premium.

I estimate a panel-model of the unrestricted / restricted ownership premium using monthly prices for the period from January 1994 to December 1999 for companies that show moderate to high trading activity in both, series A and B, in a wide variety of sectors, e.g. cement, holding companies, machinery and equipment, health services, construction and tourism, telecommunications and transport.[10]

The model that characterizes the determinants of market-segmentation is as follows (Model I):

$$\begin{aligned} PREM_{i,t} = {} & \beta_1 PREM_{i,t-1} + \beta_2 SRATIO_{i,t} + \beta_3 VRATIO + \beta_4 MCAP_{i,t} + \beta_5 IRATIO_t + \\ & + \beta_6 FFLOAT_{i,t} + \alpha_i + \varepsilon_{i,t}. \end{aligned}$$

where $PREM_{i,t}$ is the ratio of the price of unrestricted **B** series to the price of restricted **A** series; $SRATIO_{i,t}$ is the ratio of outstanding unrestricted **B** shares to total outstanding shares; $VRATIO_{i,t}$ is the ratio of trading volume in unrestricted **B** series to total shares; $MCAP_{i,t}$ is the natural logarithm of the firm market capitalization; $IRATIO_t$ is the interest ratio which is

[10] From the companies listed on Table V.5, some of them show no trading on series A. Thus, in order to find the determinants of price premia, the firms included in the analysis are ARISTOS, CEMEX, DESC, DINA, KIMBER, MEDICA, POSADAS, SAN LUIS, SIDEK, SYNKRO, TELMEX, TMM and TLEVISA.

common to all firms but varies over time and it is measured by the ratio of 28 days government debt (CETES) to Treasury Bill yield; $FFLOAT_{i,t}$ is the free-float, i.e. ratio of shares available to be traded to total shares; α_i is the unobservable company-specific fixed effect; and ε_{it} is the error term.

Table V.7 shows the results of Model I that contains the estimates of the panel-data model already described. The coefficient on the lagged premium is 0.866, indicating that the premium exhibits a very strong mean reversion with a p-value that makes this coefficient highly significant. This result suggests that short-run order imbalances in the restricted and unrestricted series stock cause temporary changes in stock price premia that are eventually reversed.

As for the relative supply of **B** series concerns (measured by $SRATIO_{i,t}$) this variable is negative and shows a level of significance beyond the 10% level. The firm's objective is to issue new shares so as to raise the maximum amount of equity capital, net of the expected capital costs in the form of the investments needed to make the promised dividend. Since the relative scarcity of shares is a choice factor for firms, which is subject to ownership constraint imposed by the government and control constraint on the issuance of unrestricted shares, this result suggests that some segmentation is optimal (as it was established by the Stulz-Wasserfallen (1995) hypothesis).

TABLE V.7

Panel Data Model I

This table contains OLS coefficient estimates and associated p-values, of the following panel data model for foreign and domestic equity ownership restrictions for the Mexican Stock Exchange. The Model is as follows:

$$PREM_{i,t} = \beta_1 PREM_{i,t-1} + \beta_2 SRATIO_{i,t} + \beta_3 VRATIO + \beta_4 MCAP_{i,t} + \beta_5 IRATIO_t + \\ + \beta_6 FFLOAT_{i,t} + \alpha_i + \varepsilon_{i,t}.$$

Where i indexes firms (**ARISTOS,CEMEX, DESC, DINA, KIMBER, MEDICA, POSADAS, SAN LUIS, SIDEK, SYNKRO, TELMEX, TMM, TLEVISA**) and t indexes observation by month, for the period from January 1994 to December 1999. The variables are **PREM**, ratio of the price of B shares to A shares; **SRATIO**, the ratio of outstanding B shares to total shares; **VRATIO**, the ratio of trading volume in B shares to total shares, **MCAP**, natural logarithm of market capitalization; **IRATIO**, interest ratio, measured by the ratio of 28 days government debt (CETES) to Treasury Bill yield; **FFLOAT**, free-float, ratio of shares available to be traded to total shares; α_i, the unobservable firm effect; and $\varepsilon_{i,t}$ the error term.

Variables	β_i	P-value
Lagged premium	0.886	0.000
Ratio of B/total shares outstanding	-0.096	0.073
Ratio of B/total traded volume	0.075	0.030
Market Capitalization	-0.015	0.015
Interest Ratio	-0.004	0.333
Free Float	0.256	0.012

The coefficient of the ratio of traded volumes $VRATIO_{i,t}$ (our measure of the liquidity of the unrestricted **B** series shares) is positive and statistically significant and it has an opposite direction with respect of the factor $SRATIO_{i,t}$. This outcome is consistent with the liquidity hypothesis that predicts that an increase in the relative liquidity of unrestricted shares will affect the premia of those series in the same direction.

As already noted, the liquidity hypothesis and the information hypothesis contradict each other. The factor that accounts for Market Capitalization ($MCAP_{i,t}$) is in Model I negative and statistically significant. This outcome is exactly what the liquidity hypothesis predicts, a negative coefficient since cost differentials and hence premia should decrease with firm size Larger companies may show sufficient activity for both **A** and **B** series, and then the transaction cost differential, and hence premium, are small. Smaller companies tend to be closely held; thus, spreads in the restricted series will be high relative to spreads in the unrestricted series. Thus, I will observe larger premia.

By contrast, the negative coefficient of Market Capitalization contradicts the information hypothesis. This outcome suggests that transactions costs, being smaller in larger companies, offset the effect over premia caused by greater demand for larger companies. Another reason could be that information is spread out with the same quality for both small and large companies. Therefore the difference in information has no impact in the level of premium.

The interest ratio $IRATIO_t$ nonetheless, is not statistically significantly different from zero, possibly because the differential between yields on risk free instrument for both CETES and

Treasury Bills does not affect foreign investor's choice on the Mexican market. Therefore, I drop this variable in the models performed later.

Finally, the free-float factor $FFLOAT_{i,t}$ is positive and statistically significant. This result supports the price discrimination hypothesis, since greater levels of free-float mean that the firm is being demanded by a greater number of investors, and since it is not owned by a small number of participants (possibly family members). Thus, companies adjust the availability of series **A** and **B** in order to achieve an equilibrium price ratio. Consequently, the premium will be higher in those companies that show larger free-float.

Table V.8 shows panel-data models 1 to model 5. For model 1, I drop the variable $IRATIO_t$ and by comparing the results displayed in Table V.8 with those of Table V.7, I conclude that dropping this factor does not affect the coefficients or the significance of the other variables. This result provides some confidence that our conclusions regarding the determinants of price premium are robust. The variables $SRATIO_{i,t}$ and $VRATIO_{i,t}$ have different directions in all of the models, but when I drop $SRATIO_{i,t}$ in model 2, then $VRATIO_{i,t}$ is affected in its level and not significantly different from zero; while dropping $VRATIO_{i,t}$ in model 3, then the coefficient of $SRATIO_{i,t}$ becomes reduced and is not statistically significant, suggesting that it is a necessary condition to perform the experiment including both variables.

TABLE V.8

Panel Data Models II

This table contains OLS coefficient estimates and associated p-values (in parenthesis), of the following panel data model for foreign and domestic equity ownership restrictions for the Mexican Stock Exchange. The Model is as follows:

$$PREM_{i,t} = \beta_1 PREM_{i,t-1} + \beta_2 SRATIO_{i,t} + \beta_3 VRATIO_{i,t} + \beta_4 MCAP_{i,t} + \\ + \beta_5 FFLOAT_{i,t} + \beta_6 IRATIO_t + \alpha_i + \varepsilon_{i,t}.$$

Where i indexes firms (**ARISTOS, CEMEX, DESC, DINA, KIMBER, MEDICA, POSADAS, SAN LUIS, SIDEK, SYNKRO, TELMEX, TMM, TLEVISA**), and t indexes observation by month, for the period from January 1994 to December 1999. The variables are **PREM**, ratio of the price of B shares to A shares; **SRATIO**, the ratio of outstanding B shares to total shares; **VRATIO**, the ratio of trading volume in B shares to total shares, **MCAP**, natural logarithm of market capitalization; **FFLOAT**, free-float, ratio of shares available to be traded to total shares; **IRATIO**, interest ratio, measured by the ratio of 28 days government debt (CETES) to Treasury Bill yield, I include this variable only in Model 5; α_i is the unobservable firm effect and $\varepsilon_{i,t}$ is the error term. In Model 2, the coefficient of **SRATIO** is set to zero. In Model 3, the coefficient of **VRATIO** is set to zero. In Model 4 and Model 5, the coefficient of lagged premium is set to zero.

Variables	Model 1	Model 2	Model 3	Model 4	Model 5
$PREM_{i,t-1}$	0.887	0.890	0.893		
	(0.000)	(0.000)	(0.000)		
$SRATIO_{i,t}$	-0.093		-0.018	-0.412	-0.419
	(0.080)		(0.651)	(3.9 E-04)	(3.1 E-04)
$VRATIO_{i,t}$	0.073	0.037		0.356	0.359
	(0.032)	(0.192)		(1.89 E-06)	(1.56 E06)
$MCAP_{i,t}$	-0.014	-0.010	-0.010	-0.109	-0.111
	(0.019)	(0.069)	(0.077)	(3.64 E-17)	(1.6 E-17)
$FFLOAT_{i,t}$	0.248	0.174	0.135	1.836	1.856
	(0.014)	(0.059)	(0.119)	(2.69 E-17)	(1.44 E17)
$IRATIO_t$					-0.013
					(0.179)

The lagged premium variable $PREM_{i,t-1}$ is dropped in model 4 and model 5 and as a result of this, all coefficients increase their original value several times and all of them show a high degree of significance. This suggests that the lagged premium captures much of the variation of the premium itself since the dynamic of the price premia tends to be stable. It is also important to point out that all coefficients remain with the same direction and in particular the coefficient of $IRATIO_t$ is still not statistically significant when I include it in model 5.

One can observe from table V.6 that returns in both restricted and unrestricted series are negative for the years of 1995 and 1998. Thus, I have performed a panel-data model for those critical years 95 & 98, and the results are shown in table V.9. The relative supply of **B** shares measured by *SRATIO* does not determine the level of price premia during those critical years since its coefficient is not statistically significantly different from zero, suggesting that segmentation due to the relative scarcity of **B** series is not optimal in times of crisis. Nevertheless, the rest of the variables remain unchanged in their direction and significance, suggesting that, in spite of the negative returns in the exchange, the explanatory power of the variables I have chosen continue to be robust.

The reason for which the lagged premium has a very high explanatory power over the level of price premia is due to the fact that both $PREM_{i,t}$ and $PREM_{i,t-1}$ are highly correlated. From the correlation matrix of table V.10, one can see that the level of correlation between those variables is 90%. Furthermore, as expected $SRATIO_{i,t}$ and $VRATIO_{i,t}$ are negatively correlated meaning that the level of outstanding **B** series to total shares is inversely proportional to the trading volume in **B** series to total shares.

TABLE V.9

Panel Data Model for critical years 1995 & 1998

This table contains OLS coefficient estimates and associated p-values, of the following panel data model for foreign and domestic equity ownership restrictions for the Mexican Stock Exchange. The Model is as follows:

$$PREM_{i,t} = \beta_1 PREM_{i,t-1} + \beta_2 SRATIO_{i,t} + \beta_3 VRATIO + \beta_4 MCAP_{i,t} + \beta_5 IRATIO_t + \\ + \beta_6 FFLOAT_{i,t} + \alpha_i + \varepsilon_{i,t}.$$

Where i indexes firms (**ARISTOS, CEMEX, DESC, DINA, KIMBER, MEDICA, POSADAS, SAN LUIS, SIDEK, SYNKRO, TELMEX, TMM, TLEVISA**) and t indexes observation by month, for the period from January 1994 to December 1994 and January 1998 to December 1998. The variables are **PREM**, ratio of the price of B shares to A shares; **SRATIO**, the ratio of outstanding B shares to total shares; **VRATIO**, the ratio of trading volume in B shares to total shares, **MCAP**, natural logarithm of market capitalization; **IRATIO**, interest ratio, measured by the ratio of 28 days government debt (CETES) to Treasury Bill yield; **FFLOAT**, free-float, ratio of shares available to be traded to total shares; α_i is the unobservable firm effect and $\varepsilon_{i,t}$ is the error term.

