LUND UNIVERSITY
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The day-of-the-week effect on stock returns and volatility

The case of Latin America

Master Essay

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Abstract

It has been found that the behavior of stock markets follow patterns that are not necessarily consistent with the Efficient Market Hypothesis. Anomalies have been classified into different groups of which calendar anomalies such as the *day-of-the-week* effect has been under study for many years. Many authors have been following the evolution of this calendar seasonality in developed stock markets. As for emerging stock markets, investigation has received much less attention. The aim of this paper is to investigate the *day-of-the-week* effect on stock returns and volatility in four major Latin American stock markets namely, Argentina, Brazil, Chile, and Mexico for the period of 1998 through 2010. The empirical analysis is conducted using three types of time-varying conditional models, namely GARCH, EGARCH, and APARCH assuming two types of distributions.

The main findings of this research indicate that evidence of the *day-of-the-week* seasonality is present in three out of four stock markets. For Chile the anomaly is present on stock returns, for Mexico a clear *Monday-effect* is observed on stock return volatility, and for Brazil on both. A clear *weekend-effect* is observed for Chile and Brazil while Friday represents the day with the lowest volatility for Brazil and Mexico. As for Argentina, the same volatility pattern was observed however; the estimated coefficients are statistically insignificant. It is important to point out that results may vary depending on the choice of model with which the anomaly was examined.

Keywords: Day-of-the-week effect; Emerging markets; Volatility; GARCH; EGARCH; APARCH

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1. Introduction

Financial markets have been under study for many years. Understanding the evolution, behavior, and complexity of stock markets is crucial not only for investors but also for economic policy makers because changes in the market have important implications for macroeconomic stability.

Nowadays stock markets are more open and flexible. There exist a vast number of tools which facilitate the access to up-to-date information. In this sense, financial decision makers have been changing their behavior in order to adapt to new forms of trading. Many researchers state that the behavior of stock markets follows patterns that do not necessarily correspond to the stipulations of classical economy and therefore the Efficient Market Hypothesis (hereafter EMH) does not always hold. In this context the importance of determining the existence of anomalies in the stock markets has become of major significance.

There are several classifications of anomalies in stock markets; one of them regards calendar anomalies which include effects such as *January effect, Day-of-the-week effect, Holiday effect* among others. A prominent paper about the *day-of-the-week effect* was written by French (1980). He found out that stocks in the U.S. tend to exhibit relatively large returns on Fridays compared to those on Mondays. This finding contradicts the EMH which states that average returns are similar for all the trading days in a week.

Since investors are normally risk-averse by nature they are not only interested in the variation of their returns but also on its volatility. Following the fall of the Bretton Woods system, financial markets have experienced increased volatility in comparison to previous decades. Hence, financial theory has paid particular attention to the study of the evolution of volatility in stock markets and consequently has developed models which analyze stock market volatility through a conditional variance component. Furthermore, as indicated by Ho and Cheung (1994) "a formal test on the variations of volatility across days of the week is interesting because it is important to know if the higher return on a particular weekday is just a reward for higher risk on that day". Thus, when carrying out the decision-making process, rational financial decision makers concentrate not only on returns but also on risk or volatility of returns.

The *day-of-the-week* effect has been analyzed in different stock markets around the world finding evidence that returns and their volatilities in certain days of the week are significantly and systematically different from those of the other days of the week. As Kiymaz and Berument (2003) pointed out, "it is important to know whether there are variations in volatility of stock returns by *day-of-the-week* patterns and whether a high (low) return is associated with a corresponding high (low) return for a given day".

Given the widespread scientific diffusion of the *day-of-the-week* effect, the improvement of information technologies and communications as well as the development of new financial products; the *day-of-the-week* effect is acquiring a better knowledge by investors implying that improvements in market efficiency over time can lead to the disappearance of this anomaly. Kohers et al. (2004) studied the evolution of the *day-of-the-week* effect seasonality for the largest developed equity markets. They found out that during the 1980's the vast majority of developed markets indeed show significance of this anomaly while starting the 1990's the effect appears to have faded away. In contrast Cho et al. (2007) provided a test of the *day-of-the-week* effect based on the stochastic dominance criterion. They found strong evidence of a *Monday effect*[1] on a number of stock indexes including U.S. large caps and small caps as well as U.K. and Japanese indexes.

Finding certain patterns in volatility may be useful in numerous ways. Investors have a better insight when implementing investment strategies for hedging and speculative purposes. Financial advisors, financial managers, and bankers also benefit from them, for instance by determining a specific day for the initial stock issuance and as Engle (1993) indicated, "investors that dislike risk may adjust their portfolios by reducing their investments in those assets whose volatility is expected to increase".

On the contrary of developed stock markets, emerging stock markets have not been as deeply studied and analyzed as developed markets. The question as to which extent the *day-of-the-week* effect has been taken into consideration by financial decision makers in emerging stock markets comes to mind.

The aim of this paper is therefore to investigate the *day-of-the-week* effect on returns and conditional variance (volatility) of returns and thus the volatility patterns for the four major stock markets in the Latin American region namely; Argentina, Brazil, Chile, and Mexico for the period March 26, 1998 to March 26, 2010. Speidell and Sappenfield (1992) found that

[1] On average, stock returns are less on Mondays than returns on any other day of the week.

investing in younger, less developed markets could be a valuable investment strategy. Kohers et al. (1998) have proved that emerging markets play a worthful part in international portfolios[2].

The empirical investigation is conducted using models of time-varying conditional volatility. It has been well documented (Tavares et al, 2007) that empirical distributions of financial assets returns exhibit characteristics, generally referred to as stylized facts such as *volatility clustering* (large shocks in financial asset returns tend to be followed by large shocks and vice versa), *leptokurtosis* (excess kurtosis which means that empirical distribution has fat tails) and *leverage effects* (changes in return volatility may be negatively related to the returns that is, negative shocks increases volatility more than positive shocks).

Empirical evidence based on the work of Engle (1982) showed that a high order ARCH is needed to capture the dynamic behavior of conditional variance. As a way to model persistence movements in volatility without estimating a very large number of coefficients of high order ARCH terms, Bollerslev (1986) suggested the Generalized ARCH model (hereafter GARCH). Both models are able to capture volatility clustering and leptokurtosis however, they fail to model the leverage effect. In order to overcome this difficulty many non-linear extensions of GARCH models have been proposed namely the Exponential GARCH (EGARCH) model by Nelson (1991) and the Asymmetric Power ARCH (APARCH) model by Ding et al. (1993) among others.

In order to account for each of these stylized facts, I will conduct the empirical analysis using three types of models namely the GARCH, EGARCH, and APARCH. Bollerslev (1987) argued that GARCH models with conditionally normal errors do not always seem to fully capture the leptokurtosis; to address this problem he proposed to combine the models with the Student’s t-distribution. Therefore, the assumptions of conditional normality and conditional Student’s t-density are taken into consideration in this investigation.

The main findings of this research indicate that evidence of the *day-of-the-week* seasonality is present in three out of four stock markets. For Chile the anomaly is present on stock returns, for Mexico a clear *Monday-effect* is observed on stock return volatility, and for Brazil on both. A clear *weekend-effect* is observed for Chile and Brazil on stock returns whereas Friday represents the day with the lowest volatility for Brazil and Mexico. As for Argentina, the

[2] See Kohers, T., Kohers, G., Pandey, V., 1998. The contribution of emerging markets in international diversification strategies. Applied Financial Economics 445-454.

same volatility pattern was observed however; the estimated coefficients are statistically insignificant indicating the rejection of a *day-of-the-week* seasonality on both stock returns and volatility. It is important to point out that results may vary depending on the choice of model with which the anomaly was examined.

The remainder of the paper is structured as the following: Section 2 gives a theoretical framework of theories of the *day-of-the-week* effect on stock market returns and volatility. Section 3 gives a short overview of the four major Latin American stock market indexes and introduces the data and some preliminary statistical tests. Section 4 specifies the time-varying conditional volatility models used in the investigation. Section 5 presents the obtained empirical results. Finally Section 6 summarizes the results and concludes the most important findings.

2. Theoretical framework

The day-of-the-week effect on stock market returns and volatility

Financial literature has always been concerned about the behavior of financial markets. In an empirical work, Fama[3] (1970) postulated that securities markets were extremely efficient in reflecting information about individual stocks and about the stock market as a whole. He states that the Efficient Market Hypothesis can be divided into three categories depending on the nature of the information subset of interest: *strong-form* tests are concerned with whether individual investors have monopolistic access to any information relevant for price formation, *semi-strong-form* tests in which the information subset of interest includes all obviously publicly available information and, *weak-form* tests in which the information subset is just historical price or return sequences. Hence, as Ajayi et al. (2004) stated "an efficient market is one where all unexploited profit opportunities are eliminated by arbitrage".

Many researchers have found, however, evidence against the *weak* and *semi-strong-form* of the EMH. This evidence is considered as anomaly. Anomalies indicate either market inefficiency or inadequacies in the underlying asset-pricing model[4] (Schwert, 1996). Empirical studies have found that stock returns exhibit a pattern, also called calendar anomaly, during market trading days suggesting that historical stock prices can be used to predict the future movements of the stock prices. These calendar anomalies are divided into several categories such as *day-of-the-week* effect and the *January-effect*[5] among others.

