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Departamento de Ciencias Económico Administrativas

Doctorado en Dirección y Finanzas

The Efficient Markets Hypothesis and Calendar Anomalies in the Mexican Stock Market

(La Hipótesis de los Mercados Eficientes y Anomalías de
Calendario en el Mercado Accionario Mexicano)

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SE APRUEBA LA TESIS: "THE EFFICIENT MARKETS HYPOTHESIS
AND CALENDAR ANOMALIES IN THE MEXICAN STOCK
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Dedication

To my beloved parents, Dacio (†) and María de la Luz (†).

To Lucy.

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Jesús Dacio Villarreal Samaniego

Abstract

This research examines the efficiency of the Mexican stock market by analyzing six seasonal anomalies: the day-of-the-week, holiday, turn-of-the-month, and January effects, as well as the Halloween indicator and the January barometer. The period considered was from January 3, 2000, to September 28, 2018, in the case of the Price and Quotation Index (IPC), and from October 26, 2006, to September 28, 2009, in the case of the large, medium, and small-capitalization indices of the Mexican Stock Exchange. These time intervals were further divided into two or four subperiods, depending on the number of available observations.

To test for the presence of the calendar anomalies in the returns and volatility of the stock indices, OLS estimations with dummy variables were used when the ARCH-LM test failed to reject the hypothesis of homoskedasticity in the error term. When the test rejected such a hypothesis, GARCH family models were applied to study the returns of the indices. The Kruskal-Wallis and ANOVA tests were also used to examine the differences in the medians and means of the return series.

The returns of the IPC, as well as those of the large- and small-capitalization indices, showed evidence of the day-of-the-week effect. Also, the turn-of-the-month effect was consistently present in the returns of the four indices under examination. The latter anomaly disappeared from the IPC only, whereas the day-of-the-week effect did not fade away from any of the three indices where it emerged.

Similarly, the day-of-the-week and holiday effects were consistently present in the volatility of the four indices. The day-of-the-week anomaly faded away from the volatility of the IPC, as well as from the small-capitalization index's. The holiday effect did not disappear from the volatility of any of the indices. The presence of the Halloween indicator was found only in the returns of the small-capitalization index, but such an anomaly recently vanished. Finally, the January barometer and the January effect were absent from the indices. However, a March anomaly recently appeared in the returns and volatility of the IPC and the large-capitalization index.

Thus, according to the results concerning these six seasonal effects, the conclusion is that the Mexican Stock Exchange reasonably complies with the weak form of market efficiency, since several of such anomalies were nonexistent in the returns or volatility of the stock indices under analysis. Nonetheless, some seasonal effects did exist, and their presence was persistent, particularly those anomalies related to daily observations.

Resumen

Esta investigación examina la eficiencia del mercado bursátil mexicano analizando seis anomalías estacionales: los efectos día de la semana, día festivo, cambio de mes y enero, así como el indicador de Halloween y el barómetro de enero. El periodo de tiempo considerado fue del 3 de enero de 2000 al 28 de septiembre de 2018 en el caso del Índice de Precios y Cotizaciones (IPC) y del 26 de octubre de 2006 al 28 de septiembre de 2018 en el caso de los índices de capitalización grande, mediana y pequeña de la Bolsa Mexicana de Valores. Estos intervalos de tiempo fueron divididos en dos o cuatro sub-periodos, dependiendo del número de observaciones disponibles.

Para probar la presencia de las anomalías de calendario en los rendimientos y la volatilidad de los índices bursátiles, se usaron estimaciones MCO con variables binarias cuando la prueba ARCH-LM no pudo rechazar la hipótesis de homocedasticidad en el término de error. Cuando la prueba rechazó dicha hipótesis, se aplicaron modelos de la familia GARCH para estudiar los rendimientos de los índices. Se usaron también las pruebas de Kruskal-Wallis y ANOVA para examinar las diferencias en las medianas y las medias de las series de rendimiento.

Los rendimientos del IPC, así como los de los índices de capitalización grande y pequeña, mostraron evidencia del efecto día de la semana. Además, el efecto cambio de mes estuvo consistentemente presente en los rendimientos de los cuatro índices bajo examen. Esta última anomalía desapareció de los rendimientos del IPC únicamente, mientras que el efecto día de la semana no desapareció de ninguno de los tres índices en donde emergió.

De forma similar, los efectos día de la semana y día festivo estuvieron consistentemente presentes en la volatilidad de los cuatro índices. La anomalía día de la semana se desvaneció de la volatilidad del IPC, así como de la del índice de pequeña capitalización. El efecto día festivo no desapareció de la volatilidad de ninguno de los índices. La presencia del indicador de Halloween fue encontrada únicamente en el índice de pequeña capitalización, pero dicha anomalía se desvaneció recientemente. Finalmente, el barómetro de enero y el efecto enero

estuvieron ausentes de los índices. Sin embargo, recientemente apareció una anomalía en marzo en los rendimientos y en la volatilidad del IPC y del índice de gran capitalización.