Variables	β_i	**P-value**
Lagged premium	0.809	0.000
Ratio of B/total shares outstanding	-0.132	0.161
Ratio of B/total traded volume	0.162	0.011
Market Capitalization	-0.029	0.026
Interest Ratio	-0.006	0.368
Free Float	0.429	0.036

TABLE V.10

Correlation Matrix

This table contains correlation coefficient for the variables **Prem t**, ratio of the price of B shares to A shares; **Prem t-1**, Lagged premia; **SRATIO,** the ratio of outstanding B shares to total shares; **Vratio**, the ratio of trading volume in B shares to total shares, **MCAP**, natural logarithm of market capitalization; **Int. Ratio**, interest ratio, measured by the ratio of 28 days government debt (CETES) to Treasury Bill yield; **Ffloat**, free-float, ratio of shares available to be traded to total shares; Data was obtained in a monthly basis from the Mexican Stock Exchange , for the period of from January 1994 through December 1999.

	Prem t	**Prem t-1**	**S RATIO**	**Vratio**	**MCAP**	**Int. Ratio**	**Ffloat**
Prem t	1.0000	0.9013	-0.0414	0.0509	-0.1321	-0.0147	0.0943
Prem t-1	0.9013	1.0000	-0.0469	0.0413	-0.1308	-0.0041	0.0967
S RATIO	-0.0414	-0.0469	1.0000	-0.5946	0.2382	0.0069	0.0784
Vratio	0.0509	0.0413	-0.5946	1.0000	-0.2371	-0.0016	0.4069
MCAP	-0.1321	-0.1308	0.2382	-0.2371	1.0000	-0.0821	0.6779
Int. Ratio	-0.0147	-0.0041	0.0069	-0.0016	-0.0821	1.0000	-0.0109
Ffloat	0.0943	0.0967	0.0784	0.4069	0.6779	-0.0109	1.0000

The high correlation between $PREM_{i,t}$ and $PREM_{i,t-1}$ could be explained by using the definition of price premia, in other words, the ratio between price of unrestricted **B** series to the price of restricted **A** series; premia = P_B / P_A, and since the premia is greater than one (see table V.6) then, $P_B = P_A + \Delta$, where Δ is a positive price differential. One can rearrange the definition of premia to be equal to $1 + \frac{\Delta}{P_A}$; the second term $\frac{\Delta}{P_A}$ is very stable in the sense that if a particular stock price goes up (down), then both series **B** and **A** tend to increase (decrease) their price by a similar amount, and that causes $PREM_{i,t}$ and $PREM_{i,t-1}$ to be highly correlated.

PREDICTABILITY ON RESTRICTED AND UNRESTRICTED SERIES

Weekly and Monthly Return Autocorrelation on series A and B

Finally, to determine the extent to which market segmentation can explain return autocorrelation, I perform a vector autoregressive model for the weekly (monthly) returns of **A** and **B** series, in order to evaluate the level of predictability on both series. The definition of the model is as follows:

$$\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=5} \rho_{jt} R_{it-j} + \widetilde{u}_{it},$$

where R_{it-j} is the return on series **A** or **B** within firm i in week (month) t-j, ρ_{jt} is the autocorrelation coefficient for the lagged weekly (monthly) return R_{it-j}; and α_0 is a constant and $\tilde{u}_{it}$ is the error term.

The results are displayed in Tables A.27, A.28 and A.29 (See Appendix) for the weekly return autocorrelation of the first five lags for 1994, 1995 and 1996 respectively. I compare the result of the first lag autocorrelation coefficient of weekly returns of **A** series with that of **B** series. A summary of this outcome is shown in Table V.11.

I repeat the same model for the years 1997, 1998 and 1999, and the results are shown in Tables A.30, A.31 and A.32 respectively (See Appendix). A summary of the first lag autocorrelation coefficient of weekly returns of **A** series and **B** series for 1997, 1998 and 1999 is displayed on Table V.12.

The weekly return autocorrelation of first lag (ρ_1) for the restricted series is significant for all years except for 1996 and 1999. For the unrestricted series, the same coefficient is only statistically significantly different from zero in 1994 and 1995. Also, ρ_1 for restricted series is greater than ρ_1 for unrestricted series (in the cases where both are statistically significant). The above has the following interpretation: restricted series since they are thinly traded are subject to be more predictable in their returns than the generally more traded **B** series. The fact that the volume of trade in the restricted series is much lower than that of the unrestricted series along with the fact that there are more missing data in the time series of **A** shares, might create an autocorrelation that is consequently larger in restricted series; nonetheless,

TABLE V.11

SUMMARY FOR FIRST LAGGED AUTOCORRELATION ON WEEKLY RETURNS

YEARS 1994, 1995 & 1996

The following table compares the first lagged autocorrelation on weekly returns for Restricted Series, Unrestricted Series. The Model in all cases is $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=5} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on series i in week t-j, ρ_{jt} is the autocorrelation coefficient for the lagged weekly return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term. Below is described the Mean and Std. Error of ρ_1 as well as the extremes values and 25, 50 and 75 percentiles. Data was obtained from the Mexican Stock Exchange for the period January 1994 to December 1999.

94:01:04 – 94:12:30

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
Restricted ρ1	-0.053	0.004	0.066	0.143	0.424	0.089	0.019
Unrestricted ρ1	-0.346	-0.054	0.076	0.151	0.346	0.048	0.026

95:01:03 – 95:12:29

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
Restricted ρ1	-0.068	0.035	0.074	0.127	0.208	0.079	0.012
Unrestricted ρ1	-0.228	-0.022	0.011	0.123	0.338	0.056	0.023

96:01:03 – 96:12:31

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
Restricted ρ1	-0.324	-0.123	-0.062	0.098	0.422	-0.002	0.030
Unrestricted ρ1	-0.396	-0.092	0.016	0.155	0.416	0.024	0.032

TABLE V.12

SUMMARY FOR FIRST LAGGED AUTOCORRELATION ON WEEKLY RETURNS.

YEARS 1997, 1998 & 1999

The following table compares the first lagged autocorrelation on weekly returns for Restricted Series, Unrestricted Series. The Model in all cases is, $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=5} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on series i in week t-j, ρ_{jt} is the autocorrelation coefficient for the lagged weekly return R_{it-j}, α_0 is a constant and $\tilde{u}_{it}$ is the error term. Below is described the Mean and Std. Error of ρ_1 as well as the extremes values and 25, 50 and 75 percentiles. Data was obtained from the Mexican Stock Exchange for the period from January 1997 through December 1999.

97:01:03 – 97:12:31

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
Restricted ρ1	-0.133	-0.052	0.016	0.137	0.268	0.038	0.018
Unrestricted ρ1	-0.276	-0.141	-0.009	0.171	0.347	0.000	0.028

98:01:05 – 98:12:31

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
Restricted ρ1	-0.088	-0.042	0.042	0.090	0.489	0.062	0.023
Unrestricted ρ1	-0.231	-0.022	0.015	0.093	0.309	0.036	0.022

99:01:05 – 99:12:30

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
Restricted ρ1	-0.529	-0.209	-0.030	0.070	0.157	-0.112	0.034
Unrestricted ρ1	-0.292	-0.107	-0.016	0.054	0.245	-0.012	0.022

the maximum level of the first-order weekly return autocorrelation is 8.9% (in 1994) for the restricted series **A**, and that means that only 0.7% of the variation in the weekly returns on the restricted series **A** is predictable by using previous weekly-stock return. For the case of unrestricted series **B** the maximum level of first-order weekly autocorrelation of 5.6% and that means a predictability of 0.3%.

The results for monthly returns autocorrelation of both **A** and **B** series are displayed on Tables A.33, A.34, A.35 for the period of time of 1994 to 1999, 1994 to 1996 and 1997 to1999 respectively (see Appendix). These six-year period and three-year period are chosen so I include enough data to perform a robust test, since I have only twelve observations per year.

A summary of the first lag monthly return autocorrelation for both series is shown in Table V.13. Interesting is to see that in all cases the monthly return autocorrelation is negative. This means that monthly returns for both series are reverting to the mean. Furthermore, in both cases this autocorrelation coefficient is statistically significant for the six-year period. Both are not significant for the three-year period from 1994 to 1996 and both are again significant for the next three-year period from 1997 to 1999. One based upon the results shown in Table V.13 can conclude that there is not difference between the monthly autocorrelation coefficient of first lag of restricted series and that of the unrestricted series. One explanation of this finding could be that, whenever the horizon of the returns is larger (e.g. monthly returns versus weekly returns), both restricted and unrestricted series tend to revert to the mean and converge approximately to the same level.

TABLE V.13

SUMMARY FOR FIRST LAGGED AUTOCORRELATION ON MONTHLY RETURNS

TIME PERIOD 1994-1999

The following table compares the first lagged autocorrelation on monthly returns for Restricted Series, Unrestricted Series . The Model in all cases is $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=5} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on series i in month t-j, ρ_{jt} is the autocorrelation coefficient for the lagged monthly return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term. Below are described the Mean and Std. Error of ρ_1 as well as the extremes values and 25, 50 and 75 percentiles. Data was obtained from the Mexican Stock Exchange for the period from January 1994 through December 1999.

94:01:03 – 99:12:30

ρ monthly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
Restricted ρ1	-0.316	-0.220	-0.044	0.041	0.264	-0.077	0.021
Unrestricted ρ1	-0.328	-0.262	-0.089	0.035	0.239	-0.074	0.023

94:01:03 – 96:12:31

ρ monthly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
Restricted ρ1	-0.460	-0.245	0.067	0.166	0.384	-0.018	0.047
Unrestricted ρ1	-0.599	-0.276	-0.046	0.211	0.391	-0.033	0.057

97:01:03 – 99:12:30

ρ monthly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
Restricted ρ1	-0.379	-0.214	-0.080	-0.022	0.255	-0.099	0.031
Unrestricted ρ1	-0.297	-0.214	-0.091	-0.010	0.052	-0.113	0.021

IMPLICATIONS OF THE RESULTS ON PREDICTABILITY AND MARKET SEGMENTATION

The predictability of the Mexican Stock Exchange has been decreasing over time and that implies that the exchange is currently more efficient. This trend is consistent with the fact that the CNBV [11] has regulated the exchange in a stricter way, with special emphasis on the information's dissemination and the protection of small investors;[12] and those policies have prevented, to a great extent, the use and dispersion of inside information and other practices that negatively affect the free interaction of the market.

The improvement of market efficiency has positive implications for all participants. The perception of an efficient market generates a larger level of confidence that consequently causes larger investments, especially for foreign investors whose level of investment is larger than that of domestic investors. In the same way, to have an improvement of market efficiency implies that regulators have been successful in implementing the right legislation to reduce miss-practices without causing a reduction on the activity of the market.

In recent years the Mexican Stock Exchange has been concentrated in fewer stocks—stocks with the largest market capitalization--. This is evident in practice, for example, in 1994 there was a true interest for small-caps stocks—stocks with market capitalization value lower than 500 millions pesos—and as a result of this the market had a greater level of depth. Since the 1995 crisis there have been very few successful public offerings of large market

[11] Comisión Nacional Bancaria y de Valores, is an organism of the Secretaría de Hacienda y Crédito Público which regulates the BMV.
[12] For example, see CNVB "Circular 11-31" on www.cnbv.gob.mx

capitalization firms and the market started to concentrate in stocks that generally compounded the IPC index. Furthermore, the investor's choice is currently oriented toward large companies that are related with U.S. firms--for example Walmex-- or their choice is oriented toward firms with international operations such as Cemex. This concentration might have driven the market to have a lower level of predictability through time. In the section of Future Lines of Research, I define studies that can be performed to test hypotheses related with the issue of concentration and predictability.

It is widely known that series **B** has larger trading activity than that of series **A** because both domestic and foreign investors can buy the unrestricted series. The higher demand induces price premia on series **B**. Such is the case of Posadas, in which the series with more trading activity are series **L,** that have no voting rights, but they are available for foreign investors. Due to the latter, the price is higher.

Ownership restrictions function as a shield for domestic firms to maintain control over the company. Furthermore, it has been seen that free-float is one of the ways companies use to protect themselves against a hostile takeover; nonetheless, this level of free-float is restricted to be not less than twelve percent.[13] Actually, companies with a higher level of free-float are more attractive than those with a lower level of free-float. In practice, financial intermediates issue public offerings with high levels of free-float to minimize the risk of not completely selling the series.

[13] See "Circular 11-31" CNBV.

Companies are not going to lose control if they have high level of free-float because that induces higher-price premia on series with no voting rights. Furthermore, foreign investors are more interested for the stock to be bought or sold without difficulties more than to have control over the companies. Currently the trend on the BMV is that firms are issuing only one series without restrictions, which implies that companies are looking forward to having trading activity.