The *day-of-the-week* effect refers to the variation of stock market returns by day of the week in which Monday is generally considered to exhibit negative returns whereas Friday exhibits positive and the highest returns in a week. There exist a vast number of studies regarding the *day-of-the-week* effect for several stocks markets around the world. This phenomenon goes back to Fields (1931) who, using the Dow-Jones Index, observed that returns tend to be negative and positive on Mondays and Fridays respectively. One of the most emblematic studies on this effect is attributed to French (1980). Based on daily returns of the S&P 500 from 1953 to 1977 and dividing the sample into two subsamples corresponding the full period

[3] See Fama, E., 1970. Efficient Capital Markets: A Review of theory and empirical work. Journal of Finance 383-418.
[4] See Schwert, G., 1996. Anomalies and Market Efficiency. Journal of Financial Economics 15, 936-972.
[5] Returns in January are significantly higher than other monthly returns.

and a five five-year subperiods the author demonstrated that the mean return for Monday was significantly negative while the average return for the other four days of the week was positive. These results are clearly inconsistent with the trading time[6] and calendar time[7] models. Gibbons and Hess (1981) examined further the S&P 500 along with the Treasury bill market. They confirmed the result of previous studies stating that negative return for Monday is remarkably uniform across individual stocks and that treasury bills earn a below-average return on Monday. Keim and Stambaugh (1983) concluded that the *Monday-effect* has to do with the high Friday return hypothesis considered as a measurement error. Lakonishok and Levi (1985) argued that one presumable reason behind the *day-of-the-week* effect also has to do with measurement errors as they pointed out that realized daily rates of return cannot be computed from only two consecutive closing prices. Payments for a stock purchased on any day except on Friday will in general occur eight calendar days[8] after the trade. For Fridays, payments cannot be made on Saturdays hence resulting in a delay of two more days. Many other hypotheses have been put forward to explain some possible reasons behind the cause of the *day-of-the-week* seasonality. These include Patell and Wolfson (1982) who suggested that the timing of corporate announcements has to do with the negative returns shown on Mondays; Rystrom and Benson (1989) concluded that investor psychology has to do with the *Monday-effect* due to the "blue Monday" when investors tend to be more pessimistic about the outlook for the securities they hold; Admati and Pfleiderer (1989) attributed the cause of the anomaly to pricing rules of market makers; and Miller (1988), Dyl and Holland (1990), Lakonishok and Maberly (1990), and Ziemba (1993) granted the anomaly to the individual trader decision making process.

A number of investigations regarding developed stock markets have been proposed. For instance, Theobald and Price (1984) concluded that the *day-of-the-week* effect is caused mainly due to the Settlement Date system employed on the London Stock Exchange. Authors like Jaffe and Westerfield (1985) studied not only the U.S. stock market but also the markets in the U.K., Canada, Japan, and Australia finding that the *Monday-effect* applies for stock market returns for the U.S., U.K., and Canada whereas for the Japanese and the Australian stock markets the lowest mean return occurs on Tuesday; Santesmases (1986) investigate the

[6] Under the trading time hypothesis returns are generated only during active trading so if the model is correct the expected return will be the same for each day of the week.

[7] Under calendar time hypothesis the process operates continuously so that the return for Monday represents a three-calendar day investment hence the expected return for Monday will be three times the expected return for other days of the week.

[8] The eight days are divided as follows: five business days for settlement, one day for check clearing, and two weekend days.

behavior of the Madrid Stock Exchange Index and found no *day-of-the-week* effect; Barone (1990) found that the largest falls in stock prices for the MIB index from Italy occur in the first two days of the week and are more pronounced on Tuesday. He advised that when account is taken of the different times zones the calendar effect may be imported from the U.S.; Solnik and Bousquet (1990) followed the behavior of the CAC index of the Paris Bourse finding strong and persistent negative mean return on Tuesday; Yadav and Pope (1992) studied the seasonality in the pricing of the U.K. stock index futures in relation to the FTSE 100, they found that abnormal Monday returns accrued during the trading day on Monday and not over the weekend nontrading interval; Athanassakos and Robinson (1994) conducted their study using data from the Toronto Stock Exchange/Western concluding that there is a strong statistically significant negative *Tuesday-effect* which has been getting stronger over time and positive Friday returns; Easton and Faff (1994) examined the robustness of the *day-of-the-week* effect for the Sydney Stock Exchange; Dubois and Louvet (1996) found negative returns on Monday which are compensated by abnormal positive returns on Wednesday for seven out of nine markets studied (U.S-DJ and U.S.-S&P., Canada, Germany, France, Switzerland and H.K.); and Arsad and Coutts (1997) followed the behavior of the FT 30 (which is the first major U.K. stock market index) from July 1935 through December 1994 finding strong evidence of the *Monday-effect*.

The journals mentioned above have concentrated the analysis only on mean returns. Nevertheless, several studies claim that the *day-of-the-week* effect also has an impact on the conditional variance of stock returns. This evidence goes back to Fama (1965) who reported that Monday's variance is approximately 22% greater than the within week variance for the Dow-Jones Industrial Average. According to French and Roll (1986) returns on Mondays may have a higher variance relative to other days. Two factors lie behind this finding: 1) the arrival of public information may be more frequent during the business day, and 2) private information is received throughout the week. Barclay et al. (1990), and Foster and Viswanathan (1990) also agreed that on Monday the trading costs and the variance of price changes are highest than on the remaining days of the weekday due to solely the second factor stated by French and Roll.

Later on Kiymaz and Berument (2001) tested a model with *day-of-the-week* effect dummies in both the conditional mean and the conditional variance functions for daily observations of the S&P 500 finding that the highest and lowest returns are observed on Wednesday and Monday respectively while the highest and lowest volatility are observed on Friday and Wednesday respectively. They attribute the highest volatility on Friday to macroeconomic news releases taking place on Thursday and Friday. Many other studies about the *day-of-the-week* effect on mean return and conditional variance have been proposed. Balaban et al. (2001) analyzed daily observations of stock market indexes from 19 countries: Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Hong Kong, Italy, Japan, The Netherlands, New Zealand, Norway, Spain, Sweden, Switzerland, U.K., and U.S.. They found evidence for predictable time-varying daily volatility in all the stock markets for which eight countries also exhibit a significant leverage effect on conditional volatility, only in three countries there is a significantly positive relationship between index returns and their estimated conditional volatility, the nature of the *day-of-the-week* effect on returns and their conditional volatility differs greatly among countries and across days that is to say; only seven countries exhibit seasonality in mean returns, eight exhibit seasonality in volatility, and only two countries on both. Wednesday is found to be the only day with no evidence of negative effect on mean returns or positive effect in volatility. Some years later, Kiymaz and Berument (2003) studied further the behavior of other markets besides the U.S. and found that the *day-of-the-week* is present in both equations (mean and volatility) with the highest volatility occurring on Mondays for Germany and Japan, Fridays for Canada and U.S., and Thursdays for the U.K. Furthermore, they conclude that for most of the markets the days with the highest volatility also coincide with that market's lowest trading volume. Guidi (2010) analyzed the MIB stock market index disaggregated at the sub-sectoral level for the period 1999-2009 finding evidence of the calendar anomaly for the finance, manufacturing, and services sectors.

Many researchers argue that due to improvements in market efficiency over long time periods the effects of certain anomalies, for instance the *day-of-the-week* seasonality may have disappeared. Using both parametric and nonparametric statistical tests, Kohers et al. (2004) examined the evolution of the *day-of-the-week* effect for the world's largest equity markets which by then were the U.S., Japan, U.K., France, Germany, Canada, Italy, the Netherlands, Switzerland, Hong Kong and Australia for the period January 1980 through June 2002. Their results demonstrate a prevalent *day-of-the-week* seasonality in the vast majority of developed markets during the 1980's while starting the 1990's the anomaly appears to have faded away with the exception of Japan which was found to be the only country retaining this anomaly. Gregoriou et al. (2004) investigated the behavior of the FTSE 100 by taking into consideration the bid-ask spread as a proxy for transaction costs. They found that once returns become robust to transaction costs the *day-of-the-week* effect appears to fade away likewise the volatility of stock returns. Recently, Marrett and Worthington (2008) examined the anomaly in Australian daily stock returns at the market and industry levels and for small capitalization stocks. Their analysis indicate that, at significant levels, the Australian market overall provides no evidence of *day-of-the-week* effect; however there is evidence of a small cap daily seasonality with systematically higher returns on Thursdays and Fridays. They argued that the low level of observed daily seasonality implies that the Australian stock market overall is approximately *weak-form efficient*. They attributed this argument to several possible factors such as the growth in derivative markets, the increasing internationalization and liberalization of the domestic capital market, increased trading by institutional rather than individual investors, and the dramatic fall in transaction costs. Thus, given the widespread scientific diffusion of the *day-of-the-week* effect, the improvement of information technologies and communications as well as the development of new financial products; the *day-of-the-week* effect is acquiring a better knowledge by investors implying that improvements in market efficiency over time can lead to the disappearance of this anomaly.

When it comes to emerging stock markets, research in terms of calendar anomalies has been proposed since mid 1980's when Kim (1988) demonstrated the weekly seasonality for common stock returns in the stock market of South Korea finding low returns in the beginning of the week and high returns at the end of it. Later on Cheung et al. (1993) studied the intraday stock returns and trading volume relationship in what they called "one of the most open among emerging Asian markets[9] –Hong Kong"; finding evidence of *day-of-the-week* variations in the 15-minute stock return. Choudhry (2000) based his analysis on seven emerging Asian stock markets for which results indicate the significant presence of the anomaly in both stock returns and volatility (though not identical in all seven countries). The author argued that these effects may be due to a possible spill-over from the Japanese stock market. In contrast with the Asian stock markets, Ajayi et al. (2004) found that for the Eastern European emerging markets (EEEMs) there was no statistical evidence suggesting the presence of a *Monday-effect* (with the exception of Estonia). They believe that the EEEMs do exhibit a certain level of market efficiency despite speculation that emerging markets might show inefficiencies at their early stage of development. Thereafter, Alagidede (2008) found similar results for four out of seven African stock markets (Kenya, Egypt, Morocco and

[9] Anders C. Johansson (2007) writes in his book *"Essays in Empirical Finance"* that the definition of "emerging market" has changed over time and although many countries have per definition undergone the transition from being developing to developed, some of them are still considered emerging in terms of their financial markets. For instance, Morgan Stanley (among others) has selected to classify Singapore and H.K. as developed markets while The Economist (among others) defines them as emerging.

Tunisia) for which no evidence of *day-of-the-week* effect was present when accounting for market risk whereas the remaining three markets (Zimbabwe, Nigeria and South Africa) did exhibit the anomaly. In the case of Arab stock markets, Kamaly and Tooma (2009) observed the presence of the *day-of-the-week* effect in both return and volatility. Furthermore, they tested the risk-return relationship finding that, with the exception of Qatar, the signs of all the significant risk premium measures are positive confirming the positive relation between risk and return for a characteristic risk-averse agent.