Por tanto, de acuerdo con los resultados relacionados con estos seis efectos estacionales, la conclusión es que la Bolsa Mexicana de Valores cumple razonablemente con la forma débil de eficiencia del mercado, ya que varias de tales anomalías estuvieron ausentes de los rendimientos o la volatilidad de los índices bursátiles bajo análisis. No obstante, existieron algunos efectos estacionales, y su presencia fue persistente, particularmente aquellas anomalías relacionadas con las observaciones diarias.

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Chapter 1: Introduction and Organization

“Discovery commences with the awareness of anomaly... And it closes only when the paradigm theory has been adjusted so that the anomalous has become the expected” (Kuhn, 1970, p. 52-53).

1.1 Background

According to the Efficient Markets Hypothesis (EMH), formalized by Fama (1970), stocks and other financial assets reflect all available relevant information at any point in time and, therefore, it is not possible for any investor to systematically outperform the market. Such a hypothesis proposes that asset price changes are unpredictable, that is, prices do not follow any foreseeable pattern; so, it is not possible to predict their future behavior. The EMH asserts that such unpredictability is due to price movements are determined by new information, and such information follows a random pattern, an idea that was originally proposed in the early twentieth century by Bachelier (1900). However, the ideas about market efficiency have been increasingly challenged mainly since the 1980s, at a time when the EMH had undoubtedly become one of the most important foundations of the mainstream financial economics theory. To date, the notions proposed by the EMH are still very influential, and they are of particular interest in research.

The existence of the so-called market anomalies reported in a large number of empirical studies is one of the most important challenges to the propositions of the EMH. Such anomalies are return patterns that, according to the literature, allow investors to anticipate price changes and, as a consequence, their existence oppose the concept of returns randomness put forward by market efficiency theory. Some anomalous market return patterns are known as functional anomalies. One example of this type of anomalies is the price-to-earnings ratio pattern, which arguably is useful to predict stock returns (Basu, 1977). Another functional anomaly refers to the return patterns of value stocks since such assets had

systematically outperformed the risk-adjusted returns of growth stocks (Fama & French, 1992)¹.

The focus of this research, however, is on those seemingly predictable patterns of stock market returns, which are determined by the calendar year, known as seasonal effects or calendar anomalies. While several seasonal effects have been described and analyzed in the literature in different international stock markets, the interest in this research is on the existence of six calendar anomalies in the Mexican Stock Exchange (BMV), namely, the day-of-the-week effect (Fields, 1931; French, 1980), the holiday effect (Fields, 1934; Lakonishok & Smidt, 1988), the turn-of-the-month effect (Ariel, 1987), the January effect (Rozeff & Kinney, 1976), the Halloween indicator (Bouman & Jacobsen, 2002), and the January barometer (Cooper, McConnell, & Ovtchinnikov, 2006; Hirsch, 1974).

Several studies for each of these calendar anomalies conclude that they are present in numerous stock markets of different countries, including the Mexican stock market (Cabello & Ortiz, 2003; Kristjanpoller, 2012b; Seif, Docherty, & Shamsuddin, 2017; Winkelried & Iberico, 2018). Other studies conclude that such anomalies do not exist or that, in any case, they faded away at some point in time from the markets where they were present (Duarte, Sierra, & Garcés, 2013; Kristjanpoller, 2012a; Lloyd, Zhang, & Rydin, 2017; Seif et al., 2017).

So, there is conflicting evidence on the presence of seasonal effects in the stock markets of many countries. While there is a significant body of research on these calendar anomalies in developed markets, this is not the case for emerging markets, where research on the subject is relatively scarce.

¹ Value stocks are those with low book-to-market ratios. Conversely, growth stocks exhibit high book-to-market ratios.

Furthermore, several studies that include the Mexican stock market do so in the context of the analysis of several other markets at the same time (Kristjanpoller & Arenas, 2015; Seif et al., 2017; Spoor & Rodriguez, 2015), and do not specifically focus on such market, where the number of research works on the subject is relatively limited.

1.2 Research Problem and Hypotheses

1.2.1 Research Problem

It is of research interest to study whether there is significant evidence of the existence of the day-of-the-week, holiday, turn-of-the-month, January, Halloween, and January barometer effects in the Mexican Stock Exchange between January 3, 2000, and September 28, 2018².

The fundamental argument in this research is that these seasonal effects have existed in the returns and volatility of the Mexican Stock Exchange. However, as argued in the literature, it is also proposed that such anomalies have lessened or even disappeared. So, the premise is that, from the standpoint of the calendar anomalies, the Mexican stock market complies with the weak form of market efficiency put forward by the EMH.

1.2.2 General Hypotheses

Considering the preceding arguments, the general hypotheses for the six seasonal effects in the Mexican stock market studied in this research are:

H_A: Average stock returns are not the same across different times of the week, month, or year in the Mexican Stock Exchange.