CONCLUSIONS

The search for predictability in asset returns in equity exchanges has occupied the attention of speculators and scientists since the arrival of organized financial markets. The evidence I present suggests that the Mexican Stock Exchange is predictable to a moderate degree, which has been decreasing over time. The fine structure of securities markets and frictions in the trading process may generate predictability. Predictability to some extent could be viewed as a necessary reward for an investor to bear certain dynamic risks. I use the stock-return autocorrelation of first order as a measurement of predictability; in other words, I evaluate the extent to which the variation of returns (daily, weekly or monthly) of the Mexican Stock Exchange is predictable by using only previous observations of the stock return. My results show that the magnitude and decay pattern of the first five return autocorrelations in the daily, weekly and monthly cases, suggests the presence of a predictable component in stock returns. The magnitude of the first-order autocorrelation return is larger for short-horizon stock returns than for long-horizon stock returns. In addition my results indicate that the extent of the first-order return autocorrelation is inversely proportional to the level of trading activity for weekly returns. As for the daily and monthly return-autocorrelation concerns, trading activity does not create any statistically significant difference in the first-order return autocorrelations between the least trading active stocks and the most trading active stocks. Furthermore, the level of the first-order daily return autocorrelation is larger in the past than that of current times. This type of tendency is also seen for first-order autocorrelation on weekly and monthly returns. In summary, these results indicate the level of predictability on the Mexican Stock Exchange is moderately low, and it is decreasing over the sample period. My results show that only 3.6% of the variation in the daily stock returns is predictable when using previous day stock return for 1989, and this figure decreases over time to the level of 0.74% for 1999.

Ownership restrictions create market segmentation in the Mexican Stock Exchange. These types of restrictions on equity ownership are quite common in both developed and emerging markets. I find that unrestricted shares trade at a statistically significant premium to restricted shares. The premia vary longitudinally and across individual firms. I analyze different hypotheses to explain the determinants of the premia by performing a panel-data model.

The results show that the premia of unrestricted to restricted shares exhibit a strong mean reversion. This suggests that short-run order imbalances in the restricted and unrestricted series stock cause temporary changes in stock price premia that are eventually reversed. In addition I find that the relative supply of the unrestricted **B** series inversely affects the level of premium, which suggests that companies may intentionally limit the extent of foreign involvement and thus induce market segmentation. This outcome is consistent with the Stulz and Wasserfallen (1995) hypothesis, in which firms segment the market to exploit differences in the demand elasticities of different customers. Indeed, I find that, in times of crisis, the relative supply of **B** series does not have a statistically significant effect on the level of stock premia.

I find that the premia decreases with the level of market capitalization; such result supports the liquidity hypothesis that predicts that premia should decrease with firm size since cost differentials are smaller for larger firms. Furthermore, my results show that premia increases with the relative liquidity of unrestricted shares, and these findings are also consistent with the liquidity hypothesis that affirms that changes in traded volume of the unrestricted shares affect changes in premia in the same direction. On the same line, I find that the premium is directly proportional to the level of free-float. In fact, when I drop the explanatory variable lagged premium from the model, then I see that free-float is the variable with the largest effect on stock premia.

FUTURE LINES OF RESEARCH

The results in both the predictability and market segmentation analyses suggest additional directions for future research. A similar study on predictability could be done for other Latin American countries and compared with the Mexican case. Event-studies on political actions in México and the impact on the Mexican Stock Exchange shall be conducted in the future and extended to other emerging Latin American Exchanges such as those of Brazil, Chile and Argentina. Political actions could affect both the predictability and market segmentation of the market due to the actions' effects on both domestic and foreign investors' expectations.

Research on concentration and implications for predictability of the Mexican Stock Exchange should be conducted; specifically this research should describe this concentration through time and test whether this concentration affects the level of predictability. It seems that the higher the concentration, the lower the level of predictability. Furthermore, one can also test if attractive companies for foreign investors have lower levels of first-order return autocorrelation.

From the study on Market Segmentation, one sees that ownership restrictions might benefit domestic firms, but these hurdles may discourage future equity investment by other international investors. In the future, an investigation of whether exogenously imposed ownership restrictions reduce the overall cost of capital for domestic firms would be important. Indeed, one could also build a model to see if there is an optimal level of free-float that makes the price-premia maximum, and test the model; furthermore, since the current trend for companies is to issue only unrestricted series, one could test whether stocks with unrestricted series perform better than those stocks with two or more—restricted and unrestricted—series.

APPENDIX

The following theorem investigates the large sample properties of the estimated autocovariances and autocorrelations.

Theorem A.1 Let X_t be a finite moving average time series defined by

$$X_t = \sum_{j=0}^{M} \alpha_j e_{t-j},$$

where the e_t are independent $(0, \sigma^2)$ random variables with fourth moment $\eta\sigma^4$ and sixth moment ξ. Let K be fixed. Then the limiting distribution of $n^{\frac{1}{2}}[\hat{\gamma}(0) - \gamma(0), \hat{\gamma}(1) - \gamma(1), \ldots, \hat{\gamma}(K) - \gamma(K)]'$ is multivariate normal with mean zero an covariance matrix **V** where the elements of **V** are defined as

$$\mathbf{V} = Cov\{\tilde{\gamma}(h), \tilde{\gamma}(q)\}, \text{ and also } \tilde{\gamma}(h) = \frac{1}{n-h}\sum_{t=1}^{n-h} X_t X_{t+h}.$$

Proof. The estimated covariance, for h=0,1,2,…,K, is

$$\hat{\gamma}(h) = \frac{1}{n}\sum_{t=1}^{n-h}(X_t - \bar{x}_n)(X_{t+h} - \bar{x}_n)$$

$$= \frac{1}{n}\sum_{t=1}^{n-h} X_t X_{t+h} - \frac{1}{n}\bar{x}_n \sum_{t=1}^{n-h}(X_t X_{t+h}) + \frac{n-h}{n}\bar{x}_n^2. \qquad \text{A.1}$$

The last two terms will converge in probability to zero when multiplied by $n^{1/2}$. Thus, in searching for the limiting distribution of $n^{1/2}[\hat{\gamma}(h) - \gamma(h)]$, one needs only to consider the first term on the right of equation A.1. Let

$$S_n = n^{1/2}\sum_{h=0}^{K}\lambda_h\left[\frac{1}{n}\sum_{t=1}^{n-h} X_t X_{t+h} - \gamma(h)\right]$$

$$= n^{-1/2}\sum_{h=0}^{K}\sum_{t=1}^{n-h}\lambda_h[Z_{th} - E\{Z_{th}\}] - n^{-1/2}\sum_{h=0}^{K} h\lambda_h\gamma(h),$$

where the λ_h are arbitrary real numbers (not all zero) and

$$Z_{th} = X_t X_{t+h}, \qquad h = 0,1,2,\dots,K.$$

Z_{th} is an (M+h)-dependent covariance stationary time series with mean $\gamma_X(h)$ and covariance function

$$\gamma_{Z_h}(s) = E\{(X_t X_{t+h})(X_{t+s} X_{t+s+h})\}$$

$$= (\eta - 3)\sigma^4 \sum_{j=-\infty}^{\infty} \alpha_j \alpha_{j+h} \alpha_{j+s} \alpha_{j+s+h}$$

$$+ \gamma^2(h) + \gamma^2(s) + \gamma(s+h)\gamma(s-h),$$

where $\alpha_j = 0$ for $j > M$ *and* $j < 0$. Thus the weighted average of the Z_{th}'s,

$$Y_t = \sum_{h=0}^{K} \lambda_h Z_{th} = \sum_{h=0}^{K} \lambda_h X_t X_{t+h},$$

is a stationary time series. Furthermore, the time series Y_t *is* $(M+K)$- dependent and has finite third moment, and

$$\lim_{n\to\infty} n^{-1/2} \sum_{h=0}^{K} h\lambda_h \gamma(h) = 0.$$

Therefore by Fuller (1976 Theorem 6.3.2), S_n converges in distribution to a normal random variable. Since the λ_h were arbitrary, the vector random variable $n^{\frac{1}{2}}[\hat{\gamma}(0)-\gamma(0), \hat{\gamma}(1)-\gamma(1),\dots,\hat{\gamma}(K)-\gamma(K)]'$ converges in distribution to a multivariate normal by Fuller [(1976) Theorem 5.3.3].

Corollary A.1.1 Let the assumptions in **Theorem A.1** hold. Then the vector $n^{\frac{1}{2}}[\hat{r}(1)-\rho(1), \hat{r}(2)-\rho(2),\dots,\hat{r}(K)-\rho(K)]'$ converges in distribution to a multivariate normal with mean zero and covariance matrix **G**, where the *hq*th element of **G** is $\sum_{p=-\infty}^{\infty}[\rho(p)\rho(p-h+q) + \rho(p+q)\rho(p-h) - 2\rho(q)\rho(p)\rho(p-h) -$ $- 2\rho(h)\rho(p)\rho(p-q) + 2\rho(h)\rho(q)\rho^2(p)]$.

ALGORITHM FOR ADJUSTING PRICES

Price adjusted process due to dividends

Whenever a dividend is paid in cash, the price is adjusted by a factor, as follows:

$$\text{Adjusted Price} = \text{Adjusting Factor} * \text{Observed Price}.$$

where,

$$\text{Adjusting Factor} \equiv 1 - \frac{\text{Dividend}}{\text{Observed price}}.$$

$$\text{Observed price} \equiv \text{Closed price of the day before.}$$

For example, if somebody holds 100 shares of stock and the Market Price is $10.0, and if the dividend is equal to $1.0 per share of stock, the adjusting factor will be 0.9 and therefore the Adjusted Price will be equal to $9.0. Exhibit A illustrates this process:

EXHIBIT A.

Number of Shares	Market Price	Capitalization
100	$10.0	$1000
	(Dividend per share) =$1.0	$100
100	(Adjusted Price) = $9.0	$900

Furthermore, the adjusting price process works backward and on a cumulative basis every time that there is an event. For example, the table below (EXHIBIT B) shows the different Corporate Actions that TELMEX has done for its stock TLMX–L during 1999 and 2000 (Source: Economatica).

EXHIBIT B.

TELEFONOS DE MEXICO L. Corporate Actions.
Prices and Dividends in pesos.

Date	Description	Observed Price	Adjusted Price
3/22/99	Dividend of 0.175 per share	31.10	14.972
6/21/99	Dividend of 0.20 per share	38.45	18.616
9/20/99	Dividend of 0.20 per share	34.05	16.572
12/20/99	Dividend of 0.20 per share	52.50	25.702
1/31/00	Split: Each share will be replaced by 2.00 new shares	51.40	25.26
3/19/00	Dividend of 0.10 per share	32.55	31.992
6/19/00	Dividend of 0.115 per share	26.90	26.52
9/18/00	Dividend of 0.115 per share	25.20	24.951
12/18/00	Dividend of 0.115 per share	21.55	21.435

Notice how the process works backward from the present to the past thru the entire time series, and in a cumulative basis. Source: Economatica.

Whenever the dividend is paid off with more stocks, the price is adjusted in such a way that the capitalization does not change. For example, if an investor holds 100 shares of stock worth of $1000, in other words $10 per share, and if he receives stock dividend in a ratio of 1: 4, --this case, and 25 shares--the adjusted price will be equal to $8, based upon the following relationship:

$$\text{Adjusted Price} = \frac{\text{Observed Price}}{(1 + \text{Dividend payoff ratio})}.$$

Price adjusted process due to subscription

Sometimes companies give the chance to the shareholders to buy, at a particular price, a pre-determined number of shares as a proportion of the number of shares outstanding.

The two elements in this process to be considered are the proportion of shares the stockholder can buy and the subscription price. Suppose that a given shareholder has 100 stocks and the market price is $10.0 per share; if the firm allows a subscription of one share of stock for each ten outstanding at a subscription price of $9.0, the adjusted price will be such that the capitalization will equate the sum of all capitalization. Exhibit C illustrates this:

EXHIBIT C.

Number of shares	Price (Market or Subscription)	Capitalization
100	$10.0	$1000.0
New shares = 10	$9.0	$90.0
Total shares = 110	Adjusted price = $9.909	$1090.0

The adjusted price goes after the following relationship:

$$\text{Adjusted Price} = \frac{\text{MP} + (\text{SR} * \text{SP})}{1 + \text{SR}}$$

where MP and SP are the market price and subscription price respectively, and where SR is the subscription ratio expressed in decimal.

Price adjusted process due to stock split

Usually when the price of a particular stock has gone up too high, the firm replaces the old shares for a number (greater than one) of new shares. This strategy is known as stock split, and makes the stock more manageable in terms of prices. For example on January 31, 2000, Teléfonos de México made the following split: Each share was replaced by 2.0 new shares (see Exhibit B). Therefore, the new price should be half of the former one, in order to maintain the same capitalization level. In this example, the observed price is \$51.40 pesos, and the adjusted price is \$25.26, which is not exactly half of the observed price due to the effect of an ex-post dividend payoff stream.