As for Latin American countries, the *day-of-the-week* effect was found to be present in stock markets such as Argentina, Brazil, Chile, Colombia, Mexico, and Peru during the period 1993-2007 according to the research proposed by Rodríguez (2009). The results proved that for BOVESPA of Brazil, stock returns were less on Monday and Thursday than returns on any other day of the week while there was strong evidence of the *weekend-effect* observed on Friday. Thursday, on the other hand, was found to exhibit the highest volatility. The results for both the IPC of Mexico and MERVAL of Argentina exhibited a *Monday-effect* in both stock market returns and volatility. For IPSA of Chile there was also strong evidence of the *Monday-effect* nevertheless; stock returns on Wednesday were higher than any other day of the week. Peru's ISVL stock market returns displayed a *weekend-effect* whereas Monday and Tuesday were found to exhibit the highest volatility. Finally, in terms of stock market returns the IGBC of Colombia presented evidence of the *Tuesday-effect* as well as the *weekend-effect* whilst the highest volatility occurred on Thursday. With regards to Colombia, Rivera Palacio (2009) corroborated further the conclusions proposed by Rodríguez for the IGBC stock market returns.

The existence of the *day-of-the-week* effect has been extensively documented for different stock markets around the world. It is important to bear in mind that the results for a specific country may vary depending on the specific time-period chosen as well as the choice of model with which the anomaly was examined.

3. The Data

3.1. Overview of the major Latin American stock market indexes

In this paper I investigate the existence of the so called *day-of-the-week* effect on four of the major stock markets in Latin America, namely Argentina, Brazil, Chile, and Mexico using the main index of each country, that is to say MERVAL, BOVESPA, IPSA, and IPC respectively.

Argentina's MERVAL exercised since June 1986, is the main indicator of the Argentina Stock Exchange. It is constituted of 14 equities that represent Argentina's leading companies. Shares in the MERVAL index are re-calculated quarterly in terms of trading volume and operations over the last six months.

Brazil's BOVESPA exercised since 1968, is the main indicator of the Brazilian stock market's average performance. IBOVESPA's relevance comes from two factors; 1) it reflects the variation of BOVESPA's most traded stocks, and 2) it has tradition, having maintained the integrity of its historical series without any methodological change since its inception. The index is constituted of 63 equities and reflects not only the variation of the stock prices but also the impact of the distribution of benefits. The stocks that integrate IBOVESPA's theoretical portfolio represent more than 80% of the number of trades and the financial value registered on BOVESPA's cash market while the issuing companies of the stocks that compose the same portfolio are responsible, in average, for approximately 70% of the sum of all BOVESPA's companies' capitalization.

Chile's IPSA (Índice de Precios Selectivo de Acciones) exercised since 1977, is the main indicator of the Chilean Stock Exchange. It is constituted of 40 major equities that are weighted quarterly and which market capitalization exceeds 200.000.000 USD.

Mexico's IPC (Índice de Precios y Cotizaciones) exercised since October 1978, is the main indicator of the Mexican Stock Exchange. It expresses the yield of the stock market in relation to price variations of a balanced, weighted and representative group of stocks which is composed of 35 equities. The IPC is a reliable indicator of the stock market fluctuations in terms of two fundamental concepts: 1) Representativeness: its constituent list reflects the trading behavior and dynamics of the Mexican market, and 2) Investment: its constituent equities count with the trading and liquidity qualities that facilitate the buying and selling transactions that respond to the Mexican market needs.

For a detailed list of constituent equities, refer to Table A1 in Appendix.

3.2 Preliminary statistical tests

The data[10] sets analyzed in this paper are the *Bolsa de Valores de São Paulo (BOVESPA), Índice de Precios y Cotizaciones (IPC), Índice de Precios Selectivo de Acciones (IPSA),* and *Mercado de Valores de Buenos Aires (MERVAL)* stock market daily closing price indexes; not adjusted for dividends[11] and excluding nontrading days. Altogether, there are 3132 observations from March 26, 1998 to March 26, 2010.

Returns in each market are expressed in local currencies and are calculated as following:

$$r_t = \ln p_t - \ln p_{t-1}$$

which is the continuously compounded return[12] for each index at time t ($t = 1, \ldots, 3132$).

Visual inspection of the plot of the series p_t and r_t , see Graphs1 and 2 respectively, indicate that there is an upward trend for p_t for each of the indexes in question; however during the last quarter of 2008 there is a drastic fall for BOVESPA of Brazil and MERVAL of Argentina indexes in particular[13]. More about this period is discussed in section 5. With regards to the returns r_t there is evidence of the existence of periods with low volatility and periods with high volatility (*volatility clustering*) as well as stability around the mean, 0.000559, 0.000605, 0.000404, and 0.000388 for BOVESPA, IPC, IPSA, and MERVAL respectively.

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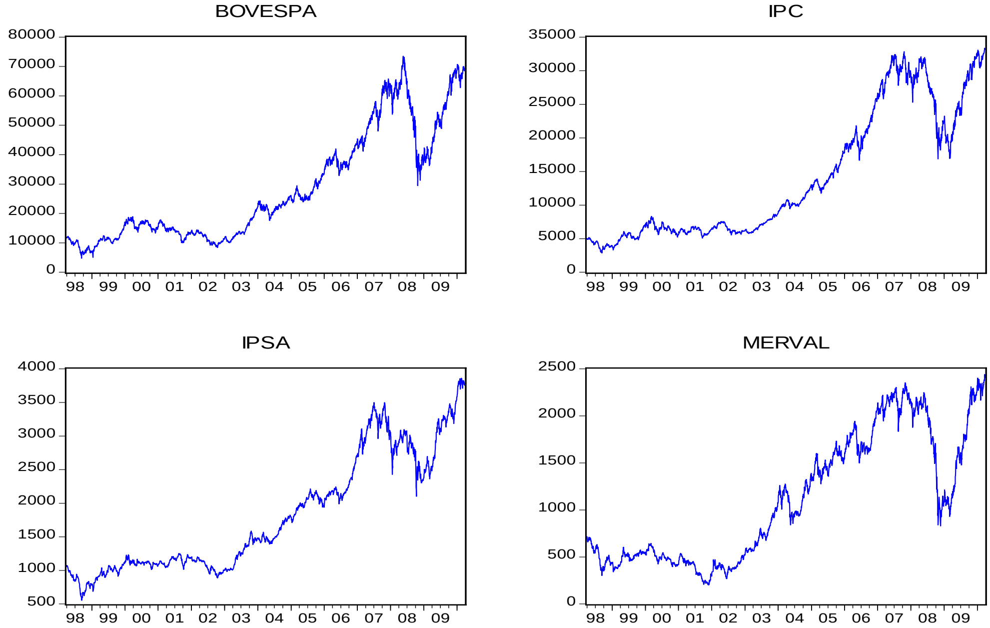
[10] All the data used in this research were obtained from DATASTREAM.

[11] Lakonishok and Smidt (1988) investigated the *day-of-the-week* effect and discussed the sensitivity of their results to the pattern of dividend payments concluding that the omission of dividends does not seem to affect their outcomes.

[12] In order to achieve stationarity, the series were transformed into continuously compounded returns. The ADF-test corroborates the stationarity assumption, see Table A2 in Appendix.

[13] For more information, see *Latin America: Still bearish equities*, 2009/03/09 on www.emergingmarketsmonitor.com

Graph 1: Daily closing prices for BOVESPA, IPC, IPSA, and MERVAL 03/98 – 03/10



Graph 2: Daily returns for BOVESPA, IPC, IPSA, and MERVAL 03/98 – 03/10

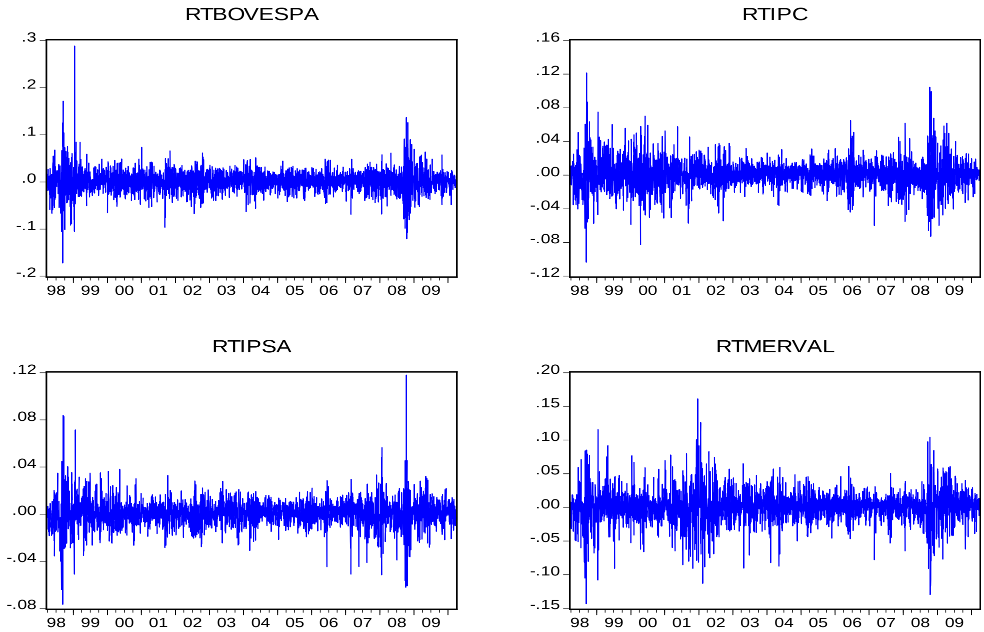


Table 1 reports the descriptive statistics for returns for each day of the week and for each stock market index. For BOVESPA the highest mean return is observed on Monday while the lowest is on Friday. Looking at the standard deviations, Thursday is the day with the highest variance; on the contrary Tuesday shows less volatility than any other day of the week. Monday, Tuesday, and Wednesday represent the days with the highest volatility, highest mean returns and lowest volatility respectively for both IPC and MERVAL. For IPSA the highest mean return is observed on Thursday while the lowest is on Wednesday. Monday is the day with the highest variance whereas the day with less volatility is Wednesday.

Returns reflect negative skewness (except for Tuesday for MERVAL) indicating that they are asymmetric. Kurtosis is higher than that of a normal distribution in all the cases showing the fat tails stylized fact of the empirical distributions. Finally, the Jarque-Bera test clearly rejects the assumption of normality for each of the indexes studied (refer also to Graph A1 in Appendix).