H_B: There are dissimilarities in the volatility of stock returns across different moments of the week, month, or year in the stock market in Mexico.

H_C: The dissimilarities in average stock returns across different times of the week, month, or year in the Mexican stock market have disappeared.

² The time interval corresponding to the size indices considered in the study was from October 26, 2006, to September 28, 2009, due to data availability constraints.

H₀: The inequalities in volatility across different times of the week, month, or year in the Mexican stock market have faded away.

Section 4.3.1 presents the specific hypotheses of construct for each of the calendar anomalies examined in this research.

1.3 Research Objectives

1.3.1 General Objective

To empirically determine, using econometric and statistical methods, whether six of the main seasonal effects reported in the literature were significantly present and persistent in the Mexican stock market between January 3, 2000, and September 28, 2018.

1.3.2 Specific Objectives

To examine the performance of the returns of the Mexican stock market as proxied by the Price and Quotation Index (S&P/BMV IPC) between January 2000 and September 2018, as well as the returns performance of the large-capitalization (S&P/BMV IPC LargeCap), medium-capitalization (S&P/BMV IPC MidCap) and low capitalization (S&P/BMV IPC SmallCap) indices between October 2006, and September 2018.

To determine whether the day-of-the-week, holiday, turn-of-the-month, month-of-the-year, Halloween, and January barometer effects existed in the four stock indices under analysis.

To prove the statistical significance of the calendar anomalies in case they existed in the period under examination.

To establish whether there is a correction in the Mexican stock market that makes it closer to the weak form conditions proposed by the EMH through the disappearance of the seasonal anomalies in case they existed in the period under analysis.

1.4 Justification for the Research

Asset returns and volatility are two variables of great interest in financial economics. According to the efficient markets hypothesis, it is not possible to consistently attain higher returns than those corresponding to the risk level of an asset, since through investors' buying and selling decisions, the asset market price quickly reflects all relevant information at any point in time (Fama, 1970). In simple terms, it is not possible for any investor to systematically beat the market. Nevertheless, the findings of several seasonal effects and other anomalies in asset returns suggest that markets are seemingly less efficient than implied by the EMH.

The study of such anomalies and calendar effects provides evidence concerning the degree of market efficiency and increases the understanding of its features. Moreover, the analysis of stock market anomalies, as well as the finding of their existence, characteristics, and patterns, eventually contribute to their disappearance and to increase market efficiency.

The mainstream financial economics established in the 1960s is the foundation of the finance theory currently studied in universities and other higher education institutions around the world. That is, the premise of the non-predictability of asset returns and the concepts proposed by the EMH and the capital asset pricing model (CAPM) are the basis of present neoclassical financial theory. The existence of market anomalies in general and seasonal effects, in particular, represents a significant challenge to these ideas.

Considering that the main focus of this research is on the Mexican Stock Exchange, it is necessary to determine, first, whether seasonal effects exist in such a market and, second, whether the anomalies have disappeared, as has been reported in the literature for several stock markets (Alt, Fortin, & Weinberger, 2011; Duarte et al., 2013; Lloyd et al., 2017). From the theoretical point of view, thus, it is relevant to study calendar anomalies to look for evidence on the degree of efficiency of the stock market in Mexico.

Also, conflicting views exist that the findings regarding market anomalies are the result of data snooping, or that such findings are related to specific conditions prevailing in certain

markets. Thus, the study of calendar effects in Mexico provides an out-of-sample perspective, which allows testing the robustness of the anomalies (Lakonishok & Smidt, 1988; Seif et al., 2017).

The degree of market efficiency is meaningful not only to investors, but also to financial regulators and policymakers since they are interested in verifying whether fair game conditions are present in the market and, if so, to what extent. Market efficiency is also an essential piece of information that individual and institutional investors have to consider to make sensible asset allocation decisions. The study of calendar effects in the Mexican Stock Exchange contributes to determine the degree of efficiency of such a market and to distinguish the possible existence of abnormal return opportunities that may be exploitable by investors. Confirmation about the existence of such anomalies in the Mexican stock market might be the first step for investors to develop investment strategies meant to attain higher returns, given the level of risk they are willing to assume.

From the standpoint of society as a whole, insurance companies, mutual and pension funds, where many small investors save for several purposes, including their retirement, might benefit from strategies based on seasonal anomalies as well. So, the design and implementation of such investment schemes could take into consideration, among other variables, the presence and characteristics of the calendar effects studied in this research.

Issuing companies might also consider the existence of seasonal anomalies when making financing decisions. That is, timing the market while issuing securities when prices are more favorable leads to decreasing the company's marginal weighted average cost of capital and, consequently, to rising the net present values of its capital budgeting projects and increasing the market value of the firm.

As in the case of most emerging markets, there is a limited number of research papers about market anomalies in Mexico. Whereas studies exist about seasonal effects that include the Mexican stock market, many of them also comprise several other markets. Furthermore, some calendar anomalies, such as the January barometer or the Halloween effect, have been

scarcely researched in Mexico. Thus, it is of research interest to extend the analysis to specifically focus on the Mexican stock market.