TABLE A.1

DAILY STOCK RETURN AUTOCORRELATION. AGGREGATE.

Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on security i in day t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). Two hundred fifty securities were analyzed, thus there are 250 autocorrelation coefficients per each lag. Below, are displayed only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	133	53.2	120	48.0	13	5.2
2	61	24.4	53	21.2	8	3.2
3	42	16.8	28	11.2	14	5.6
4	45	18.0	33	13.2	12	4.8
5	39	15.6	32	12.8	7	2.8
6	32	12.8	25	10.0	7	2.8
7	26	10.4	11	4.4	15	6.0
8	20	8.0	13	5.2	7	2.8
9	20	8.0	13	5.2	7	2.8
10	15	6.0	12	4.8	3	1.2
11	13	5.2	6	2.4	7	2.8
12	27	10.8	19	7.6	8	3.2
13	20	8.0	13	5.2	7	2.8
14	18	7.2	11	4.4	7	2.8
15	16	6.4	9	3.6	7	2.8
16	18	7.2	10	4.0	8	3.2
17	15	6.0	10	4.0	5	2.0
18	28	11.2	17	6.8	11	4.4
19	17	6.8	12	4.8	5	2.0
20	16	6.4	12	4.8	4	1.6
21	15	6.0	8	3.2	7	2.8
22	15	6.0	10	4.0	5	2.0
23	24	9.6	16	6.4	8	3.2
24	24	9.6	16	6.4	8	3.2
25	20	8.0	6	2.4	14	5.6

TABLE A.2

DAILY STOCK RETURN AUTOCORRELATION. Q1 LEAST ACTIVE STOCKS.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in day t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). Securities are classified by activity (using as a proxy: number of price changes); four quartiles were obtained, Q1 being the least active and Q4 being the most active. For this bin (Q1), 97 securities were analyzed, thus I obtained 97 autocorrelation coefficients per each lag. The table below shows only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	49	50.5	42	43.2	7	7.3
2	34	35.1	32	32.9	2	2.2
3	22	22.7	16	16.5	6	6.2
4	26	26.8	19	19.6	7	7.2
5	23	23.7	21	21.6	2	2.1
6	20	20.6	17	17.5	3	3.1
7	12	12.4	6	6.2	6	6.2
8	13	13.4	9	9.3	4	4.1
9	13	13.4	8	8.2	5	5.2
10	7	7.2	4	4.1	3	3.1
11	7	7.2	3	3.1	4	4.1
12	19	19.6	14	14.4	5	5.2
13	9	9.3	8	8.2	1	1.1
14	9	9.3	7	7.2	2	2.1
15	10	10.3	7	7.2	3	3.1
16	10	10.3	6	6.2	4	4.1
17	10	10.3	8	8.2	2	2.1
18	10	10.3	5	5.2	5	5.1
19	9	9.3	5	5.2	4	4.1
20	5	5.2	4	4.1	1	1.1
21	9	9.3	5	5.2	4	4.1
22	10	10.3	7	7.2	3	3.1
23	10	10.3	6	6.2	4	4.1
24	14	14.4	8	8.2	6	6.2
25	13	13.4	4	4.1	7	9.3

TABLE A.3

DAILY STOCK RETURN AUTOCORRELATION. SECOND QUARTILE.

Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on security i in day t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). Securities are classified by activity (using as a proxy number of price changes); four quartiles were obtained, Q1 being the least active and Q4 being the most active. For the second quartile 47 securities were analyzed, thus I obtained 47 autocorrelation coefficients per each lag. The table below shows only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	25	53.2	22	46.8	3	6.4
2	9	19.1	8	17.0	1	2.1
3	5	10.6	5	10.6	0	0.0
4	10	21.3	6	12.8	4	8.5
5	8	17.0	5	10.6	3	6.4
6	9	19.1	7	14.9	2	4.2
7	8	17.0	2	4.3	6	12.7
8	3	6.3	1	2.1	2	4.2
9	1	2.1	1	2.1	0	0.0
10	2	4.3	2	4.2	0	0.1
11	3	6.3	1	2.1	2	4.2
12	4	8.5	2	4.2	2	4.3
13	9	19.1	4	8.5	5	10.6
14	3	6.4	1	2.1	2	4.3
15	3	6.4	2	4.2	1	2.2
16	6	12.8	3	6.4	3	6.4
17	3	6.4	1	2.1	2	4.3
18	9	19.1	4	8.5	5	10.6
19	5	10.6	4	8.5	1	2.1
20	4	8.5	3	6.4	1	2.1
21	2	4.2	1	2.1	1	2.1
22	3	6.4	2	4.3	1	2.1
23	6	12.8	3	6.4	3	6.4
24	2	4.3	2	4.3	1	0.0
25	1	2.1	0	0.0	1	2.1

TABLE A.4

DAILY STOCK RETURN AUTOCORRELATION. THIRD QUARTILE.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in day t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). Securities are classified by activity (using as a proxy number of price changes); four quartiles were obtained, Q1 being the least active and Q4 being the most active. For the third quartile 25 securities were analyzed, thus I obtained 25 autocorrelation coefficients per each lag. The table below shows only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	13	52.0	13	52.0	0	0.0
2	5	20.0	4	16.0	1	4.0
3	6	24.0	5	20.0	1	4.0
4	3	12.0	2	8.0	1	4.0
5	4	16.0	2	8.0	2	8.0
6	1	4.0	0	0.0	1	4.0
7	3	12.0	2	8.0	1	4.0
8	2	8.0	2	8.0	0	0.0
9	1	4.0	1	4.0	0	0.0
10	2	8.0	2	8.0	0	0.0
11	1	4.0	1	4.0	0	0.0
12	3	12.0	3	12.0	0	0.0
13	1	4.0	0	0.0	1	4.0
14	2	8.0	1	4.0	1	4.0
15	2	8.0	0	0.0	2	8.0
16	1	4.0	0	0.0	1	4.0
17	1	4.0	0	0.0	1	4.0
18	3	12.0	2	8.0	1	4.0
19	3	12.0	3	12.0	0	0.0
20	3	12.0	2	8.0	1	4.0
21	0	0.0	0	0.0	0	0.0
22	0	0.0	0	0.0	0	0.0
23	3	12.0	2	8.0	1	4.0
24	2	8.0	1	4.0	1	4.0
25	4	16.0	1	4.0	3	12.0

TABLE A.5

DAILY STOCK RETURN AUTOCORRELATION. MOST ACTIVE STOCKS.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in day t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). Securities are classified by activity (using as a proxy number of price changes); four quartiles were obtained, Q1 being the least active and Q4 being the most active. For the most active stocks, the fourth quartile, 81 securities were analyzed, thus I obtained 81 autocorrelation coefficients per each lag. The table below shows only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	46	56.8	43	53.1	3	3.7
2	13	16.0	9	11.1	4	4.9
3	9	11.1	2	2.5	7	8.6
4	6	7.4	6	7.4	0	0.0
5	4	4.9	4	4.9	0	0.0
6	2	2.5	1	1.2	1	1.3
7	3	3.7	1	1.2	2	2.5
8	2	2.5	1	1.2	1	1.3
9	5	6.2	3	3.7	2	2.5
10	4	4.9	4	4.9	0	0.0
11	2	2.5	1	1.2	1	1.3
12	1	1.2	0	0.0	1	1.2
13	1	1.2	1	1.2	0	0.0
14	4	4.9	2	2.5	2	2.4
15	1	1.2	0	0.0	1	1.2
16	1	1.2	1	1.2	0	0.0
17	1	1.2	1	1.2	0	0.0
18	6	7.4	6	7.4	0	0.0
19	0	0.0	0	0.0	0	0.0
20	4	4.9	3	3.7	1	1.2
21	4	4.9	2	2.5	2	2.4
22	2	2.5	1	1.2	1	1.3
23	5	6.2	5	6.2	0	0.0
24	6	7.4	5	6.2	1	1.2
25	2	2.5	1	1.2	1	1.3

TABLE A.6

WEEKLY STOCK RETURN AUTOCORRELATION. AGGREGATE.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in week t-j, ρ_{jt} is the autocorrelation coefficient for the lagged weekly return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). I observe prices on Wednesday; if the price is missed I took the next available day. 235 securities were analyzed, thus I obtained 235 autocorrelation coefficients per each lag. The table below shows only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	65	27.7	59	25.1	6	2.6
2	45	19.1	31	13.2	14	5.9
3	34	14.4	26	11.1	8	3.3
4	38	16.2	28	11.9	10	4.3
5	26	11.1	14	6.0	12	5.1
6	20	8.5	12	5.1	8	3.4
7	21	9.0	6	2.6	15	6.4
8	22	9.4	9	3.8	13	5.6
9	26	11.1	9	3.8	15	7.3
10	10	4.3	5	2.1	5	2.2
11	13	5.5	7	2.9	6	2.6
12	16	6.8	9	3.8	7	3.0
13	14	6.0	11	4.7	3	1.3
14	25	10.6	12	5.1	13	5.5
15	21	8.9	10	4.3	11	4.6
16	14	5.9	9	3.8	5	2.1
17	19	8.1	9	3.8	10	4.3
18	15	6.4	10	4.3	5	2.1
19	23	9.8	11	4.7	12	5.1
20	15	6.4	9	3.8	6	2.6
21	9	3.8	5	2.1	4	1.7
22	14	6.0	7	3.0	7	3.0
23	11	4.7	5	2.1	6	2.6
24	9	3.8	2	1.0	7	2.8
25	14	6.0	7	3.0	7	3.0

TABLE A.7

WEEKLY STOCK RETURN AUTOCORRELATION. Q1 LEAST ACTIVE STOCKS

Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on security i in week t-j, ρ_{jt} is the autocorrelation coefficient for the lagged weekly return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). I observe prices on Wednesday; if the price is missed I took the next available day. Securities are classified by activity (using as a proxy: number of price changes); four quartiles were obtained, Q1 being the least active and Q4 being the most active. For this bin (Q1), 52 securities were analyzed, thus I obtained 52 autocorrelation coefficients per each lag. The table below shows only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	21	40.4	20	38.5	1	1.9
2	14	27.0	9	17.3	5	9.7
3	14	27.0	13	25.0	1	2.0
4	13	25.0	11	21.1	2	3.9
5	8	15.4	4	7.7	4	7.7
6	8	15.4	6	11.5	2	3.9
7	3	5.8	2	3.8	1	2.0
8	8	15.4	3	5.8	5	9.6
9	8	15.4	5	9.6	3	5.8
10	6	11.5	5	9.6	1	1.9
11	5	9.6	3	5.8	2	3.8
12	4	7.7	3	5.8	1	1.9
13	5	9.6	4	7.7	1	1.9
14	7	13.5	4	7.7	3	5.8
15	7	13.5	5	9.6	2	3.9
16	3	5.8	2	3.8	1	2.0
17	6	11.5	2	3.8	4	7.7
18	5	9.6	3	5.8	2	3.8
19	6	11.5	5	9.6	1	1.9
20	5	9.6	3	5.8	2	3.8
21	4	7.7	2	3.8	2	3.9
22	5	9.6	5	9.6	0	0.0
23	4	7.7	2	3.8	2	3.9
24	3	5.8	0	0.0	3	5.8
25	4	7.7	3	5.8	1	1.9

TABLE A.8

WEEKLY STOCK RETURN AUTOCORRELATION. SECOND QUARTILE.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in week t-j, ρ_{jt} is the autocorrelation coefficient for the lagged weekly return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). I observe prices on Wednesday; if the price is missed I took the next available day. Securities are classified by activity (using as a proxy: number of price changes); four quartiles were obtained, Q1 being the least active and Q4 being the most active. For this bin (Q2), 45 securities were analyzed, thus I obtained 45 autocorrelation coefficients per each lag. The table below shows only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	11	24.4	8	17.8	3	6.6
2	13	28.9	7	15.6	6	13.3
3	10	22.2	6	13.3	4	8.9
4	11	24.4	7	15.6	4	8.8
5	6	13.3	2	4.4	4	8.9
6	5	11.1	3	6.7	2	4.4
7	0	0.0	0	0.0	0	0.0
8	4	8.9	2	4.4	2	4.5
9	6	13.3	2	4.4	4	8.9
10	1	2.2	0	0.0	1	2.2
11	4	8.8	2	4.4	2	4.4
12	7	15.6	4	8.9	3	6.7
13	4	8.9	4	8.9	0	0.0
14	8	17.8	3	6.7	5	11.1
15	4	8.9	2	4.4	2	4.5
16	4	8.9	2	4.4	2	4.5
17	7	15.6	6	13.3	1	2.3
18	2	4.4	1	2.2	1	2.2
19	8	17.8	3	6.7	5	11.1
20	1	2.2	0	0.0	1	2.2
21	2	4.4	1	2.2	1	2.2
22	5	11.1	1	2.2	4	8.9
23	5	11.1	2	4.4	3	6.7
24	2	4.4	1	2.2	1	2.2
25	3	6.7	3	6.7	0	0.0