Table 1: Descriptive statistics for indexes returns

BOVESPA	Mean	Maximum	Minimum	Std. Dev.	Skewness	Kurtosis	Jarque-Bera
Monday	0.002833	0.261933	-0.292621	0.049318	-0.375079	6.703851	371.9075
Tuesday	0.002815	0.221282	-0.210452	0.046586	-0.276999	5.681091	195.1865
Wednesday	0.002819	0.312040	-0.266314	0.046729	-0.272698	9.507231	1110.456
Thursday	0.002822	0.369974	-0.318544	0.051789	-0.102376	12.50137	2352.028
Friday	0.002808	0.217421	-0.223273	0.047057	-0.397865	5.769673	216.2572
IPC							
Monday	0.003014	0.200449	-0.208832	0.040427	-0.313929	6.158285	270.0252
Tuesday	0.003032	0.144783	-0.175405	0.036765	-0.404261	4.932134	114.2409
Wednesday	0.003027	0.135917	-0.194438	0.036344	-0.319143	5.697404	200.0885
Thursday	0.003022	0.172988	-0.168067	0.036775	-0.324202	5.300264	148.7407
Friday	0.003007	0.185786	-0.179285	0.038046	-0.090687	6.533963	326.0883
IPSA							
Monday	0.002039	0.130112	-0.143343	0.030399	-0.307833	5.673076	195.9475
Tuesday	0.002032	0.138990	-0.160425	0.029449	-0.471996	6.285472	304.3085
Wednesday	0.002024	0.118021	-0.215317	0.028753	-0.853884	9.743548	1260.206
Thursday	0.002048	0.118771	-0.192084	0.028983	-0.955622	8.724002	948.3608
Friday	0.002037	0.146680	-0.215977	0.029590	-0.784065	9.516797	1169.992
MERVAL							
Monday	0.001945	0.315531	-0.336678	0.055110	-0.119235	7.429217	512.3654
Tuesday	0.001975	0.261678	-0.254252	0.052612	0.141087	5.931861	225.9227
Wednesday	0.001973	0.245877	-0.231362	0.051448	-0.278283	5.833855	217.2006
Thursday	0.001923	0.238861	-0.253442	0.053187	-0.353060	6.552900	341.7109
Friday	0.001935	0.237673	-0.311814	0.052434	-0.299745	7.226018	474.4432

Thus, the initial findings indicate that daily returns are leptokurtic, skewed, are not normally distributed, and display evidence of volatility clustering.

4. Empirical Models

The empirical analysis[14] is conducted using three types of time-varying conditional models namely; GARCH, EGARCH, and APARCH and assuming that the error terms follow a conditional normal distribution and a conditional Student's t- distribution. As mentioned previously, these models are able to capture characteristics such as volatility clustering, leptokurtosis, and asymmetry.

Bekaert and Harvey (1997) studied the behavior of emerging stock markets finding that returns tend to be serially correlated due to market inefficiency and the existence of asymmetric information. Therefore, there is a need to check for autocorrelation and correct it.

The estimation of the models when assuming that the error term follows a conditional normal distribution is based on the Quasi-Maximum Likelihood (QML). The robust standard errors are also computed as indicated by Bollerslev and Wooldridge (1992).

For each of the three models used in this investigation, the conditional mean equation is basically the same and is denoted as:

$$r_t = \pi_0 + \chi_{MON} D_{1t} + \chi_{TUE} D_{2t} + \chi_{THU} D_{3t} + \chi_{FRI} D_{4t} + \sum_{i=1}^{n} \rho_i \, r_{t-i} + \varepsilon_t \qquad (1)$$

where D_{1t} is a dummy variable which gets the value of 1 if it is a Monday and 0 otherwise; similarly D_{2t} is equal to 1 if it is a Tuesday and 0 otherwise; and so on, *n* is the lag order, and ε_t is the error term. The reason behind eliminating Wednesday's dummy variable is to avoid the dummy variable trap[15]. The coefficients $\chi_{MON}, \chi_{TUE}, \chi_{THU}$, and χ_{FRI} represent the size and direction of the effect of each day of the week on stock returns.

The error term is assumed to follow two types of distributions:

- Normal distribution: $\varepsilon_t | \Omega_{t-1} \sim N\,(0, \sigma_t^2)$ (2.1)

- Student's t-distribution: $\varepsilon_t | \Omega_{t-1} \sim t.d.\,(0, \sigma_t^2, \vartheta)$ (2.2)

where ϑ indicates the degrees of freedom.

[14] Models are estimated using E-views.
[15] Dummy variable trap implies exact multicollinearity.

4.1 Generalized autoregressive conditional heteroskedasticity model (GARCH)

Following Bollerslev (1986), the GARCH (p,q) model applied to investigate the *day-of-the-week* effect can be specified as following:

The conditional variance equation depends on past values of the squared errors as well as on past conditional variances and is denoted as:

$$\sigma_t^2 = \eta_0 + \sum_{i=1}^{p} \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^{q} \beta_j \sigma_{t-j}^2 + \varphi_{MON} D_{1t} + \varphi_{TUE} D_{2t} + \varphi_{THU} D_{3t} + \varphi_{FRI} D_{4t} \quad (3)$$

where $\eta_0 > 0, \alpha_i \geq 0 \; \forall \; i = 1, \dots, p, \; \beta_j \geq 0 \; \forall \; j = 1, \dots, q; \; \sum_{i=1}^{p} \alpha_i + \sum_{j=1}^{q} \beta_j < 1$ to ensure the positivity of the conditional variance[16] (Harris and Sollis, 2003) and similarly to the mean equation, the coefficients $\varphi_{MON}, \varphi_{TUE}, \varphi_{THU}$, and φ_{FRI} represent the size and direction of the effect of each day of the week on volatility. Note that since no restrictions are placed on dummy variables, it is important to check that negative effect estimates do not lead to negative variances.

The most commonly used model in the GARCH class is the GARCH (1,1) which often performs very well[17] (Campbell et al., 2008). The conditional variance equation becomes:

$$\sigma_t^2 = \eta_0 + \alpha \varepsilon_{t-1}^2 + \beta \sigma_{t-1}^2 + \varphi_{MON} D_{1t} + \varphi_{TUE} D_{2t} + \varphi_{THU} D_{3t} + \varphi_{FRI} D_{4t} \quad (4)$$

4.2 Exponential GARCH model (EGARCH)

Nelson (1991) found that GARCH models are somewhat restrictive since they impose some important limitations in their structure such as:

- σ_t^2 is a function of lagged σ_t^2 and ε_t^2 and so is invariant to changes in the algebraic sign of the $\varepsilon_t's$ thus, only the size and not the sign of lagged residuals determines σ_t^2.

[16] Eviews is somewhat restrictive since it does not impose those restrictions. However, the model will be taken as valid as long as the negative effect estimates do not lead to negative variances.
[17] Bollerslev (1986) investigated the GARCH (1,1) specification in great detail demonstrating that the model is sufficient to capture the volatility dynamics.

- $\eta_0 > 0, \alpha_i \geq 0 \; \forall \; i, \; \beta_j \geq 0 \; \forall \; j$ are restrictions imposed to the model in order to ensure that σ_t^2 remains non-negative. These constraints imply that researchers are in the need to impose further restrictions to prevent that negative effect estimates spillover to σ_t^2.
- In GARCH (1,1) models shocks may persist in one norm and die out in another so the conditional moments of the model may explode even when the process itself is strictly stationary.

The EGARCH model is able to address these drawbacks through its conditional variance equation denoted as:

$$\log \sigma_t^2 = \eta_0 + \sum_{i=1}^{p} \alpha_i \frac{|\varepsilon_{t-i}|}{|\sigma_{t-i}|} + \gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \sum_{j=1}^{q} \beta_j \log \sigma_{t-j}^2 + \varphi_{MON} D_{1t} + \varphi_{TUE} D_{2t} + \varphi_{THU} D_{3t} + \varphi_{FRI} D_{4t} \tag{5}$$

where $\log \sigma_t^2$ is made linear in some function of time and lagged $\varepsilon_t's$ to ensure that σ_t^2 remains nonnegative, $\gamma \frac{\varepsilon_{t-1}}{\sigma_{t-1}}$ captures asymmetry (also known as “leverage effect”) as long as $\gamma \neq 0$; when $\gamma < 0$ positive shocks generate less volatility than negative shocks (“bad news”) (Verbeek, 2008), β controls the persistence of conditional variance and $\beta < 1$ is sufficient for the process ε_t to be stationary, and again the coefficients $\varphi_{MON}, \varphi_{TUE}, \varphi_{THU}$, and φ_{FRI} represent the size and direction of the effect of each day of the week on volatility.

4.3 Asymmetric Power ARCH model (APARCH)

Following Ding et al. (1993), the APARCH model can be specified as following:

The conditional variance equation is denoted as:

$$\sigma_t^\delta = \eta_0 + \sum_{i=1}^{p} \alpha_i \left(|\varepsilon_{t-i}| - \gamma_i \epsilon_{t-i}\right)^\delta + \sum_{j=1}^{q} \beta_j \, \sigma_{t-j}^\delta + \varphi_{MON} D_{1t} + \varphi_{TUE} D_{2t} + \varphi_{THU} D_{3t} + \varphi_{FRI} D_{4t} \tag{6}$$

where $\eta_0 > 0, \delta \geq 0, \alpha_i \geq 0 \; \forall \; i = 1, \dots, p, \; -1 < \gamma_i < 1, \beta_j \geq 0 \; \forall j = 1, \dots, q$. Asymmetry is introduced via the parameter γ_i. If $\gamma_i > 0$ negative shocks increase volatility more than positive shocks and if $\gamma_i < 0$positive shocks increase volatility more than negative shocks (Asgharian, 2009).

The APARCH model includes seven ARCH models as a special case:

- ARCH(p) when δ=2, $\gamma_i = 0$, and $\beta_j = 0$
- GARCH(p,q) when δ=2 and $\gamma_i = 0$
- Taylor/Schwert's GARCH when δ=1 and$\gamma_i = 0$
- GJR model when δ=2
- Zakoian's TARCH when δ=1 and $\beta_j = 0$
- Higgins and Bera's NARCH when $\gamma_i = 0$ and $\beta_j = 0$
- Geweke and Pantula's log-ARCH when$\delta \to 0$.