1.5 Delimitations of the Research

The returns sample considered for the Mexican Stock Exchange's IPC was from the first trading day of 2000 to the last trading day of September 2018. More specifically, from January 3, 2000, to September 28, 2018. The corresponding returns sample for the Mexican stock market's IPC LargeCap, IPC MidCap, and IPC SmallCap was from October 26, 2006, to September 28, 2018. No other indices of the Mexican Stock Exchange, individual company stocks, or dates outside those just mentioned were included in the research.

Although this report mentions some of the explanations for the existence of each of the six calendar anomalies considered in the research, they are not further examined here. Such a task is well beyond the scope intended for this study.

1.6 Outline of the Report

Chapter 0 presents the most relevant aspects of neoclassical financial economics and provides a closer look at the research about calendar anomalies in different countries, including Mexico. Chapter 3 overviews the context of the economic and political environment throughout the sample period selected for this study. Chapter 4 deals with the data used and the methodology applied. Chapter 5 describes the results of the research. Chapter 6, lastly, focuses on the discussion of the outcomes as well as on the conclusions of the study and closes reviewing several implications for future research.

Chapter 2: Literature Review

2.1 Introduction

This chapter depicts the theoretical foundation for the research carried out for this report. The chapter presents an introduction to the ideas regarding portfolio theory, capital asset pricing, and market efficiency, all of which have been very relevant for financial economics from the mid-twentieth century to date.

Section 2.3 explains the basics of modern portfolio theory and asset pricing models. Section 2.4 describes the efficient markets hypothesis (EMH), its fundamental ideas, and its implications for financial economics. That section also reviews the controversy EMH has caused and the challenges to its principles, including those arising from behavioral finance and the evidence in favor of market anomalies. Section 2.5 briefly presents the ideas of the Adaptive Markets Hypothesis (AMH), that tries to reconcile the concepts proposed by the EMH with those suggested by behavioral finance.

Section 2.6 presents a more detailed assessment of six of the main calendar anomalies reported in the literature, which are of particular interest for this research in the context of the Mexican stock market. Finally, section 2.7 briefly discusses the statistical methods and econometric models most frequently used in previous studies regarding calendar anomalies.

2.2 A Brief Historical Background

Before the 1950s, the concepts of risk and return on assets were applied vaguely by financial market participants. Investors knew that diversification was beneficial and that it was not wise to place all their resources in a single asset, but such allocation of resources among different investment alternatives was done intuitively. In the early fifties, Markowitz (1952) introduced the concept of formal and systematic diversification and demonstrated how and why it works. This idea, nowadays known as the modern portfolio theory (MPT), opened a new era in financial economics.

Based on the ideas put forward by the MPT, researchers have proposed several models to determine asset price equilibrium, among which Sharpe's (1964) capital asset pricing model (CAPM) is the best known and most widely used. Market efficiency is implicitly needed for these asset pricing models to work. That is, such models require that asset prices include all relevant information. That way, it is not possible for investors to systematically obtain a higher return than the one corresponding to the risk level of an asset.

In the early twentieth century, Bachelier (1900) proposed the first ideas about market efficiency, but several decades later, Fama (1965), Roberts (1967), and Samuelson, (1965) formalized such propositions. Such a set of ideas is currently known as the Efficient Markets Hypothesis, which recognizes three forms of efficiency: weak, semi-strong, and strong. Those forms of efficiency specify, respectively, that historical information on prices and volumes is reflected in the current prices of assets, that such prices include all publicly available information, and that even privileged information is reflected in current asset prices (Fama, 1970).

Although the EMH was widely spread and agreed during the years following its formulation, the challenges to its proposals have increased since the 1980s. This is the result of several research findings related to the predictability of stock returns, as well as to empirical reports regarding the influence of irrational investors' decisions on asset prices and about some aspects related to inconsistencies in the behavior of investors that cause markets to be inefficient. Many of these challenges have arisen from a new school of thought in financial economics known as behavioral finance, which has recently received considerable attention³.

Reports on the existence of various calendar effects, or seasonal anomalies, have been considered evidence on the predictability of asset returns. Among such seasonal anomalies are the day-of-the-week, holiday, turn-of-the-month, and month-of-the-year effects, as well

³ Several researchers related to behavioral finance such as Daniel Kahneman, Vernon L. Smith, Robert J. Shiller, and Richard H. Thaler have been awarded the Nobel Prize in Economics.

as the Halloween indicator and the January barometer. The findings related to these anomalies are regarded as one of the most important objections to the ideas proposed by the EMH. Such calendar effects have been associated with the irrational behavior of investors, and they bear a particular interest for the present study due to the scarce study on the subject of their presence in the Mexican stock market.