TABLE A.9

WEEKLY STOCK RETURN AUTOCORRELATION. QUARTILE 3.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in week t-j, ρ_{jt} is the autocorrelation coefficient for the lagged weekly return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). I observe prices on Wednesday; if the price is missed I took the next available day. Securities are classified by activity (using as a proxy: number of price changes); four quartiles were obtained, Q1 being the least active and Q4 being the most active. For this bin (Q3), 35 securities were analyzed, thus I obtained 35 autocorrelation coefficients per each lag. The table below shows only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	11	31.4	10	28.6	1	2.8
2	6	17.1	5	14.3	1	2.8
3	3	8.6	1	2.9	2	5.7
4	7	20.0	4	11.4	3	8.6
5	8	22.8	5	14.3	3	8.5
6	5	14.3	2	5.7	3	8.6
7	8	22.8	4	11.4	4	11.4
8	4	11.4	2	5.7	2	5.7
9	2	5.7	1	2.9	1	2.8
10	0	0.0	0	0.0	0	0.0
11	2	5.7	1	2.9	1	2.8
12	1	2.9	1	2.9	0	0.0
13	4	11.4	2	5.7	2	5.7
14	4	11.4	2	5.7	2	5.7
15	5	14.3	1	2.8	4	11.5
16	3	8.6	2	5.7	1	2.9
17	5	14.3	1	2.8	4	11.5
18	5	14.3	4	11.4	1	2.9
19	1	2.9	0	0.0	1	2.9
20	5	14.3	3	8.6	2	5.7
21	1	2.9	1	2.9	0	0.0
22	1	2.9	0	0.0	1	2.9
23	1	2.9	0	0.0	1	2.9
24	2	5.7	0	0.0	2	5.7
25	3	8.6	1	2.9	2	5.7

TABLE A.10

WEEKLY STOCK RETURN AUTOCORRELATION. MOST ACTIVE STOCKS.

Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on security i in week t-j, ρ_{jt} is the autocorrelation coefficient for the lagged weekly return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). I observe prices on Wednesday; if the price is missed I took the next available day. Securities are classified by activity (using as a proxy: number of price changes); four quartiles were obtained, Q1 being the least active and Q4 being the most active. For the most active stocks, the fourth quartile, 103 securities were analyzed, thus I obtained 103 autocorrelation coefficients per each lag. The table below shows only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	22	21.4	21	20.4	1	1.0
2	12	11.7	10	9.7	2	2.0
3	7	6.8	6	5.8	1	1.0
4	7	6.8	6	5.8	1	1.0
5	4	3.9	3	2.9	1	1.0
6	2	1.9	1	1.0	1	0.9
7	10	9.7	0	0.0	10	9.7
8	6	5.8	2	1.9	4	3.9
9	10	9.7	1	1.0	9	8.7
10	3	2.9	0	0.0	3	2.9
11	2	1.9	1	1.0	1	0.9
12	4	3.9	1	1.0	3	2.9
13	1	1.0	1	1.0	0	0.0
14	6	5.8	3	2.9	3	2.9
15	5	4.9	2	1.9	3	3.0
16	4	3.9	3	2.9	1	1.0
17	1	1.0	0	0.0	1	1.0
18	3	2.9	2	1.9	1	1.0
19	8	7.8	3	2.9	5	4.9
20	4	3.9	3	2.9	1	1.0
21	2	1.9	1	1.0	1	0.9
22	3	2.9	1	1.0	2	1.9
23	1	1.0	1	1.0	0	0.0
24	2	1.9	1	1.0	1	0.9
25	4	3.9	0	0.0	4	3.9

TABLE A.11

MONTHLY STOCK RETURN AUTOCORRELATION. AGGREGATE.

Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=12} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on security i in month t-j, ρ_{jt} is the autocorrelation coefficient for the lagged monthly return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). 187 securities were analyzed, thus I obtained 187 autocorrelation coefficients per each lag. The table below shows only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	43	23.0	36	19.3	7	3.7
2	32	17.1	15	8.0	17	9.1
3	19	10.2	11	5.9	8	4.3
4	19	10.2	13	7.0	6	3.2
5	27	14.4	9	4.8	22	9.6
6	23	12.3	4	2.1	19	10.2
7	8	4.3	4	2.1	4	2.2
8	14	7.5	11	5.9	3	1.6
9	8	4.3	7	3.7	1	0.6
10	8	4.3	2	1.1	6	3.2
11	7	3.7	4	2.1	3	1.6
12	11	5.9	3	1.6	8	4.3
13	10	5.3	1	1.0	9	4.3
14	8	4.3	0	0.0	8	4.3
15	7	3.7	2	1.1	5	2.6
16	5	2.7	1	1.0	4	1.7
17	6	3.2	4	2.1	2	1.1
18	5	2.7	1	1.0	4	1.7
19	2	1.1	1	1.0	1	0.1
20	4	2.1	4	2.1	0	0.0
21	4	2.1	3	1.6	1	0.5
22	2	1.1	1	1.0	1	0.1
23	3	1.6	1	1.0	2	0.6
24	2	1.1	0	0.0	2	1.1
25	2	1.1	1	1.0	1	0.1

TABLE A.12

MONTHLY STOCK RETURN AUTOCORRELATION. Q1 LEAST ACTIVE STOCKS.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=12} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in month t-j, ρ_{jt} is the autocorrelation coefficient for the lagged monthly return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). I observe prices on the first trading day of each month; if the price is missed I took the next available day. Securities are classified by activity (using as a proxy: number of price changes); four quartiles were obtained, Q1 being the least active and Q4 being the most active. For this quartile Q1, 15 securities were analyzed, thus I obtained 15 autocorrelation coefficients per each lag. The table below shows only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	2	13.3	2	13.3	0	0.0
2	2	13.3	1	6.7	1	6.6
3	1	6.7	1	6.7	0	0.0
4	1	6.7	1	6.7	0	0.0
5	2	13.3	2	13.3	0	0.0
6	0	0.0	0	0.0	0	0.0
7	2	13.3	1	6.7	1	6.6
8	1	6.7	1	6.7	0	0.0
9	1	6.7	1	6.7	0	0.0
10	0	0.0	0	0.0	0	0.0
11	1	6.7	1	6.7	0	0.0
12	0	0.0	0	0.0	0	0.0
13	0	0.0	0	0.0	0	0.0
14	0	0.0	0	0.0	0	0.0
15	0	0.0	0	0.0	0	0.0
16	0	0.0	0	0.0	0	0.0
17	0	0.0	0	0.0	0	0.0
18	1	6.7	0	0.0	1	6.7
19	0	0.0	0	0.0	0	0.0
20	1	6.7	1	6.7	0	0.0
21	0	0.0	0	0.0	0	0.0
22	0	0.0	0	0.0	0	0.0
23	0	0.0	0	0.0	0	0.0
24	0	0.0	0	0.0	0	0.0
25	1	6.7	1	6.7	0	0.0

TABLE A.13

MONTHLY STOCK RETURN AUTOCORRELATION. SECOND QUARTILE.

Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=12} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on security i in month *t-j*, ρ_{jt} is the autocorrelation coefficient for the lagged monthly return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). I observe prices on the first trading day of each month; if the price is missed I took the next available day. Securities are classified by activity (using as a proxy: number of price changes); four quartiles were obtained, Q1 being the least active and Q4 being the most active. For this quartile Q2, 20 securities were analyzed, thus I obtained 20 autocorrelation coefficients per each lag. The table below shows only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	11	55.0	9	45.0	2	10.0
2	5	25.0	4	20.0	1	5.0
3	4	20.0	3	15.0	1	5.0
4	3	15.0	2	10.0	1	5.0
5	4	20.0	2	10.0	2	10.0
6	3	15.0	2	10.0	1	5.0
7	1	5.0	1	5.0	0	0.0
8	1	5.0	1	5.0	0	0.0
9	2	10.0	2	10.0	0	0.0
10	1	5.0	1	5.0	0	0.0
11	3	15.0	2	10.0	1	5.0
12	4	20.0	2	10.0	2	10.0
13	3	15.0	1	5.0	2	10.0
14	0	0.0	0	0.0	0	0.0
15	2	10.0	1	10.0	1	0.0
16	0	0.0	0	0.0	0	0.0
17	1	5.0	1	5.0	0	0.0
18	1	5.0	1	5.0	0	0.0
19	0	0.0	0	0.0	0	0.0
20	1	5.0	1	5.0	0	0.0
21	2	10.0	2	10.0	0	0.0
22	0	0.0	0	0.0	0	0.0
23	1	5.0	1	5.0	0	0.0
24	0	0.0	0	0.0	0	0.0
25	0	0.0	0	0.0	0	0.0

TABLE A.14

MONTHLY STOCK RETURN AUTOCORRELATION. THIRD QUARTILE

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=12} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in month t-j, ρ_{jt} is the autocorrelation coefficient for the lagged monthly return R_{it-j}, for the sample period of January 2[nd] 1987 to Oct 29[th] 1999 in the Mexican Stock Exchange (BMV). I observe prices on the first trading day of each month; if the price is missed I took the next available day. Securities are classified by activity (using as a proxy: number of price changes); four quartiles were obtained, Q1 being the least active and Q4 being the most active. For this quartile Q3, 17 securities were analyzed, thus I obtained 17 autocorrelation coefficients per each lag. The table below shows only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	5	29.4	5	29.4	0	0.0
2	3	17.6	2	11.8	1	5.8
3	1	5.9	0	0.0	1	5.9
4	1	5.9	0	0.0	1	5.9
5	2	11.8	1	5.8	1	6.0
6	2	11.8	0	0.0	2	11.8
7	0	0.0	0	0.0	0	0.0
8	3	17.6	2	11.8	1	5.8
9	1	5.9	0	0.0	1	5.9
10	2	11.8	0	0.0	2	11.8
11	1	5.9	1	5.9	0	0.0
12	2	11.8	1	5.9	1	5.9
13	1	5.9	0	0.0	1	5.9
14	0	0.0	0	0.0	0	0.0
15	2	11.8	1	5.9	1	5.9
16	0	0.0	0	0.0	0	0.0
17	1	5.9	1	5.9	0	0.0
18	1	5.9	0	0.0	1	5.9
19	1	5.9	1	5.9	0	0.0
20	1	5.9	1	5.9	0	0.0
21	1	5.9	0	0.0	1	5.9
22	0	0.0	0	0.0	0	0.0
23	0	0.0	0	0.0	0	0.0
24	0	0.0	0	0.0	0	0.0
25	0	0.0	0	0.0	0	0.0

TABLE A.15

MONTHLY STOCK RETURN AUTOCORRELATION. MOST ACTIVE STOCKS.

Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=12} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on security i in month t-j, ρ_{jt} is the autocorrelation coefficient for the lagged monthly return R_{it-j}, for the sample period of January 2nd 1987 to Oct 29th 1999 in the Mexican Stock Exchange (BMV). I observe prices on the first trading day of each month; if the price is missed I took the next available day. Securities are classified by activity (using as a proxy: number of price changes); four quartiles were obtained, Q1 being the least active and Q4 being the most active. For this quartile Q4, 135 securities were analyzed, thus I obtained 135 autocorrelation coefficients per each lag. The table below shows only those autocorrelation coefficients which show at least 95% level of significance, i.e. $\left|\sqrt{T}\hat{\rho}\right| \geq 1.96$.