4.4 Validity of the model and Goodness-of-fit

To assess the general validity of the conditional mean and the conditional variance equations, two types of tests are performed:

- The Ljung-Box portmanteau test for autocorrelation on the standardized residuals (to check the conditional mean) as well as the squared standardized residuals (to check the conditional variance) considering 8 and 16 lags in each case.
- The ARCH-LM test for homoskedasticity and evidence of ARCH effects considering 10 lags.

In order to decide which of the above mentioned models performs the best and should therefore be preferred to describe the *day-of-the-week* effect on stock returns and volatility on each stock market index, I use the Akaike Information Criterion (AIC), the Bayesian Information Criterion (BIC) and the Log-likelihood. The models with the lowest AIC and BIC and the highest log-likelihood are typically preferred.

5. Empirical Results

The results are presented and discussed separately for each stock market index. Since Wednesday´s dummy variable was excluded, this will be the base category with which results are to be compared. For a better overview of the main findings, only parts of the estimates are reported. For the conditional mean equation it was found that for IPC, IPSA, and MERVAL indexes, returns follow a stochastic AR (*p*) process; whereas for BOVESPA, returns have no statistically significant autocorrelation[18]. To check whether the drastic fall observed in the last quarter of 2008 affects the results considerably, a robustness test was performed finding no significant changes in the outcomes therefore, the sample size remains as originally[19]. I have also tested a number of specifications to describe the conditional variance equation for each time-varying conditional model selecting the ones shown in the tables below[20]. The assumption that the error term follows a Student's t-density is found to best describe the conditional distribution of each stock market index[21].

BOVESPA

Table 2 shows the results for BOVESPA stock market index. Given the outcomes of the conditional mean equation, one can conclude that a *Monday-effect* is present on stock returns. This pattern is present in the three models in which Monday represents the day with significant negative effect on stock returns, that is to say, returns on Mondays are lower than returns on Wednesdays. Even though Tuesday's coefficient is also negative and statistically significant in the GARCH and APARCH models, it is not as low as that of Monday. Friday, indeed shows that returns are higher than returns on Wednesday in the EGARCH and APARCH models however, its coefficients are not statistically significant.

In terms of volatility, results are rather ambiguous. On the one hand, for the EGARCH model Tuesdays and Fridays' coefficients impose a significant negative effect on stock return

[18] Refer to Table A3 in Appendix.
[19] The robustness test was performed excluding the last three years of the sample (2008-2010). Results are not reported to save space but are available upon request.
[20] The comparison of various GARCH, EGARCH, and APARCH specifications was based on the AIC and BIC information criteria. Results are not reported to save space but are available upon request.
[21] Results when assuming conditional normal distribution are reported in Tables A4-A7, see Appendix.

volatility which means that volatility is lower those days than on Wednesday. The GARCH model also follows the same pattern for Friday. The APARCH model, on the other hand, shows the same volatility pattern but all the coefficients are statistically insignificant implying that no *day-of-the-week* effect on stock return volatility exists.

Based on the information criteria measures, the EGARCH and APARCH models with Student's t-distribution outperform the GARCH model indicating that asymmetry plays a role when investigating the *day-of-the-week* effect. As to which extent one model should be preferred over the other is difficult to say. One possible reason behind preferring the EGARCH (2,1) model is because of the Ljung-Box and ARCH-LM tests which indicate no evidence of autocorrelation nor heteroskedasticity whereas the APARCH (1,1) model does show little evidence of ARCH effects. Consequently, the EGARCH (2,1) model seems to best capture the calendar anomaly on both stock returns and volatility.

Table 2: *Day-of-the-week* effect estimation results for Brazil's BOVESPA index.

BOVESPA	GARCH (1,1) Student's t-dist.	**EGARCH (2,1) Student's t-dist.**	**APARCH (1,1) Student's t-dist.**
Mean equation			
π	0.002625***	0.001855***	0.001937***
χ_{MON}	-0.002870***	**-0.002401****	**-0.002416****
χ_{TUE}	-0.001625*	-0.001428	**-0.001675***
χ_{THU}	-0.001876*	-0.001439	-0.001608
χ_{FRI}	-0.000410	0.000145	0.000154
Variance equation			
η	4.26E-05	-0.296967***	0.000539
α_1	0.080928***	0.009656	0.063771***
α_2		0.160418***	
γ		-0.111163***	0.762314***
δ			1.357234***
β	0.893431***	0.962176***	0.906805***
φ_{MON}	3.44E-05	0.194101	0.000344
φ_{TUE}	-5.46E-05	**-0.323579****	-0.000692
φ_{THU}	-3.04E-05	-0.077816	-0.000402
φ_{FRI}	-0.000109***	**-0.468818*****	-0.001160
DOF	7.852353***	9.263978***	9.719433***
Standardized residuals			
L-B Q1(8)	4.8990	6.1254	6.1627
L-B Q1(16)	19.245	15.873	17.144
Standardized squared residuals			
L-B Q2(8)	11.469	10.022	15.771
L-B Q2(16)	21.220	19.815	28.662
ARCH (10)	16.67641	15.16814	[23.29936]
Log-L	8006.086	**8043.086**	**8043.151**
AIC	-5.105772	**-5.128129**	**-5.128170**
BIC	-5.080656	**-5.099149**	**-5.099190**

Notes: **bold** indicates the best fitted model, * ** *** imply significance at 10%, 5%, and 1% level respectively, Std. Dev. is given in Table A4 see Appendix, and [brackets] mean rejection of the null hypothesis.

IPC

Table 3: *Day-of-the-week* effect estimation results for Mexico's IPC index.

IPC	GARCH (1,1) Student's t-dist.	**EGARCH (1,1) Student's t-dist.**	APARCH (1,1) Student's t-dist.
Mean equation			
π	0.001571***	0.001069**	0.001024**
χ_{MON}	-0.000816	-0.000540	-0.000558
χ_{TUE}	-0.000430	-0.000453	-0.000441
χ_{THU}	-5.08E-05	0.000263	0.000261
χ_{FRI}	-0.000713	-0.000412	-0.000355
ρ_{t-1}	0.086223***	0.088452***	0.088847***
ρ_{t-2}	-0.041316**	-0.027529	-0.029617*
Variance equation			
η	-4.73E-07	-0.242873**	0.000299
α	0.091538***	0.155078***	0.083238***
γ		-0.103229***	0.685078***
δ			1.095748***
β	0.897346***	0.979311***	0.912567***
φ_{MON}	2.49E-05	**0.237288***	0.000933
φ_{TUE}	1.85E-05	-0.051990	-4.88E-05
φ_{THU}	-1.00E-05	-0.111064	-0.000493
φ_{FRI}	-1.27E-05	**-0.339871*****	-0.000817
DOF	5.958061***	7.071299***	7.108172***
Standardized residuals			
Q1(8)	6.9588	3.5985	3.4621
Q1(16)	15.747	11.830	11.847
Standardized squared residuals			
Q2(8)	5.7455	6.8472	6.7658
Q2(16)	9.6115	14.413	14.569
ARCH (10)	6.376181	10.00710	9.888684
Log-L	8992.842	**9031.096**	9031.433
AIC	-5.738473	**-5.762286**	-5.761862
BIC	-5.709478	**-5.731357**	-5.729000

Notes: **bold** indicates the best fitted model, * ** *** imply significance at 10%, 5%, and 1% level respectively, Std. Dev. is given in Table A5 see Appendix, and [brackets] mean rejection of the null hypothesis.

Table 3 shows the results for IPC stock market index. Based on the outcomes of the conditional mean equation, all the models follow the pattern of a *weekend-effect* but the coefficients are all statistically insignificant thus; one can conclude that no *day-of-the-week* effect is present on stock returns.

In terms of volatility, results for the EGARCH model are in accordance with Rodriguez's (2009) findings who observed a clear *Monday-effect*. The estimated coefficients for Monday and Friday are statistically significant being the former positive (0.237288) and the latter negative (-0.339871). Hence, stock return volatility is higher on Mondays and lower on Fridays than on Wednesdays. Regarding the other two models, there is no evidence of the *day-of-the-week* seasonality. Furthermore, for the GARCH model the estimated volatility coefficient for the constant term is negative and insignificant implying that the positivity of the conditional variance is not satisfied.

According to the information criteria measures, the EGARCH (1,1) model outperforms the GARCH (1,1) and APARCH (1,1) models showing again that a model that takes into consideration the asymmetry effect is better to describe the calendar seasonality. This model should therefore be preferred to describe the *day-of-the-week* effect in the Mexican market.

IPSA

Table 4 shows the results for IPSA stock market index. Based on the outcomes of the conditional mean equation, one can conclude that the *day-of-the-week* effect is present on stock returns. All the models follow the same pattern in which Monday and Tuesday impose a significant negative effect on stock returns. Hence, returns on these days are lower than returns on Wednesday being Monday the day with the lowest stock return. Friday shows higher returns but its coefficient is not statistically significant.

When it comes to stock return volatility, results are rather ambiguous. On the one hand, for the EGARCH model, Friday imposes a significant negative effect on stock return volatility and Monday a significant positive effect which means that volatility is lower on Friday and higher on Monday than on Wednesday. This model clearly suggests a *Monday-effect* again in accordance with Rodriguez's (2009) findings. The GARCH and APARCH models, on the other hand, show the same volatility pattern as that of a *Tuesday-effect* nevertheless; all the coefficients are statistically insignificant implying no evidence of a *day-of-the-week* effect.

Based on the information criteria measures, the EGARCH and APARCH models with Student's t-distribution outperform the GARCH model, implying that asymmetry plays a role when investigating the *day-of-the-week* effect. It is hard to say which model should be preferred over the other in this case. One could argue on the one hand, that the APARCH model should be preferred to describe the *day-of-the-week* effect based on the values of the Log-likelihood and AIC. On the other hand, according to the BIC criterion the EGARCH model should be chosen. Thus, it is clear from the results that a *day-of-the-week* seasonality is present on stock retuns but results are unclear when it comes to stock return volatility.

Table 4: *Day-of-the-week* effect estimation results for Chile's IPSA index.