By the mid- 2000s, Lo (2004) suggested the Adaptive Markets Hypothesis (AMH) as an alternative theory to the EMH. Specifically, the AMH puts forward some ideas that attempt to reconcile the views of the EMH and behavioral finance. According to the Adaptive Markets Hypothesis, individuals act in their interest and, although they make mistakes, they learn from them, adapt, and create competition. For the AMH, market efficiency is a matter of degrees, not one of presence or absence, and this theory offers the possibility that market anomalies may exist in the context of the investors' rational decision-making process.

2.3 Portfolio Theory

Throughout the first half of the twentieth century, two conflicting points of view about financial theory prevailed: the micro-normative and the macro-normative. The first approach was supported by business schools, and its emphasis was on the efforts of investors to maximize returns and on the attempts made by financial managers to maximize shareholder wealth, considering the prices of securities in the market as given. The second point of view was backed by economics departments that took the behavior of investors as given, considering them as a group of micro-optimizers and, from there, the way prices of securities should evolve in the market was inferred.

At the beginning of the 1950s, these points of view began to converge based on Markowitz's (1952) work on optimal portfolio selection, which would eventually be the foundation of modern portfolio theory (MPT), and that also gave rise to the neoclassical synthesis of the micro-normative and macro-normative approaches (Azofra, 2012).

2.3.1 Markowitz's Modern Portfolio Theory

The return of an asset is its expected utility level, that is, the reward of investing in that asset. However, in the vast majority of cases, there is a series of possible outcomes for the return on the asset, which means that asset utility outcomes are subject to dispersion. In other words, asset returns are subject to a certain level of risk.

In terms of the MPT, risk can be defined as the possibility that the realized return on an asset differs from its expected return (Smart, Gitman, & Joehnk, 2017). Thus, the larger the dispersion of the possible return outcomes vis-a-vis the expected return, the larger the risk of the asset and vice versa. Consequently, the total level of risk of an investment alternative can be determined through statistical measures of dispersion, such as the variance and the standard deviation of its returns.

The MPT suggests a set of feasible portfolios, also known as Markowitz's umbrella, shown in Figure 1. The MPT also involves efficient diversification, that is, a combination of assets that offers the minimum level of risk given an expected level of return, or that maximizes the expected return given a certain level of risk, considering the feasible set of portfolios. Thus, there is a set of portfolios that meet the objective while satisfying the corresponding restriction. This set is known as the efficient frontier or Markowitz's frontier so that this model does not suggest a single optimal portfolio, but a group of portfolios that dominate other alternatives in terms of expected return, risk, or both.

Each investor will select one of the portfolios on the efficient frontier based on her risk aversion to maximize her utility function (Jones & Jensen, 2016). The segment B–C–D–E in Figure 1 depicts Markowitz's efficient frontier. As can be seen in that figure, the optimal set of portfolios starts at point B, which represents the minimum variance portfolio, that is, the efficient portfolio with the lowest possible risk.

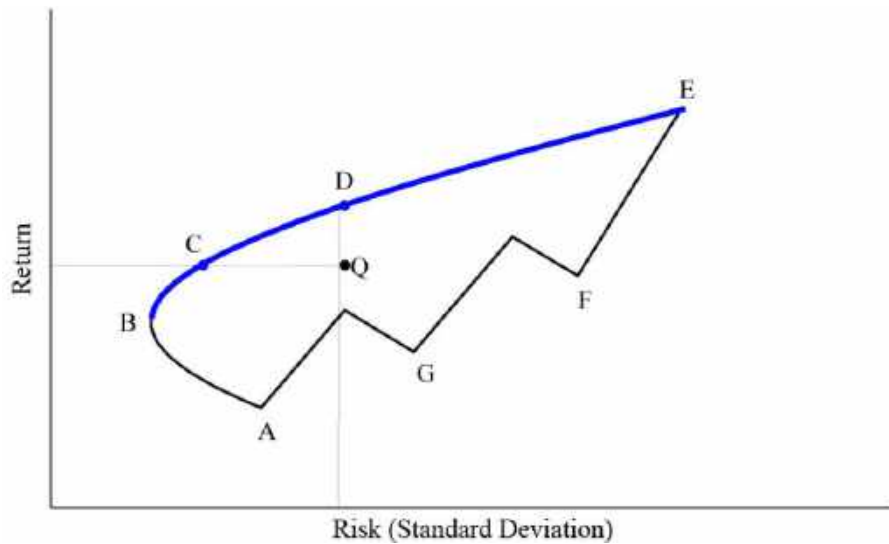


Figure 1: Feasible Portfolio Set

Source: Own elaboration

All feasible portfolios outside the efficient frontier, such as portfolios A, F, G, and Q in Figure 1, are dominated in terms of risk, expected return, or both by other portfolios on the efficient frontier. Portfolio Q, for example, is dominated in terms of expected return by portfolio D, since the latter has the same level of risk than Q, but a higher expected return. Portfolio C also dominates Q, but this time in terms of risk, since C has a lower level of risk than Q, even though both portfolios have the same expected return.