Lags	Number of Stocks with significant autocorrelation	% Stocks with significant autocorrelation	Number of Stocks with positive autocorrelation	% Stocks with positive autocorrelation	Number of Stocks with negative autocorrelation	% Stocks with negative autocorrelation
1	25	18.5	20	14.8	5	3.7
2	22	16.3	8	5.9	14	10.4
3	13	9.6	7	5.2	6	4.4
4	14	10.4	10	7.4	4	3.0
5	19	14.1	4	3.0	15	11.1
6	18	13.3	2	1.5	16	11.8
7	5	3.7	2	1.5	3	2.2
8	9	6.7	7	5.2	2	1.5
9	4	3.0	4	3.0	0	0.0
10	5	3.7	1	0.7	4	3.0
11	2	1.5	0	0.0	2	1.5
12	5	3.7	0	0.0	5	3.7
13	6	4.4	0	0.0	6	4.4
14	8	5.9	0	0.0	8	5.9
15	3	2.2	0	0.0	3	2.2
16	5	3.7	1	0.7	4	3.0
17	4	3.0	2	1.5	2	1.5
18	2	1.4	0	0.0	2	1.4
19	1	0.7	0	0.0	1	0.7
20	1	0.7	1	0.7	0	0.0
21	1	0.7	1	0.7	0	0.0
22	2	1.5	1	0.7	1	0.8
23	2	1.5	0	0.0	2	1.5
24	2	1.5	0	0.0	2	1.5
25	1	0.7	0	0.0	1	0.7

TABLE A.16

DESCRIPTIVE STATISTICS FOR AUTOCORRELATION YEAR 1989.
From first to fifth lag; daily, weekly and monthly stock returns.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in day (week) t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily (or weekly) return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term, for the Year 1989 in the Mexican Stock Exchange (BMV). For monthly returns I used the same model with 12 lags. Below are described the Mean and Std. error of ρ_i (five lags) as well as the extremes values and 25, 50 and 75 percentiles. Box-Pierce statistic (Q5) is also displayed.

89:01:02-89:12:28

ρ daily	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.118	0.075	0.188	0.295	0.772	0.192	0.034
ρ2	-0.186	-0.086	-0.024	0.059	0.346	-0.008	0.021
ρ3	-0.307	-0.075	-0.031	0.027	0.107	-0.042	0.017
ρ4	-0.331	-0.018	0.024	0.073	0.262	0.025	0.020
ρ5	-0.067	-0.010	0.019	0.058	0.174	0.023	0.010

Box'Pierce Q5 statistic for ρ daily: 27.364
Number of Stocks 31

89:01:11- 89:12:27

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.109	0.061	0.139	0.259	0.538	0.164	0.032
ρ2	-0.323	-0.140	-0.025	0.060	0.253	-0.033	0.028
ρ3	-0.288	-0.014	0.049	0.089	0.379	0.049	0.028
ρ4	-0.309	-0.100	-0.047	0.013	0.142	-0.067	0.024
ρ5	-0.250	-0.064	0.012	0.074	0.278	0.005	0.024

Box'Pierce Q5 statistic for ρ weekly: 6.588
Number of Stocks 27

89:01:02-92:12:01

ρ monthly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.567	-0.051	0.139	0.257	0.724	0.119	0.037
ρ2	-0.959	-0.129	0.002	0.089	0.381	-0.045	0.032
ρ3	-0.492	-0.059	0.107	0.240	2.468	0.143	0.053
ρ4	-3.359	-0.377	-0.158	-0.009	0.286	-0.265	0.070
ρ5	-0.949	-0.228	-0.047	0.083	0.604	-0.068	0.037

Box'Pierce Q5 statistic for ρ monthly: 33.014
Number of Stocks 57

TABLE A.17

DESCRIPTIVE STATISTICS FOR AUTOCORRELATION YEAR 1990. From first to fifth lag; daily, weekly and stock returns.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in day (week) t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily (or weekly) return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term, for the Year 1990 in the Mexican Stock Exchange (BMV). Below are described the Mean and Std. error of ρ_i (five lags) as well as the extremes values and 25, 50 and 75 percentiles. Box-Pierce (Q5) statistic is also displayed.

90:01:02-90:12:28

ρ daily	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.008	0.068	0.192	0.254	0.422	0.178	0.019
ρ2	-0.200	-0.101	-0.049	0.058	0.276	-0.019	0.021
ρ3	-0.136	-0.023	0.057	0.103	0.148	0.045	0.013
ρ4	-0.078	-0.023	0.041	0.081	0.228	0.034	0.013
ρ5	-0.320	-0.036	0.000	0.027	0.115	-0.009	0.014

Box'Pierce Q5 statistic for ρ daily: 19.079
Number of Stocks 32

90:01:10-90:12:26

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.684	0.018	0.167	0.253	0.455	0.116	0.039
ρ2	-0.387	-0.114	-0.019	0.068	0.323	-0.022	0.029
ρ3	-0.267	-0.137	-0.068	-0.021	0.151	-0.077	0.018
ρ4	-0.588	-0.066	-0.008	0.117	0.347	0.003	0.030
ρ5	-0.191	-0.045	0.000	0.155	0.408	0.056	0.026

Box'Pierce Q5 statistic for ρ weekly: 7.442
Number of Stocks 32

TABLE A.18

DESCRIPTIVE STATISTICS FOR AUTOCORRELATION YEAR 1991.
From first to fifth lag; daily, weekly stock returns.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in day (week) t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily (or weekly) return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term, for the Year 1991 in the Mexican Stock Exchange (BMV). Below are described the Mean and Std. Error of ρ_i (five lags) as well as the extremes values and 25, 50 and 75 percentiles. Box-Pierce (Q5) statistic is also displayed.

91:01:03-91:12:30

ρ daily	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.122	0.067	0.192	0.258	0.526	0.184	0.022
ρ2	-0.203	-0.086	-0.047	0.021	0.278	-0.030	0.014
ρ3	-0.173	-0.037	0.002	0.055	0.242	0.009	0.013
ρ4	-0.193	-0.083	-0.021	0.038	0.129	-0.023	0.013
ρ5	-0.164	-0.019	0.033	0.083	0.205	0.024	0.012

Box'Pierce Q5 statistic for ρ daily: 21.586
Number of Stocks 46

91:01:09-91:12:18

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.390	-0.021	0.072	0.153	0.950	0.078	0.037
ρ2	-0.752	-0.125	-0.027	0.032	0.312	-0.045	0.029
ρ3	-0.561	-0.096	-0.018	0.078	0.443	-0.026	0.030
ρ4	-0.373	-0.191	-0.079	0.009	0.213	-0.092	0.022
ρ5	-0.227	-0.052	0.023	0.140	0.359	0.043	0.022

Box'Pierce Q5 statistic for ρ weekly : 9.472
Number of Stocks 45

TABLE A.19

DESCRIPTIVE STATISTICS FOR AUTOCORRELATION YEAR 1992. From first to fifth lag; daily, weekly stock returns.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in day (week) t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily (or weekly) return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term, for the Year 1992 in the Mexican Stock Exchange (BMV). Below are described the Mean and Std. error of ρ_i (five lags) as well as the extremes values and 25, 50 and 75 percentiles. Box-Pierce (Q5) statistic is also displayed.

92:01:02-92:12:30

ρ daily	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.4740	0.0879	0.1582	0.2443	0.7322	0.1562	0.022
ρ2	-0.2778	-0.0420	0.0132	0.0661	0.3897	0.0026	0.012
ρ3	-0.1992	-0.0448	0.0076	0.0470	0.3808	0.0134	0.011
ρ4	-0.2429	-0.0737	-0.0251	0.0197	0.1352	-0.0235	0.009
ρ5	-0.1584	-0.0229	-0.0010	0.0617	0.6651	0.0283	0.013

Box'Pierce Q5 statistic for ρ daily: 23.578
Number of Stocks: 72

92:01:15-92:12:30

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.337	-0.068	0.040	0.129	2.223	0.084	0.038
ρ2	-0.980	-0.124	-0.049	0.054	0.446	-0.057	0.024
ρ3	-1.240	-0.026	0.078	0.145	0.282	0.039	0.025
ρ4	-0.305	-0.076	0.000	0.053	0.312	-0.010	0.014
ρ5	-0.911	-0.098	-0.002	0.104	1.684	0.010	0.032

Box'Pierce Q5 statistic for ρ weekly : 13.852
Number of Stocks: 71

TABLE A.20

DESCRIPTIVE STATISTICS FOR AUTOCORRELATION YEAR 1993. From first to fifth lag; daily, weekly and monthly stock returns.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in day (week) t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily (or weekly) return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term, for the Year 1993 in the Mexican Stock Exchange (BMV). For monthly returns I used the same model with 12 lags. Below are described the Mean and Std. error of ρ_i (five lags) as well as the extremes values and 25, 50 and 75 percentiles. Box-Pierce (Q5) statistic is also displayed.

93:01:04-93:12:30

ρ daily	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.4474	0.0475	0.1246	0.2151	0.6525	0.1464	0.018
ρ2	-0.1822	-0.0256	0.0254	0.0669	0.3714	0.0280	0.010
ρ3	-0.2988	-0.0391	0.0198	0.0812	0.2195	0.0159	0.010
ρ4	-0.2071	-0.0416	0.0011	0.0449	0.2327	0.0035	0.009
ρ5	-0.2481	-0.0598	-0.0167	0.0339	0.2904	-0.0073	0.009

Box'Pierce Q5 statistic for ρ daily: 19.4386
Number of Stocks: 83

93:01:13-93:12:29

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.518	-0.015	0.060	0.173	0.924	0.083	0.021
ρ2	-0.316	-0.097	-0.015	0.118	0.410	0.006	0.018
ρ3	-0.336	-0.025	0.080	0.205	1.321	0.096	0.025
ρ4	-0.748	-0.225	-0.124	-0.010	1.217	-0.099	0.025
ρ5	-0.659	-0.070	0.027	0.120	0.936	0.036	0.024

Box'Pierce Q5 statistic for ρ weekly: 11.660
Number of Stocks: 81

93:01:02-96:12:02

ρ monthly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.944	-0.130	0.014	0.163	1.382	0.003	0.029
ρ2	-1.145	-0.261	-0.133	-0.049	0.282	-0.151	0.022
ρ3	-0.779	-0.083	-0.004	0.091	0.647	0.002	0.017
ρ4	-0.434	-0.155	-0.075	0.023	0.414	-0.070	0.016
ρ5	-0.427	-0.156	-0.082	0.024	0.442	-0.052	0.017

Box'Pierce Q5 statistic for ρ monthly: 9.993
Number of Stocks : 93

TABLE A.21

DESCRIPTIVE STATISTICS FOR AUTOCORRELATION YEAR 1994. From first to fifth lag; daily, weekly stock returns.

Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on security i in day (week) *t-j*, ρ_{jt} is the autocorrelation coefficient for the lagged daily (or weekly) return R_{it-j}, α_0 is a constant and $\tilde{u}_{it}$ is the error term, for the Year 1994 in the Mexican Stock Exchange (BMV). Below are described the Mean and Std. error of ρ_i (five lags) as well as the extremes values and 25, 50 and 75 percentiles. Box-Pierce (Q5) statistic is also displayed.

94:01:04 - 94:12:30

ρ daily	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.337	0.025	0.107	0.183	0.540	0.105	0.015
ρ2	-0.359	-0.030	0.012	0.065	0.340	0.011	0.010
ρ3	-0.395	-0.035	0.022	0.072	0.292	0.011	0.011
ρ4	-0.267	-0.035	0.003	0.061	0.256	0.008	0.008
ρ5	-0.193	-0.038	0.006	0.066	0.800	0.020	0.011

Box'Pierce Q5 statistic for ρ daily: 18.252
Number of Stocks: 101

94:01:12 - 94:12:28

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.661	-0.172	-0.006	0.135	0.870	-0.003	0.024
ρ2	-0.619	-0.214	-0.098	0.018	0.745	-0.077	0.022
ρ3	-0.467	-0.073	0.015	0.135	0.688	0.017	0.018
ρ4	-0.916	-0.160	-0.068	0.027	0.253	-0.071	0.018
ρ5	-2.595	-0.097	0.001	0.138	0.427	-0.013	0.030

Box'Pierce Q5 statistic for ρ monthly: 13.406
Number of Stocks: 100

TABLE A.22

DESCRIPTIVE STATISTICS FOR AUTOCORRELATION YEAR 1995.
From first to fifth lag; daily, weekly stock returns.

Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on security i in day (week) t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily (or weekly) return R_{it-j}, α_0 is a constant and $\tilde{u}_{it}$ is the error term, for the Year 1995 in the Mexican Stock Exchange (BMV). Below are described the Mean and Std. error of ρ_i (five lags) as well as the extremes values and 25, 50 and 75 percentiles. Box-Pierce (Q5) statistic is also displayed.