IPSA	GARCH (1,1) Student's t-dist.	**EGARCH (1,1) Student's t-dist.**	**APARCH (1,1) Student's t-dist.**
Mean equation			
π	0.001184***	0.000967***	0.000898***
χ_{MON}	-0.001866***	**-0.001699*****	**-0.001634*****
χ_{TUE}	-0.000953**	**-0.000804***	**-0.000890****
χ_{THU}	0.000213	0.000223	0.000267
χ_{FRI}	0.000440	0.000528	0.000609
ρ_{t-1}	0.183637***	0.187588***	0.186047***
Variance equation			
η	2.35E-06	-0.516934***	1.22E-05
α	0.130417***	0.242330***	0.120082***
γ		-0.065779***	0.249763***
δ			1.682777***
β	0.840534***	0.963833***	0.853788***
φ_{MON}	8.04E-06	**0.211138***	3.36E-05
φ_{TUE}	1.27E-05	0.097963	4.37E-05
φ_{THU}	-5.24E-06	-0.107549	-2.21E-05
φ_{FRI}	-9.67E-06	**-0.234458***	-3.54E-05
DOF	8.520563***	8.855910***	8.951743***
Standardized residuals			
Q1(8)	16.116	14.129	13.945
Q1(16)	20.397	18.132	18.253
Standardized squared residuals			
Q2(8)	6.9311	8.8615	7.3302
Q2(16)	15.771	17.802	15.304
ARCH (10)	13.42371	16.37055	13.72319
Log-L	10197.48	**10208.87**	**10211.30**
AIC	-6.507014	**-6.513656**	**-6.514569**
BIC	-6.479958	**-6.484668**	**-6.483648**

Notes: **bold** indicates the best fitted model, * ** *** imply significance at 10%, 5%, and 1% level respectively, Std. Dev. is given in Table A6 see Appendix, and [brackets] mean rejection of the null hypothesis.

MERVAL

Table 5 shows the results for MERVAL stock market index. Rodriguez (2009) found that Monday was the day with the lowest returns for the MERVAL index during the period 1997-2007. In this analysis for the GARCH and APARCH models, returns on Monday are indeed lower than returns on Wednesday nevertheless; the estimated coefficients are not statistically significant. In fact, no evidence of the *day-of-the-week* effect was found on stock returns. As for the EGARCH model, a *Friday-effect* is surprisingly observed suggesting that returns on this day are lower than returns on Wednesday.

In terms of volatility, all the models follow the pattern of a *Monday-effect* but the coefficients for the APARCH model are statistically insignificant whereas for the other two models they are not. For the GARCH model the positivity of the conditional variance is not satisfied so the model is left out. As for the EGARCH model, there is a significant negative effect on stock return volatility on Friday implying that stock return volatility is lower on Friday than on Wednesday.

Table 5: *Day-of-the-week* effect estimation results for Argentina's MERVAL index.

MERVAL	GARCH (1,1) Student's t-dist.	EGARCH (3,4) Student's t-dist.	**APARCH (1,1) Student's t-dist.**
Mean equation			
π	0.001807***	0.001965***	0.001584***
χ_{MON}	-0.001213	-0.001133	-0.001227
χ_{TUE}	-0.001003	-0.001161	-0.001064
χ_{THU}	-0.000604	-0.000818	-0.000578
χ_{FRI}	-0.001119	-0.001400*	-0.001110
ρ_{t-1}	0.015361	0.016292	0.023221
Variance equation			
η	-1.40E-05	-0.145496	-1.52E-05
α_1	0.103865***	0.159909***	0.107545***
α_2		-0.111082**	
α_3		0.160085***	
γ		-0.053918***	0.267228***
δ			1.865262***
β_1	0.884602***	1.766320***	0.870956***
β_2		-1.416597***	
β_3		0.390971	
β_4		0.234307	
φ_{MON}	0.000137***	0.392529*	**0.000222**
φ_{TUE}	-1.17E-05	-0.717539	-2.54E-05
φ_{THU}	5.40E-05	-0.011304	9.15E-05
φ_{FRI}	-5.20E-05	-0.641268**	-8.52E-05
DOF	3.999876***	3.991185***	4.042610***
Standardized residuals			
Q1(8)	11.372	12.518	11.829
Q1(16)	29.111	[33.464]	29.684
Standardized squared residuals			
Q2(8)	3.0208	12.359	2.3087
Q2(16)	14.903	20.538	28.908
ARCH (10)	10.73328	17.72632	[24.67254]
Log-L	7989.303	8000.979	**8001.921**
AIC	-5.096040	-5.099667	**-5.102825**
BIC	-5.068985	-5.061017	**-5.071904**

Notes: **bold** indicates the best fitted model, * ** *** imply significance at 10%, 5%, and 1% level respectively, Std. Dev. is given in Table A7 see Appendix, and [brackets] mean rejection of the null hypothesis.

According to the goodness-of-fit measures, the APARCH (1,1) model with Student's t-distribution should be chosen suggesting that no *day-of-the-week* seasonality is present on neither stock returns nor volatility. It is interesting to see that the difference between the goodness-of-fit measures of the APARCH (1,1) model and the EGARCH (3,4) model is not really significant, however the results for the former indicate no evidence of the *day-of-the-week* effect whilst for the latter evidence is present on stock retuns and volatility. The *leverage effect* is the only anomaly that both models have in common.

Table 6 illustrates the main findings of this research which indicate that evidence of the *day-of-the-week* seasonality is present in three out of four stock markets. For Chile the anomaly is present on stock returns, for Mexico a clear *Monday-effect* is observed on volatility, and for Brazil on both. Returns on Monday are lower than returns on Wednesday for Chile and Brazil while Friday represents the day with the lowest volatility for Brazil and Mexico. As for Argentina, the same volatility pattern was observed however; the estimated coefficients are statistically insignificant. It is important to point out that results may vary depending on the choice of model with which the anomaly was examined.

Table 6: Main findings of the *day-of-the-week* effect

	Brazil BOVESPA		Mexico IPC		Chile IPSA		Argentina MERVAL	
	Retuns	Volatility	Retuns	Volatility	Retuns	Volatility	Retuns	Volatility
Monday	lowest	-	-	highest	lowest	not clear	-	-
Tuesday	-	-	-	-	-	not clear	-	-
Thursday	-	-	-	-	-	not clear	-	-
Friday	-	lowest	-	lowest	-	not clear	-	-

As to which extent the calendar anomaly has been taken into consideration by financial decision makers is difficult to say. Judging from the obtained results, one could presume that the stock markets of Brazil, Chile and Mexico exhibit market inefficiency as asserted by other researchers regarding other emerging stock markets. It is said that emerging markets might show inefficiencies at their early stage of development. In the case of Argentina, no *day-of-the-week* effect was found implying that the market exhibits a certain level of efficiency as suggested by Ajayi et al. (2004) for the Eastern European emerging markets.

6. Conclusions

The *day-of-the-week* effect has been under study for many years. Keim and Stambaugh (1983) acknowledge that this anomaly is one of the most enigmatic phenomena in finance because it follows patterns that do not necessarily correspond to the stipulations of accepted models of asset pricing and therefore the Efficient Market Hypothesis does not always hold. Many authors have been following the evolution of the *day-of-the-week* seasonality particularly in developed stock markets. They believe that investors have been adapting to new forms of trading implying that improvements in market efficiency over time can lead to the disappearance of this anomaly. In the case of emerging stock markets, many authors have been studying the *day-of-the-week* effect to check whether it is true that markets might show inefficiencies at their early stage of development or if they exhibit a certain level of market efficiency.

This paper has examined daily stock market returns for the four major Latin American stock markets, namely Argentina, Brazil, Chile, and Mexico for the period March 26, 1998 to March 26, 2010. The empirical analysis using three different models of time-varying conditional volatility with two different types of distributions found that the *day-of-the-week* effect is present in three out of four stock markets. IPSA index of Chile shows clear evidence of the anomaly on stock returns; however results for volatility are somewhat ambiguous. IPC index of Mexico shows clear evidence of the *day-of-the-week* effect on volatility but not on stock returns. BOVESPA index of Brazil is the only market showing evidence of the anomaly on both stock returns and volatility. No evidence of *day-of-the-week* effect was found for Argentina's MERVAL index. For all the stock markets, returns on Monday are lower than returns on Wednesday being significant in two out of four models. It is difficult to judge the extent to which the anomaly has been taken into consideration by financial decision makers in Latin America. According to the results, one could assume that Brazil, Chile, and Mexico exhibit market inefficiency while Argentina does not. These results clearly indicate the need for more research in this field for different time periods. Further interesting investigation could analyze possible reasons behind the cause of the *day-of-the-week* seasonality. Finding regular predictable patterns in stock markets will help investors in identifying adequate trading strategies while the market gains efficiency.

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Appendix

Table A1: Constituent Equities

Brazil BOVESPA		Mexico IPC	Chile IPSA	Argentina MERVAL
AGRE EMP IMO	NATURA	ALFA	ALMENDRAL	ALUA
ALL AMER LAT	NET	AMX	ANDINA-B	APBR
AMBEV	OGX PETROLEO	ARA	ANTARCHILE	BHIP
B2W VAREJO	P.ACUCAR-CBD	ASUR	BCI	BMA
BMFBOVESPA	PDG REALT	AUTLAN	BSANTANDER	BPAT
BRADESCO	PETROBRAS	AXTEL	CALICHERAA	EDN
BRADESPAR	PETROBRAS	BIMBO	CAP	ERAR
BRASIL	REDECARD	BOLSA	CCU	FRAN
BRASIL TELEC	ROSSI RESID	CEMEX	CENCOSUD	GGAL
BRASKEM	SABESP	COMERCI	CGE	MIRG
BRF FOODS	SID NACIONAL	COMPART	CHILE	PAMP
CCR RODOVIAS	SOUZA CRUZ	ELEKTRA	CMPC	PESA
CEMIG	TAM S/A	FEMSA	COLBUN	TECO2
CESP	TELEMAR	GAP	CONCHATORO	TRAN
CIELO	TELEMAR	GCARSO	COPEC	TS
COPEL	TELEMAR N L	GEO	CORPBANCA	
COSAN	TELESP	GFAMSA	EDELNOR	
CPFL ENERGIA	TIM PART S/A	GFINBUR	ENDESA	
CYRELA REALT	TIM PART S/A	GFNORTE	ENERSIS	
DURATEX	TRAN PAULIST	GMEXICO	ENTEL	
ECODIESEL	ULTRAPAR	GMODELO	FALABELLA	
ELETROBRAS	USIMINAS	GRUMA	GENER	
ELETROBRAS	USIMINAS	HOMEX	IAM	
ELETROPAULO	VALE	ICA	LA POLAR	
EMBRAER	VALE	KIMBER	LAN	
FIBRIA	VIVO	MEXCHEM	MADESCO	
GAFISA		PE&OLES	MASISA	
GERDAU		SORIANA	MULTIFOODS	
GERDAU MET		TELECOM	NORTEGRAN	
GOL		TELINT	ORO BLANCO	
ITAUSA		TELMEX	PARAUCO	
ITAUUNIBANCO		TLEVISA	PROVIDA	
JBS		TVAZTCA	RIPLEY	
KLABIN S/A		URBI	SALFACORP	
LIGHT S/A		WALMEX	SK	
LLX LOG			SM-CHILE B	
LOJAS AMERIC			SOCOVESA	
LOJAS RENNER			SONDA	
MMX MINER			SQM-B	
MRV			VAPORES	