2.3.2 The Capital Asset Pricing Model

Around the mid- 1960s, four financial economists working independently, Lintner (1965), Mossin (1966), Sharpe (1964), and Treynor (1962), developed a model based on the MPT and described the relationship between risk and required return of individual investments in the context of a well-diversified portfolio of assets. The result was the capital asset pricing model, a name taken from the research paper written by Sharpe (1964), which eventually became the best known.

The CAPM considers the possibility that investors may combine portfolios of risky assets with a risk-free asset, such as the Federation Treasury Certificates (CETES) in Mexico or the Treasury Bills (T-Bills) in the United States.

The model assumes that all individual investors will make their assessment of risk and return of available assets and their possible combinations into portfolios so that each investor will make different estimations about these variables. Nevertheless, the model also assumes that all investors will arrive at very similar results since these results are based on the same available information. This similarity of the results obtained by investors is known as the homogeneous expectations assumption of the CAPM⁴.

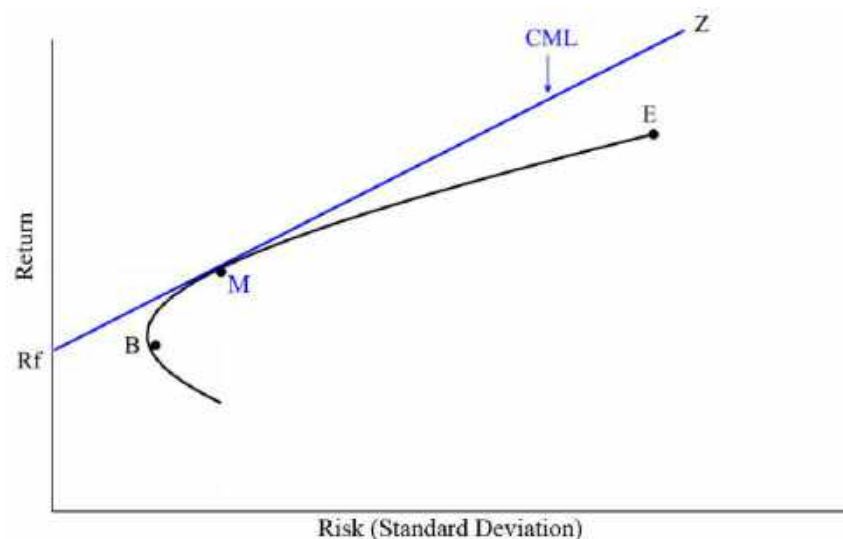


Figure 2: Capital Market Line (CML)

Source: Own elaboration

Thus, all investors will choose the same portfolio of risky assets, and according to Ross, Westerfield, & Jaffe (2013), “common sense tells us that it is a market value-weighted

⁴ This assumption does not imply that all investors have the same risk aversion, but that their expectations about the return and risk of the assets are similar.

portfolio of all existing securities. It is the market portfolio” (p. 360). Since the market portfolio is unobservable, in practice it is proxied by broad-based stock indices, such as the Price and Quotation Index (IPC, its acronym in Spanish) in Mexico or the Standard & Poor’s index (S&P 500) in the United States, which are considered proxies of the performance of the market portfolio. Point M in Figure 2 represents such a portfolio, while R_f represents the risk-free rate of return. The straight line that joins R_f and M is known as the Capital Market Line (CML).

An essential feature of the CAPM is that it measures each asset’s risk in the context of the market portfolio. According to the CAPM, systematic of market risk is the portion of total risk that cannot be avoided through diversification and represents the relevant fraction of total risk used to determine the return that each investment alternative must have to attain equilibrium. The measure for this systematic risk is called the beta coefficient (β), according to the term proposed by Sharpe (1964). The market risk for each instrument, which is the only factor considered by this model, can be determined from the relationship of its returns to the returns of the broad stock index used as a proxy for the market portfolio.

The separation theorem proposed by Tobin (1958) is yet another essential assumption of the CAPM. This theorem asserts that each investor makes two independent decisions. First, once the investor has computed the expected return and the individual risk of each asset, along with the joint risk (covariances) of every pairwise combination of assets, she is in a position to build the efficient frontier according to the proposals of the MPT, and subsequently, arrive to the market portfolio by considering the risk-free rate of return. The investor's perception of risk does not intervene in this process, but only her unbiased estimates regarding the portfolios’ expected returns and risk.

Second, the investor chooses how she will combine the risk-free asset and the market portfolio, a decision that depends on her aversion to risk. The more conservative the investor, the higher the proportion of her wealth she is willing to assign to the risk-free asset, and the closer she will be to point R_f on the $R_f - M$ segment in Figure 2. An investor with a lower risk aversion will be closer to point M on the same segment of the CML, investing a higher

portion (or all) of her wealth in the market portfolio. Finally, a highly aggressive investor, that is, an investor with a very low-risk aversion, will even be willing to borrow money at the risk-free rate to invest the proceeds of the loan in the market portfolio and, therefore, she will be on the $M - Z$ segment of the CML.