95:01:03 - 95:12:29

ρ daily	**Minimum**	**25%**	**50%**	**75%**	**Maximum**	**Mean**	**Std. Error**
ρ1	-0.162	0.025	0.127	0.253	0.519	0.145	0.016
ρ2	-0.247	-0.070	-0.030	0.024	0.541	-0.023	0.010
ρ3	-0.307	-0.063	-0.010	0.049	0.177	-0.010	0.009
ρ4	-0.143	-0.051	0.004	0.040	0.191	0.000	0.007
ρ5	-0.138	-0.026	0.015	0.062	0.167	0.015	0.007

Box'Pierce Q5 statistic for ρ daily: 16.891
Number of Stocks: 91

95:01:11 - 95:12:27

ρ weekly	**Minimum**	**25%**	**50%**	**75%**	**Maximum**	**Mean**	**Std. Error**
ρ1	-0.531	-0.030	0.088	0.146	0.502	0.066	0.019
ρ2	-0.396	-0.145	-0.075	0.023	0.508	-0.039	0.019
ρ3	-0.260	-0.037	0.049	0.129	0.320	0.041	0.013
ρ4	-0.316	-0.101	-0.032	0.060	0.363	-0.016	0.016
ρ5	-0.437	-0.093	-0.015	0.069	0.231	-0.024	0.014

Box'Pierce Q5 statistic for ρ monthly: 6.264
Number of Stocks : 88

TABLE A.23

DESCRIPTIVE STATISTICS FOR AUTOCORRELATION YEAR 1996. From first to fifth lag; daily, weekly stock returns.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in day (week) t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily (or weekly) return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term, for the Year 1996 in the Mexican Stock Exchange (BMV). Below are described the Mean and Std. error of ρ_i (five lags) as well as the extremes values and 25, 50 and 75 percentiles. Box-Pierce (Q5) statistic is also displayed.

96:01:03 - 96:12:31

ρ daily	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.165	0.031	0.096	0.172	0.582	0.106	0.012
ρ2	-0.373	-0.058	-0.013	0.044	0.251	-0.007	0.009
ρ3	-0.189	-0.053	-0.006	0.049	0.253	-0.002	0.008
ρ4	-0.281	-0.075	-0.016	0.022	0.205	-0.030	0.008
ρ5	-0.164	-0.041	-0.004	0.043	0.726	0.014	0.009

Box'Pierce Q5 statistic for ρ daily: 14.87
Number of Stocks: 110

96:01:10 - 96:12:18

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.908	-0.155	-0.061	0.098	0.648	-0.055	0.023
ρ2	-0.727	-0.153	-0.040	0.080	0.366	-0.047	0.017
ρ3	-0.404	-0.112	-0.016	0.117	0.500	0.013	0.016
ρ4	-1.033	-0.178	-0.072	0.017	0.410	-0.094	0.017
ρ5	-0.312	-0.100	-0.012	0.082	0.796	0.013	0.017

Box'Pierce Q5 statistic for ρ monthly: 9.318
Number of Stocks: 104

TABLE A.24

DESCRIPTIVE STATISTICS FOR AUTOCORRELATION YEAR 1997.
From first to fifth lag; daily, weekly and monthly stock returns.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in day (week) *t-j*, ρ_{jt} is the autocorrelation coefficient for the lagged daily (or weekly) return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term, for the Year 1997 in the Mexican Stock Exchange (BMV). For monthly returns I used the same model with 12 lags. Below are described the Mean and Std. Error of ρ_i (five lags) as well as the extremes values and 25, 50 and 75 percentiles. Box-Pierce (Q5) statistic is also displayed.

97:01:03 - 97:12:31

ρ daily	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.310	-0.074	0.053	0.150	0.748	0.069	0.016
ρ2	-0.289	-0.103	-0.024	0.033	0.202	-0.032	0.008
ρ3	-0.190	-0.038	0.017	0.068	0.240	0.016	0.007
ρ4	-0.171	-0.050	-0.008	0.032	0.260	-0.010	0.006
ρ5	-0.440	-0.064	-0.016	0.026	0.526	-0.019	0.009

Box'Pierce Q5 statistic for ρ daily: 17.02
Number of Stocks: 127

97:01:15 - 97:12:31

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.484	-0.142	-0.047	0.101	0.673	-0.008	0.019
ρ2	-0.487	-0.125	0.003	0.114	0.585	-0.004	0.016
ρ3	-0.492	-0.147	-0.067	0.022	0.384	-0.058	0.013
ρ4	-0.542	-0.149	-0.062	0.047	0.420	-0.056	0.014
ρ5	-0.955	-0.124	-0.064	0.031	0.324	-0.053	0.015

Box'Pierce Q5 statistic for ρ weekly: 8.00
Number of Stocks: 129

97:02:03 - 99:10:01

ρ monthly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.788	-0.155	-0.079	0.078	0.554	-0.040	0.018
ρ2	-0.491	-0.110	-0.010	0.149	0.422	-0.006	0.017
ρ3	-0.488	-0.212	-0.058	0.080	0.371	-0.076	0.017
ρ4	-0.553	-0.212	-0.073	0.046	0.530	-0.076	0.017
ρ5	-0.420	-0.196	-0.085	0.035	0.854	-0.064	0.018

Box'Pierce Q5 statistic for ρ monthly: 6.64
Number of Stocks 102

TABLE A.25

DESCRIPTIVE STATISTICS FOR AUTOCORRELATION YEAR 1998.
From first to fifth lag; daily, weekly stock returns.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on security i in day (week) t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily (or weekly) return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term, for the Year 1998 in the Mexican Stock Exchange (BMV). Below are described the Mean and Std. error of ρ_i (five lags) as well as the extremes values and 25, 50 and 75 percentiles. Box-Pierce (Q5) statistic is also displayed.

98:01:05 - 98:12:31

ρ daily	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.186	-0.063	0.034	0.111	0.502	0.039	0.011
ρ2	-0.216	-0.048	0.012	0.065	0.197	0.006	0.008
ρ3	-0.212	-0.069	-0.002	0.032	0.508	-0.010	0.009
ρ4	-0.199	-0.021	0.019	0.064	0.345	0.028	0.009
ρ5	-0.198	-0.030	0.020	0.074	0.216	0.025	0.008

Box'Pierce Q5 statistic for ρ daily :
12.675
Number of Stocks: 113

98:01:14 - 98:12:30

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.462	-0.078	0.048	0.206	0.687	0.055	0.020
ρ2	-0.519	-0.158	-0.055	0.044	0.596	-0.045	0.016
ρ3	-0.852	-0.109	0.004	0.097	0.460	-0.001	0.018
ρ4	-0.820	-0.118	-0.004	0.117	0.367	-0.007	0.018
ρ5	-0.662	-0.120	-0.043	0.052	0.400	-0.042	0.015

Box'Pierce Q5 statistic for ρ weekly: 8.86
Number of Stocks: 110

TABLE A.26

DESCRIPTIVE STATISTICS FOR AUTOCORRELATION YEAR 1999.
From first to fifth lag; daily, weekly stock returns.

Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=25} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on security i in day (week) t-j, ρ_{jt} is the autocorrelation coefficient for the lagged daily (or weekly) return R_{it-j}, α_0 is a constant and $\tilde{u}_{it}$ is the error term, for the Year 1999 in the Mexican Stock Exchange (BMV). Below are described the Mean and Std. error of ρ_i (five lags) as well as the extremes values and 25, 50 and 75 percentiles. Box-Pierce (Q5) statistic is also displayed.

99:01:05 - 99:10:29

ρ daily	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.189	-0.003	0.095	0.166	0.363	0.086	0.012
ρ2	-0.173	-0.051	-0.014	0.044	0.245	-0.007	0.007
ρ3	-0.207	-0.041	-0.003	0.057	0.211	0.006	0.007
ρ4	-0.257	-0.060	-0.012	0.041	0.171	-0.012	0.007
ρ5	-0.225	-0.078	-0.030	0.027	0.151	-0.029	0.008

Box-Pierce Q5 statistic for ρ daily: 10.3
Number of Stocks: 110

99:01:13 - 99:10:27

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.589	-0.109	0.045	0.146	0.626	0.020	0.019
ρ2	-0.652	-0.139	-0.012	0.065	0.478	-0.038	0.017
ρ3	-0.546	-0.030	0.065	0.165	0.650	0.081	0.017
ρ4	-0.577	-0.148	-0.085	0.029	0.446	-0.069	0.016
ρ5	-0.349	-0.133	-0.045	0.057	0.347	-0.032	0.015

Box-Pierce Q5 statistic for ρ weekly: 7.05
Number of Stocks: 111

TABLE A.27

COMPARATIVE RETURN AUTOCORRELATION BETWEEN RESTRICTED AND UNRESTRICTED STOCKS. YEAR 1994.

The following table shows descriptive statistics for the first five autocorrelation on the returns of Restricted A series, and Unrestricted Stocks Series (B, C, L, D, V and compounded series CPO, UB, UBC, UDL), for the year 1994 in the Mexican Stock Exchange (BMV). Furthermore Box-Pierce statistics is being shown to be compared with a χ^2 with five degrees of freedom. Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=5} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on series i in week t-j, ρ_{jt} is the autocorrelation coefficient for the lagged weekly return R_{it-j}, α_0 is a constant and $\tilde{u}_{it}$ is the error term. Below are described the Mean and Std. Error of ρ_i , as well as the extremes values and 25, 50 and 75 percentiles.

Restricted Series
94:01:04 – 94:12:30

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error.
ρ1	-0.053	0.004	0.066	0.143	0.424	0.089	0.019
ρ2	-0.357	-0.277	-0.075	-0.016	0.250	-0.116	0.026
ρ3	-0.145	0.032	0.076	0.159	0.215	0.074	0.014
ρ4	-0.347	-0.151	-0.104	-0.069	0.079	-0.115	0.017
ρ5	-0.179	-0.109	-0.067	-0.028	0.103	-0.066	0.011

Box – Pierce Q5 statistic for ρ weekly: 17.376

Unrestricted Series
94:01:04 – 94:12:30

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error.
ρ1	-0.346	-0.054	0.076	0.151	0.346	0.048	0.026
ρ2	-0.621	-0.187	-0.137	-0.101	-0.060	-0.191	0.023
ρ3	-0.098	-0.043	0.045	0.151	0.202	0.052	0.015
ρ4	-0.199	-0.181	-0.084	0.079	0.191	-0.045	0.021
ρ5	-0.481	-0.149	-0.085	0.004	0.174	-0.093	0.025

Box – Pierce Q5 statistic for ρ weekly: 26.876

TABLE A.28

COMPARATIVE RETURN AUTOCORRELATION BETWEEN RESTRICTED AND UNRESTRICTED STOCKS. YEAR 1995.

The following table shows descriptive statistics for the first five autocorrelation on the returns of Restricted A series, and Unrestricted Stocks Series (B, C, L, D, V and compounded series CPO, UB, UBC, UDL), for the year 1995 in the Mexican Stock Exchange (BMV). Furthermore Box-Pierce statistics is being shown to be compared with a χ^2 with five degrees of freedom. Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=5} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on series i in week t-j, ρ_{jt} is the autocorrelation coefficient for the lagged weekly return R_{it-j}, α_0 is a constant and $\tilde{u}_{it}$ is the error term. Below are described the Mean and Std. Error of ρ_i as well as the extremes values and 25, 50 and 75 percentiles.

Restricted Series
95:01:03 – 95:12:29

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.068	0.035	0.074	0.127	0.208	0.079	0.012
ρ2	-0.178	-0.076	-0.021	0.086	0.433	0.030	0.024
ρ3	-0.158	-0.104	-0.042	0.115	0.343	0.012	0.021
ρ4	-0.231	-0.058	0.010	0.051	0.177	-0.013	0.018
ρ5	-0.181	-0.088	-0.020	0.055	0.187	-0.013	0.017

Box-Pierce Q5: 15.355

Unrestricted Series
95:01:03 – 95:12:29

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.228	-0.022	0.011	0.123	0.338	0.056	0.023
ρ2	-0.161	-0.047	-0.032	0.025	0.466	0.019	0.003
ρ3	-0.258	-0.086	0.017	0.089	0.169	-0.007	0.019
ρ4	-0.217	-0.150	0.043	0.120	0.200	-0.002	0.022
ρ5	-0.202	-0.172	-0.119	-0.005	0.126	-0.085	0.015

Box-Pierce Q5: 16.151

TABLE A.29

COMPARATIVE RETURN AUTOCORRELATION BETWEEN RESTRICTED AND UNRESTRICTED STOCKS. YEAR 1996.

The following table shows descriptive statistics for the first five autocorrelation on the returns of Restricted A series, and Unrestricted Stocks Series (B, C, L, D, V and compounded series CPO, UB, UBC, UDL), for the year 1996 in the Mexican Stock Exchange (BMV). Furthermore Box-Pierce statistics is being shown to be compared with a χ^2 with five degrees of freedom. Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=5} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on series i in week *t-j*, ρ_{jt} is the autocorrelation coefficient for the lagged weekly return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term. Below are described the Mean and Std. Error of ρ_i as well as the extremes values and 25, 50 and 75 percentiles.