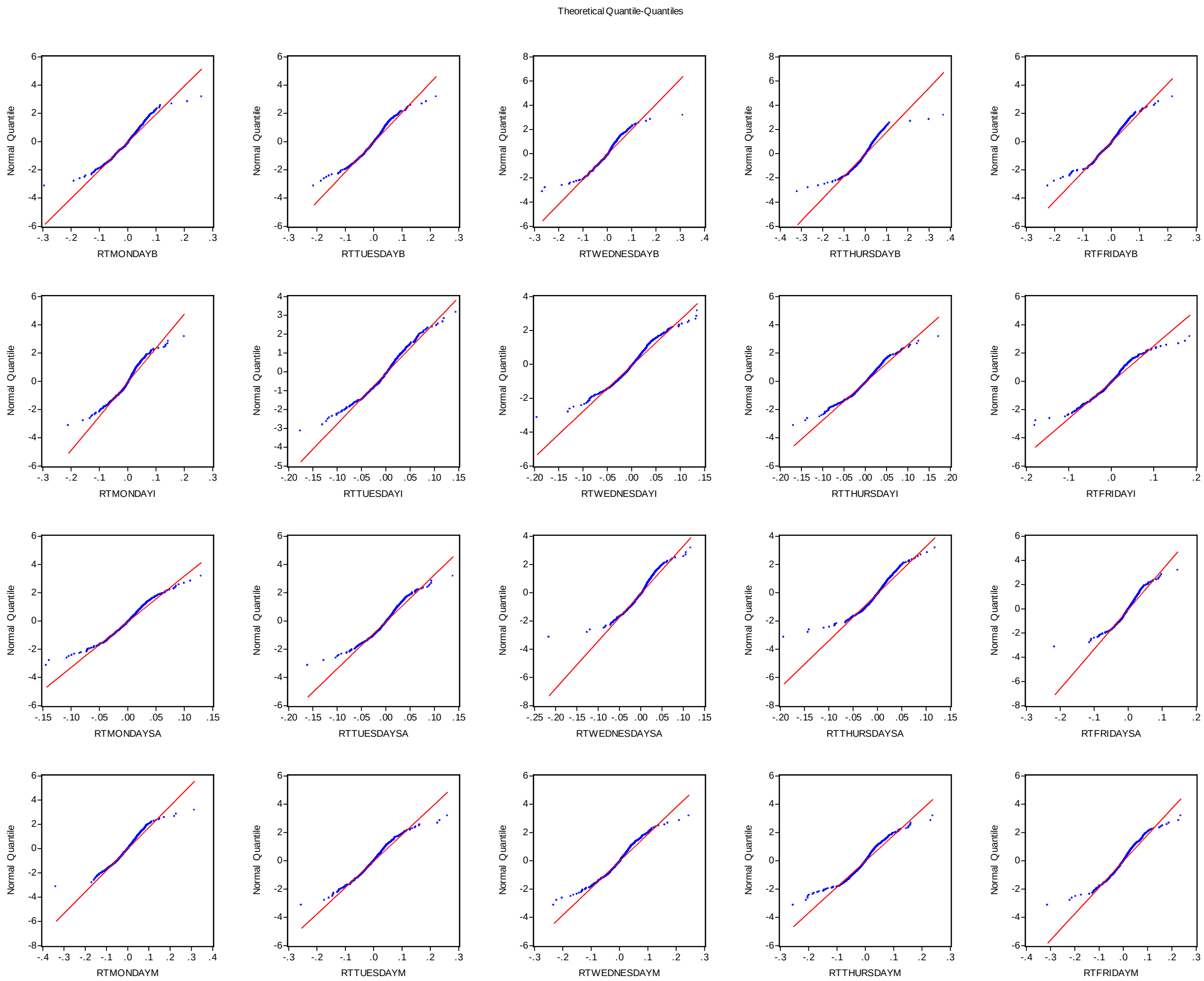
Source: Bolsa de Valores de São Paulo, Bolsa Mexicana de Valores,
Bolsa de Comercio de Santiago, and Mercado de Valores de Buenos Aires.

Table A2: Augmented Dickey-Fuller tests for returns

Index		BOVESPA	IPC	IPSA	MERVAL
Augmented Dickey-Fuller test		-55.75836*	-39.56879*	-47.33031*	-52.86014*
Test critical values	1% level	-3.960973	-3.960974	-3.960973	-3.960973
	5% level	-3.411242	-3.411243	-3.411242	-3.411242
	10% level	-3.127457	-3.127457	-3.127457	-3.127457

Notes: * rejection of the null hypothesis including constant and trend

Graph A1: Quantile-Quantile for BOVESPA, IPC, IPSA, and MERVAL 03/98 – 03/10



Note: the first row corresponds to BOVESPA, the second to IPC, the third to IPSA, and the fourth to MERVAL.

Table A3: Bayesian information criterion for indexes returns

Index	BOVESPA	IPC	IPSA	MERVAL
η	**-4.762975**	-5.411396	-6.110884	-4.734577
AR(1)	-4.760143	-5.418805	**-6.136808**	**-4.734986**
AR(2)	-4.757733	**-5.418745***	-6.134567	-4.732144
AR(3)	-4.756753	-5.415954	-6.132000	-4.729327
AR(4)	-4.754382	-5.413136	-6.131306	-4.726489

Notes: **bold** indicates the best fitted model

* indicates significance of the second lag at the 1% level

Table A4: *Day-of-the-week* effect results for Brazil's BOVESPA index including Std. dev.

BOVESPA	GARCH (1,1)		EGARCH (2,1)		APARCH (1,1)	
	Normal	Student's t-dist.	Normal	Student's t-dist.	Normal	Student's t-dist.
Mean equation						
π	0.003023	0.002625	0.001746	0.001855	0.001906	0.001937
	(0.000730)	(0.000686)	(0.000740)	(0.000644)	(0.000728)	(0.000688)
χ_{MON}	-0.003241	-0.002870	-0.002389	-0.002401	-0.002490	-0.002416
	(0.001029)	(0.000979)	(0.001012)	(0.000963)	(0.001037)	(0.000982)
χ_{TUE}	-0.002387	-0.001625	-0.002295	-0.001428	-0.002265	-0.001675
	(0.001026)	(0.000962)	(0.001006)	(0.000895)	(0.001005)	(0.000952)
χ_{THU}	-0.002646	-0.001876	-0.001969	-0.001439	-0.002115	-0.001608
	(0.001032)	(0.000987)	(0.001025)	(0.000948)	(0.001024)	(0.000978)
χ_{FRI}	-0.000998	-0.000410	0.000363	0.000145	9.23E-05	0.000154
	(0.000989)	(0.000912)	(0.000988)	(0.000863)	(0.000964)	(0.000897)
Variance equation						
η	1.62E-05	4.26E-05	-0.415595	-0.296967	0.000285	0.000539
	(3.27E-05)	(2.79E-05)	(0.150006)	(0.103309)	(0.000370)	(0.000503)
α_1	0.088530	0.080928	0.011081	0.009656	0.063578	0.063771
	(0.019307)	(0.010442)	(0.044177)	(0.045956)	(0.020214)	(0.013637)
α_2			0.164936	0.160418		
			(0.045832)	(0.047556)		
γ			-0.123289	-0.111163	0.806214	0.762314
			(0.019614)	(0.012887)	(0.270073)	(0.180072)
δ					1.405154	1.357234
					(0.258213)	(0.225404)
β	0.882744	0.893431	0.955388	0.962176	0.899886	0.906805
	(0.020728)	(0.013005)	(0.008775)	(0.006143)	(0.016686)	(0.011484)
φ_{MON}	7.04E-05	3.44E-05	0.264283	0.194101	0.000584	0.000344
	(4.23E-05)	(3.68E-05)	(0.140527)	(0.125501)	(0.000612)	(0.000434)
φ_{TUE}	-1.65E-05	-5.46E-05	-0.241465	-0.323579	-0.000344	-0.000692
	(6.32E-05)	(4.47E-05)	(0.189541)	(0.155857)	(0.000577)	(0.000664)
φ_{THU}	6.50E-06	-3.04E-05	-0.009711	-0.077816	-0.000129	-0.000402
	(4.98E-05)	(5.02E-05)	(0.160739)	(0.161720)	(0.000391)	(0.000553)
φ_{FRI}	-8.04E-05	-0.000109	-0.377545	-0.468818	-0.000790	-0.001160
	(3.99E-05)	(3.68E-05)	(0.135566)	(0.127355)	(0.000787)	(0.000958)
DOF		7.852353		9.263978		9.719433

Note: Std. Dev. is given in (parenthesis)

Table A5: *Day-of-the-week* effect results for Mexico's IPC index including Std. dev.