So, the CAPM assumes that all investors have homogeneous expectations and that all of them consider the same market portfolio of risky assets as the point of tangency of the line that connects the risk-free rate with the efficient frontier. The model also considers that the investors' risk aversion does not influence the calculations to arrive at the market portfolio. Finally, the CAPM supposes that it is possible to invest and borrow at the risk-free rate.

To measure the relationship between an asset and the market as a whole, the CAPM considers the historical returns of an individual asset (R_j), as the response (dependent) variable, and compares such returns to the historical returns of the market (R_M), as the control (independent) variable, over some time. The slope of the characteristic line that results from the OLS regression of these variables is called the beta coefficient (β_j)⁵ and represents the asset's market risk, that is, its systematic risk. In other words, the beta coefficient measures each asset's returns sensitivity to the movements of the returns of the market as a whole.

The CAPM is normative, in other words, the model states that the higher the systematic risk of an investment alternative (β_j), the higher its required return ($\hat{R}_j$) has to be to attain equilibrium. The positive relationship between systematic risk and the required return is depicted graphically in the so-called Security Market Line (SML), as shown in Figure 3.

⁵ This procedure is sometimes performed using excess returns, that is, by comparing the difference in the returns of the individual asset and R_f to the difference between the market returns and R_f .

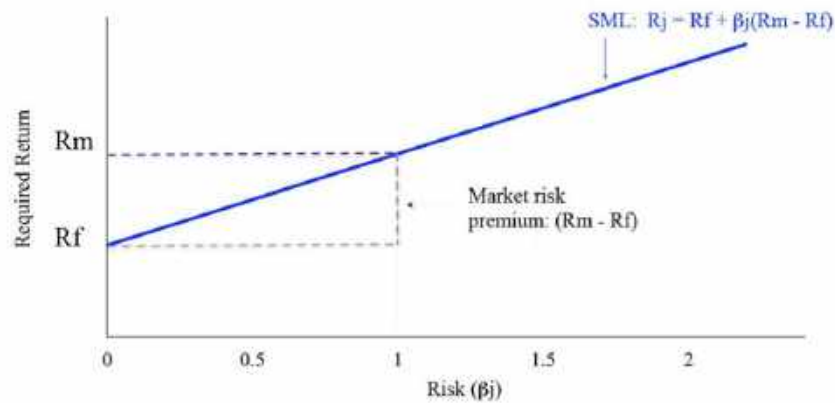


Figure 3: Security Market Line (SML)

Source: Own elaboration

There are other asset pricing models in addition to the CAPM, some of which are quite recent. Among such models is the arbitrage pricing theory (APT) (Ross, 1976), the intertemporal asset pricing model based on consumption and investment opportunities (Breedon, 1979), the generalized behavioral pricing model (Szyszka, 2008) and the three- and five-factor models (Fama & French, 1993, 2016). To date, however, the CAPM continues to be by far the dominant asset equilibrium pricing model, both from the practitioners and the academic points of view, although it is not free of criticism (O’Sullivan, 2018).

2.4 Efficient Markets Theory

Financial asset pricing models implicitly assume that prices reflect all available information, that is, the basis of asset pricing models is the premise that markets are informationally efficient. According to such models, the condition that prevents investors to systematically obtain higher (i.e., abnormal) returns given the level of risk of an asset is that the market is informationally efficient.

More specifically, efficient markets theory considers that markets are highly and increasingly competitive and, thus, all available information is reflected in asset prices very rapidly, which

prevents investors from obtaining higher than normal returns (Fama, 1970). Therefore, the notion of market efficiency is essential in neoclassical economics financial theory.

2.4.1 The Efficient Markets Hypothesis

At the beginning of the twentieth century, Bachelier (1900) suggested the underlying ideas about market efficiency. He argued that the current market price of stocks encompasses present, past, and even future events information. Three decades later, Cowles (1933) carried out an analysis of several thousand stocks investment decisions made by professional investors and concluded that they were not able to systematically beat the market since the study found no evidence that such investors could foretell the market movements. Two decades later, when studying stock prices at short time intervals, Kendall & Hill (1953) observed that those prices followed the same pattern as a randomly generated series, so they argued that the succession of returns was serially independent. This set of observations was later known as the random walk theory⁶.

In the case of financial markets, this theory specifically implies that considering the identical distribution of asset prices, the observed changes in such prices are independent of each other and evolve along an unpredictable path as new information arrives. Therefore, information on historical returns is not useful to forecast future returns, since the probability of a price increase is the same as the probability of a price decrease at any point in time. This concept means that it is not possible to obtain higher returns without assuming more risk (Fama, 1965).

By the mid-1960s, the points of view regarding market efficiency began to consolidate. Based on the ideas about price formation in competitive markets, the random walk hypothesis was considered evidence consistent with market efficiency. In this respect, Samuelson (1965) claimed that “in competitive markets... If one could be sure that a price would rise, it would have already risen” (p. 41).