Restricted Series
96:01:03 – 96:12:31

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.324	-0.123	-0.062	0.098	0.422	-0.002	0.030
ρ2	-0.270	-0.116	-0.068	0.059	0.110	-0.054	0.018
ρ3	-0.186	-0.147	-0.081	0.025	0.364	-0.031	0.022
ρ4	-0.142	-0.062	-0.024	0.066	0.169	0.004	0.014
ρ5	-0.199	0.003	0.017	0.058	0.086	0.008	0.011

Box-Pierce Q5: 12.372

Unrestricted Series
96:01:03 – 96:12:31

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.396	-0.092	0.016	0.155	0.416	0.024	0.032
ρ2	-0.407	-0.155	-0.055	0.038	0.072	-0.082	0.020
ρ3	-0.303	-0.124	-0.099	0.087	0.305	-0.026	0.026
ρ4	-0.289	-0.033	-0.016	0.041	0.207	-0.005	0.017
ρ5	-0.243	0.013	0.039	0.136	0.168	0.042	0.017

Box-Pierce Q5: 22.290

TABLE A.30

COMPARATIVE RETURN AUTOCORRELATION BETWEEN RESTRICTED AND UNRESTRICTED STOCKS. YEAR 1997.

The following table shows descriptive statistics for the first five autocorrelations on the returns of Restricted A series, and Unrestricted Stocks Series (B, C, L, D, V and compounded series CPO, UB, UBC, UDL), for the year 1997 in the Mexican Stock Exchange (BMV). Furthermore Box-Pierce statistics is being shown to be compared with a χ^2 with five degrees of freedom. Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=5} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on series i in week *t-j*, ρ_{jt} is the autocorrelation coefficient for the lagged weekly return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term. Below are described the Mean and Std. Error of ρ_i as well as the extremes values and 25, 50 and 75 percentiles.

Restricted Series
97:01:03 – 97:12:31

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.133	-0.052	0.016	0.137	0.268	0.038	0.018
ρ2	-0.386	-0.156	-0.022	0.030	0.128	-0.075	0.023
ρ3	-0.208	-0.123	-0.034	0.090	0.344	0.001	0.024
ρ4	-0.306	-0.190	-0.080	-0.023	0.001	-0.114	0.015
ρ5	-0.205	-0.037	0.009	0.058	0.131	-0.001	0.014

Box-Pierce Q5: 13.661

Unrestricted Series
97:01:03 – 97:12:31

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.276	-0.141	-0.009	0.171	0.347	0.000	0.028
ρ2	-0.217	-0.150	-0.060	-0.005	0.164	-0.056	0.016
ρ3	-0.228	-0.160	-0.029	-0.010	0.093	-0.061	0.015
ρ4	-0.353	-0.187	-0.121	0.011	0.076	-0.115	0.021
ρ5	-0.190	-0.158	-0.032	0.152	0.166	-0.020	0.020

Box-Pierce Q5: 10.580

TABLE A.31

COMPARATIVE RETURN AUTOCORRELATION BETWEEN RESTRICTED AND UNRESTRICTED STOCKS. YEAR 1998.

The following table shows descriptive statistics for the first five autocorrelations on the returns of Restricted A series, and Unrestricted Stocks Series (B, C, L, D, V and compounded series CPO, UB, UBC, UDL), for the year 1998 in the Mexican Stock Exchange (BMV). Furthermore Box-Pierce statistics are compared with a χ^2 with five degrees of freedom. Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=5} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on series i in week t-j, ρ_{jt} is the autocorrelation coefficient for the lagged weekly return, R_{it-j}, α_0 is a constant and $\tilde{u}_{it}$ is the error term. The table below describes the Mean and Std. Error of ρ_i as well as the extreme values and 25th, 50th and 75th percentiles.

Restricted Series
98:01:05 – 98:12:31

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.088	-0.042	0.042	0.090	0.489	0.062	0.023
ρ2	-0.215	-0.121	-0.063	0.015	0.170	-0.040	0.016
ρ3	-0.161	-0.081	-0.009	0.038	0.291	0.008	0.019
ρ4	-0.308	-0.121	-0.033	0.043	0.164	-0.035	0.019
ρ5	-0.220	-0.122	-0.051	-0.002	0.133	-0.054	0.014

Box-Pierce Q5: 26.657

Unrestricted Series
98:01:05 – 98:12:31

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.231	-0.022	0.015	0.093	0.309	0.036	0.022
ρ2	-0.357	-0.208	-0.142	-0.031	0.115	-0.116	0.022
ρ3	-0.135	-0.055	0.025	0.102	0.250	0.029	0.016
ρ4	-0.294	-0.193	-0.034	0.026	0.127	-0.066	0.020
ρ5	-0.125	-0.018	0.057	0.154	0.188	0.051	0.015

Box-Pierce Q5: 18.859

TABLE A.32

COMPARATIVE RETURN AUTOCORRELATION BETWEEN RESTRICTED AND UNRESTRICTED STOCKS. YEAR 1999.

The following table describes statistics for the first five autocorrelation on the returns of Restricted A series, and Unrestricted Stocks Series (B, C, L, D, V and compounded series CPO, UB, UBC, UDL), for the year 1999 in the Mexican Stock Exchange (BMV). Furthermore Box-Pierce statistics is being shown to be compared with a χ^2 with five degrees of freedom. Model: $\tilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=5} \rho_{jt} R_{it-j} + \tilde{u}_{it}$, where R_{it-j} is the return on series i in week t-j, ρ_{jt} is the autocorrelation coefficient for the lagged weekly return R_{it-j}, α_0 is a constant and $\tilde{u}_{it}$ is the error term. Below are described the Mean and Std. Error of ρ_i as well as the extremes values and 25, 50 and 75 percentiles.

Restricted Series
99:01:05 – 99:12:30

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.529	-0.209	-0.030	0.070	0.157	-0.112	0.034
ρ2	-0.280	-0.160	-0.066	0.080	0.138	-0.059	0.020
ρ3	-0.233	-0.223	-0.036	-0.027	0.098	-0.094	0.017
ρ4	-0.210	-0.023	0.008	0.021	0.049	-0.028	0.012
ρ5	-0.169	-0.119	-0.028	-0.004	0.225	-0.028	0.016

Box-Pierce Q5: 18.962

Unrestricted Series
99:01:05 – 99:12:30

ρ weekly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.292	-0.107	-0.016	0.054	0.245	-0.012	0.022
ρ2	-1.126	-0.150	-0.040	0.040	0.113	-0.137	0.050
ρ3	-0.226	-0.078	-0.025	0.017	0.051	-0.039	0.012
ρ4	-0.332	-0.235	-0.120	0.047	0.211	-0.095	0.025
ρ5	-0.494	-0.073	-0.034	0.023	0.139	-0.073	0.025

Box-Pierce Q5: 12.562

TABLE A.33

COMPARATIVE MONTHLY RETURN AUTOCORRELATION BETWEEN RESTRICTED AND UNRESTRICTED STOCKS. YEAR 1994-1999.

The following table shows descriptive statistics for the first five autocorrelation on the monthly returns of Restricted A series, and Unrestricted Stocks Series (B, C, L, D, V and compounded series CPO, UB, UBC, UDL), for the period January 1994 to December 1999 in the Mexican Stock Exchange (BMV).

Furthermore Box-Pierce statistics is being shown to be compared with a χ^2 with five degrees of freedom.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=5} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on series i in month t-j, ρ_{jt} is the autocorrelation coefficient for the lagged monthly return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term. Below are described the Mean and Std. Error of ρ_i as well as the extremes values and 25, 50 and 75 percentiles.

Restricted Series
94:01:03 – 99:12:30

ρ monthly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.316	-0.220	-0.044	0.041	0.264	-0.077	0.021
ρ2	-0.239	-0.195	-0.048	0.016	0.141	-0.077	0.016
ρ3	-0.430	-0.035	-0.021	0.058	0.346	-0.011	0.022
ρ4	-0.281	-0.161	-0.104	0.064	0.155	-0.068	0.017
ρ5	-0.139	-0.103	-0.044	0.012	0.187	-0.030	0.011
Box-Pierce Q5:	23.303						

Unrestricted Series
94:01:03 – 99:12:30

ρ monthly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.328	-0.262	-0.089	0.035	0.239	-0.074	0.023
ρ2	-0.569	-0.186	-0.102	-0.047	0.165	-0.128	0.024
ρ3	-0.360	-0.058	0.017	0.059	0.101	-0.021	0.017
ρ4	-0.296	-0.136	-0.097	0.014	0.224	-0.056	0.019
ρ5	-0.153	-0.096	0.029	0.097	0.255	0.011	0.016
Box-Pierce Q5:	28.011						

TABLE A.34

COMPARATIVE MONTHLY RETURN AUTOCORRELATION BETWEEN RESTRICTED AND UNRESTRICTED STOCKS. YEAR 1994-1996.

The following table shows descriptive statistics for the first five autocorrelation on the monthly returns of Restricted A series, and Unrestricted Stocks Series (B, C, L, D, V and compounded series CPO, UB, UBC, UDL), for the period January 1994 to December 1996 in the Mexican Stock Exchange (BMV).

Furthermore Box-Pierce statistics is being shown to be compared with a χ^2 with five degrees of freedom.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=5} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on series i in month t-j, ρ_{jt} is the autocorrelation coefficient for the lagged monthly return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term. Below are described the Mean and Std. Error of ρ_i as well as the extremes values and 25, 50 and 75 percentiles.

Restricted Series
94:01:03 – 96:12:31

ρ monthly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.460	-0.245	0.067	0.166	0.384	-0.018	0.047
ρ2	-0.442	-0.284	-0.112	-0.054	0.295	-0.142	0.034
ρ3	-0.395	-0.085	-0.014	0.069	0.223	-0.014	0.027
ρ4	-0.283	-0.161	-0.049	-0.019	0.231	-0.060	0.026
ρ5	-0.190	-0.132	-0.100	0.040	0.347	-0.041	0.026

Box-Pierce Q5: 15.177

Unrestricted Series
94:01:03 – 96:12:31

ρ monthly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.599	-0.276	-0.046	0.211	0.391	-0.033	0.057
ρ2	-0.399	-0.324	-0.269	-0.089	0.304	-0.174	0.035
ρ3	-0.230	-0.099	-0.047	0.089	0.160	-0.013	0.022
ρ4	-0.327	-0.165	-0.102	-0.044	0.357	-0.065	0.031
ρ5	-0.236	-0.097	-0.031	0.062	0.481	0.006	0.031

Box-Pierce Q5: 30.035

TABLE A.35

COMPARATIVE MONTHLY RETURN AUTOCORRELATION BETWEEN RESTRICTED AND UNRESTRICTED STOCKS. YEAR 1997-1999.

The following table shows descriptive statistics for the first five autocorrelation on the monthly returns of Restricted A series, and Unrestricted Stocks Series (B, C, L, D, V and compounded series CPO, UB, UBC, UDL), for the period January 1997 to December 1999 in the Mexican Stock Exchange (BMV).

Furthermore, Box-Pierce statistics is being shown to be compared with a χ^2 with five degrees of freedom.

Model: $\widetilde{R}_{it} = \alpha_0 + \sum_{j=1}^{j=5} \rho_{jt} R_{it-j} + \widetilde{u}_{it}$, where R_{it-j} is the return on series i in month t-j, ρ_{jt} is the autocorrelation coefficient for the lagged monthly return R_{it-j}, α_0 is a constant and $\widetilde{u}_{it}$ is the error term. Below are described the Mean and Std. Error of ρ_i as well as the extremes values and 25, 50 and 75 percentiles.

Restricted Series
97:01:03 – 99:12:30

ρ monthly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.379	-0.214	-0.080	-0.022	0.255	-0.099	0.031
ρ2	-0.272	-0.139	-0.075	-0.004	0.318	-0.057	0.027
ρ3	-0.499	-0.181	-0.118	0.070	0.304	-0.075	0.035
ρ4	-0.439	-0.213	-0.011	0.100	0.287	-0.068	0.039
ρ5	-0.215	-0.102	-0.037	0.096	0.212	-0.007	0.022

Box-Pierce Q5: 16.014

Unrestricted Series
97:01:03 – 99:12:30

ρ monthly	Minimum	25%	50%	75%	Maximum	Mean	Std. Error
ρ1	-0.297	-0.214	-0.091	-0.010	0.052	-0.113	0.021
ρ2	-0.773	-0.157	-0.115	0.016	0.068	-0.138	0.039
ρ3	-0.451	-0.072	-0.052	0.066	0.317	-0.022	0.034
ρ4	-0.407	-0.225	-0.041	0.045	0.311	-0.072	0.036
ρ5	-0.204	-0.032	-0.013	0.065	0.117	-0.003	0.016

Box-Pierce Q5: 28.043

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