IPC	GARCH (1,1)		EGARCH (1,1)		APARCH (1,1)	
	Normal	Student's t-dist.	Normal	Student's t-dist.	Normal	Student's t-dist.
Mean equation						
π	0.001695	0.001571	0.000994	0.001069	0.000946	0.001024
	(0.000515)	(0.000477)	(0.000526)	(0.000471)	(0.000518)	(0.000474)
χ_{MON}	-0.000986	-0.000816	-0.000583	-0.000540	-0.000613	-0.000558
	(0.000767)	(0.000678)	(0.000760)	(0.000667)	(0.000751)	(0.000675)
χ_{TUE}	-0.000387	-0.000430	-0.000681	-0.000453	-0.000621	-0.000441
	(0.000704)	(0.000653)	(0.000658)	(0.000631)	(0.000659)	(0.000638)
χ_{THU}	-0.000281	-5.08E-05	0.000291	0.000263	0.000300	0.000261
	(0.000707)	(0.000634)	(0.000682)	(0.000642)	(0.000663)	(0.000632)
χ_{FRI}	-0.001236	-0.000713	-0.000686	-0.000412	-0.000654	-0.000355
	(0.000714)	(0.000653)	(0.000710)	(0.000622)	(0.000700)	(0.000632)
ρ_{t-1}	0.101455	0.086223	0.103108	0.088452	0.104766	0.088847
	(0.018559)	(0.018714)	(0.018132)	(0.018188)	(0.018163)	(0.018325)
ρ_{t-2}	-0.028906	-0.041316	-0.010612	-0.027529	-0.009244	-0.029617
	(0.019308)	(0.018164)	(0.018246)	(0.017689)	(0.018031)	(0.017837)
Variance equation						
η	-1.20E-05	-4.73E-07	-0.284523	-0.242873	6.10E-05	0.000299
	(1.69E-05)	(1.52E-05)	(0.120458)	(0.099202)	(0.000682)	(0.000483)
α	0.083602	0.091538	0.140842	0.155078	0.075198	0.083238
	(0.011389)	(0.012031)	(0.016132)	(0.019807)	(0.009025)	(0.011541)
γ			-0.102751	-0.103229	0.774780	0.685078
			(0.014360)	(0.012612)	(0.117672)	(0.114949)
δ					0.986046	1.095748
					(0.160460)	(0.170395)
β	0.903452	0.897346	0.979622	0.979311	0.921893	0.912567
	(0.012537)	(0.011968)	(0.004940)	(0.003896)	(0.009756)	(0.010418)
φ_{MON}	3.49E-05	2.49E-05	0.293537	0.237288	0.001893	0.000933
	(2.11E-05)	(1.85E-05)	(0.132962)	(0.127892)	(0.001325)	(0.000851)
φ_{TUE}	3.50E-05	1.85E-05	0.018225	-0.051990	0.000400	-4.88E-05
	(3.27E-05)	(2.56E-05)	(0.185415)	(0.158097)	(0.001279)	(0.000740)
φ_{THU}	1.52E-05	-1.00E-05	-0.003863	-0.111064	7.53E-05	-0.000493
	(2.51E-05)	(2.53E-05)	(0.157591)	(0.161262)	(0.001082)	(0.000803)
φ_{FRI}	-7.84E-06	-1.27E-05	-0.295672	-0.339871	-0.001028	-0.000817
	(2.12E-05)	(1.84E-05)	(0.135678)	(0.128736)	(0.001123)	(0.000749)
DOF		5.958061		7.071299		7.108172

Note: Std. Dev. is given in (parenthesis)

Table A6: *Day-of-the-week* effect results for Chile's IPSA index including Std. dev.

IPSA	GARCH (1,1)		EGARCH (1,1)		APARCH (1,1)	
	Normal	Student's t-dist.	Normal	Student's t-dist.	Normal	Student's t-dist.
Mean equation						
π	0.001256	0.001184	0.000998	0.000967	0.000871	0.000898
	(0.000347)	(0.000345)	(0.000351)	(0.000341)	(0.000352)	(0.000348)
χ_{MON}	-0.001949	-0.001866	-0.001758	-0.001699	-0.001656	-0.001634
	(0.000473)	(0.000458)	(0.000473)	(0.000454)	(0.000475)	(0.000461)
χ_{TUE}	-0.001019	-0.000953	-0.000854	-0.000804	-0.000943	-0.000890
	(0.000448)	(0.000438)	(0.000443)	(0.000427)	(0.000449)	(0.000438)
χ_{THU}	6.21E-06	0.000213	0.000113	0.000223	0.000134	0.000267
	(0.000441)	(0.000422)	(0.000426)	(0.000411)	(0.000436)	(0.000419)
χ_{FRI}	0.000408	0.000440	0.000499	0.000528	0.000635	0.000609
	(0.000465)	(0.000443)	(0.000451)	(0.000428)	(0.000468)	(0.000444)
ρ_{t-1}	0.186984	0.183637	0.191173	0.187588	0.190299	0.186047
	(0.020046)	(0.018334)	(0.020446)	(0.017883)	(0.020579)	(0.018184)
Variance equation						
η	-2.72E-07	2.35E-06	-0.493534	-0.516934	6.62E-06	1.22E-05
	(6.08E-06)	(6.92E-06)	(0.118726)	(0.107345)	(2.75E-05)	(3.02E-05)
α	0.133065	0.130417	0.245246	0.242330	0.122592	0.120082
	(0.016921)	(0.015075)	(0.029058)	(0.023761)	(0.019709)	(0.015144)
γ			-0.058410	-0.065779	0.228545	0.249763
			(0.017716)	(0.013168)	(0.073809)	(0.056219)
δ					1.668372	1.682777
					(0.323245)	(0.264137)
β	0.843741	0.840534	0.968455	0.963833	0.857369	0.853788
	(0.016221)	(0.016953)	(0.006920)	(0.006779)	(0.016944)	(0.016744)
φ_{MON}	6.78E-06	8.04E-06	0.186414	0.211138	2.70E-05	3.36E-05
	(7.81E-06)	(8.49E-06)	(0.133436)	(0.119905)	(5.56E-05)	(5.05E-05)
φ_{TUE}	1.64E-05	1.27E-05	0.127321	0.097963	5.48E-05	4.37E-05
	(1.08E-05)	(1.14E-05)	(0.152594)	(0.149418)	(9.20E-05)	(6.50E-05)
φ_{THU}	-3.32E-06	-5.24E-06	-0.107990	-0.107549	-2.42E-05	-2.21E-05
	(9.69E-06)	(1.16E-05)	(0.149229)	(0.152136)	(5.23E-05)	(5.05E-05)
φ_{FRI}	-3.41E-06	-9.67E-06	-0.152688	-0.234458	-1.40E-05	-3.54E-05
	(8.10E-06)	(8.53E-06)	(0.124137)	(0.121300)	(4.22E-05)	(5.19E-05)
DOF		8.520563		8.855910		8.951743

Note: Std. Dev. is given in (parenthesis)

Table A7: *Day-of-the-week* effect results for Argentina's MERVAL index including Std. dev.

MERVAL	GARCH (1,1)		EGARCH (1,1)	EGARCH (3,4)	APARCH (1,1)	
	Normal	Student's t-dist.	Normal	Student's t-dist.	Normal	Student's t-dist.
Mean equation						
π	0.001688	0.001807	0.001889	0.001965	0.001182	0.001584
	(0.000737)	(0.000606)	(0.000756)	(0.000579)	(0.000656)	(0.000602)
χ_{MON}	-0.001577	-0.001213	-0.002433	-0.001133	-0.001672	-0.001227
	(0.001081)	(0.000916)	(0.001235)	(0.000874)	(0.000985)	(0.000912)
χ_{TUE}	-0.001656	-0.001003	-0.002773	-0.001161	-0.001531	-0.001064
	(0.001114)	(0.000873)	(0.001315)	(0.000831)	(0.000964)	(0.000859)
χ_{THU}	-0.000321	-0.000604	-0.000561	-0.000818	-0.000235	-0.000578
	(0.001020)	(0.000869)	(0.001041)	(0.000843)	(0.000927)	(0.000864)
χ_{FRI}	-0.000539	-0.001119	-9.89E-05	-0.001400	-0.000316	-0.001110
	(0.000986)	(0.000809)	(0.001010)	(0.000807)	(0.000875)	(0.000807)
ρ_{t-1}	0.024155	0.015361	0.025987	0.016292	0.034883	0.023221
	(0.019501)	(0.017589)	(0.020524)	(0.016497)	(0.020427)	(0.017629)
Variance equation						
η	-2.44E-05	-1.40E-05	-0.412511	-0.145496	-2.96E-06	-1.52E-05
	(4.47E-05)	(3.03E-05)	(0.163129)	(0.299059)	(3.54E-06)	(4.99E-05)
α_1	0.096276	0.103865	0.170753	0.159909	0.081307	0.107545
	(0.014361)	(0.014840)	(0.027319)	(0.037979)	(0.009584)	(0.018197)
α_2				-0.111082		
				(0.048650)		
α_3				0.160085		
				(0.043462)		
γ			-0.040495	-0.053918	0.151686	0.267228
			(0.021225)	(0.012943)	(0.022030)	(0.056452)
δ					2.498957	1.865262
					(0.209585)	(0.276819)
β_1	0.884393	0.884602	0.975476	1.766320	0.868656	0.870956
	(0.014923)	(0.013835)	(0.008504)	(0.251038)	(0.010196)	(0.015768)
β_2				-1.416597		
				(0.522838)		
β_3				0.390971		
				(0.505929)		
β_4				0.234307		
				(0.230449)		
φ_{MON}	0.000149	0.000137	0.415414	0.392529	2.20E-05	**0.000222**
	(5.53E-05)	(4.38E-05)	(0.165979)	(0.225743)	(1.85E-05)	(0.000236)
φ_{TUE}	8.84E-06	-1.17E-05	-0.092463	-0.717539	3.07E-07	-2.54E-05
	(8.80E-05)	(5.53E-05)	(0.227120)	(0.485460)	(4.11E-06)	(8.95E-05)
φ_{THU}	5.13E-05	5.40E-05	0.224201	-0.011304	6.57E-06	9.15E-05
	(6.45E-05)	(5.20E-05)	(0.200928)	(0.440589)	(6.95E-06)	(0.000124)
φ_{FRI}	-3.43E-05	-5.20E-05	-0.063593	-0.641268	-5.35E-06	-8.52E-05
	(5.11E-05)	(4.14E-05)	(0.172504)	(0.285198)	(4.78E-06)	(0.000109)
DOF		3.999876		3.991185		4.042610

Note: Std. Dev. is given in (parenthesis)

Graph A2: Conditional variance: EGARCH (2,1) for BOVESPA, EGARCH (1,1) for IPC, and APARCH (1,1) for IPSA and MERVAL respectively.