⁶ Also known as the random walk hypothesis.

Fama (1965) carried out an analysis of the distribution and serial dependence of returns in equity markets, along with a very thorough review of the literature on the performance of stock prices. This analysis concluded that there was a considerable amount of robust evidence in favor of the random walk hypothesis.

Roberts (1967) proposed the weak and strong forms of market efficiency. He claimed that it is fundamental to take into account how historical information about prices and trading volumes is included in current asset prices to determine whether the market is weak-form efficient. Likewise, besides considering historical information on prices and trading volumes, it is necessary to examine how market prices reflect non-public (i.e., privileged) information to establish whether the market is strong-form efficient. In the same research paper, Roberts (1967) suggested the name Efficient Markets Hypothesis (EMH) to group these concepts.

The ideas put forward by Samuelson (1965) and Roberts (1967) were later formalized by Fama (1970), who, based on an exhaustive review of the literature, divided the available research on market efficiency in three categories. Two of such categories matched the two levels of market efficiency suggested by Roberts (1967), but Fama (1970) added the semi-strong form of market efficiency. Such a level of efficiency encompasses all relevant public information, not only historical information about trading volumes and prices. This more comprehensive version of the EMH assumes that the strong form of market efficiency comprises the semi-strong form, which in turn includes the weak form. Figure 4 shows the three levels of market efficiency.

By the early 1970s, the idea of market efficiency was widespread in academic circles, but not so among investors. This circumstance changed when Malkiel's (1973) popular book "A Random Walk Down Wall Street" contributed to the viewpoints proposed by the EMH to be widely accepted by market participants (R. J. Shiller, 2003).

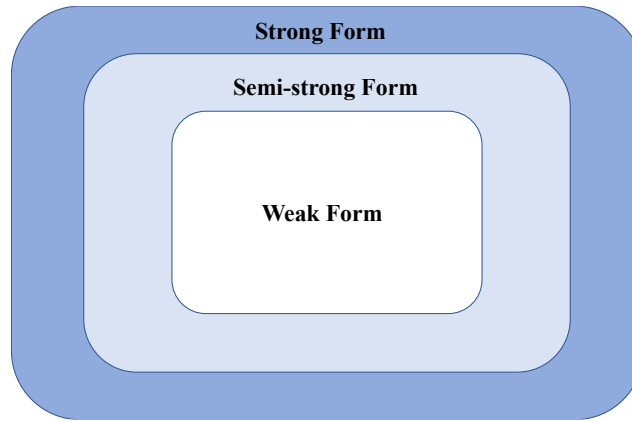


Figure 4: Cumulative Levels of Market Efficiency

Source: Own elaboration

So, in around a decade, from the mid- 1960s to the mid- 1970s, the ideas behind the Efficient Markets Hypothesis were refined and became crucial concepts not only for financial theory but also for market practitioners.

2.4.1.1 The Weak Form of Market Efficiency

Random walk theory is closely related to the weak form of market efficiency. A market meets this level of efficiency when current prices reflect all available historical information about prices, such as dividends, and trading volumes (Roberts, 1967), so that only new information, which may be randomly positive or negative, causes a corresponding positive or negative change in the price of an asset. Thus, an asset's current price is the summation of its previous price plus the expected return, plus a random component that comes from new information. Given that this component is not related to any past event, asset prices follow a random walk (Kendall & Hill, 1953).

The expression of the random walk model with drift is:

$$X_t = \alpha + X_{t-1} + \varepsilon_t; \varepsilon_t \sim iid(0, \sigma^2) \quad (1)$$

Where X_t is the dependent variable, α is the drift, X_{t-1} is the first lag of the dependent variable with a coefficient equal to one and ε_t is the random error. The term α should be

included in the model only if the mean of the dependent variable is different from zero so that the best prediction of the value of the series for today would be its value of yesterday plus the trend. On the other hand, if the conditional mean of the dependent variable is zero, then equation (1) is a purely stochastic process, that is, it randomly takes one step away from the last observed value, the drift should be excluded from the model (Yavrumyan, 2015).

Two widely used methods to determine whether a market is weak-form efficient are serial correlation analysis and the signs test (Duarte & Mascareñas, 2014; Duarte, Sierra, & Rueda, 2015; Hawaldar, Rohit, & Pinto, 2017). The signs test counts and classifies changes in the price data according to their positive or negative sign, and then compares those changes with known information about the probability distribution of a random series. Serial correlation (or autocorrelation) analysis involves the calculation of an asset's returns correlation over time. That is, by using the residuals of an OLS regression, the hypothesis that there is no serial correlation in the series is tested at a certain level of significance⁷.

2.4.1.2 The Semi-strong Form of Market Efficiency

A market is semi-strong form efficient when the behavior of the stock prices traded in that market reflects all publicly available information. Such information includes not only historical prices and trading volumes, but also the announcements made by issuing companies, the opinions of industry specialist, the outcomes from the information analysis of the financial statements of the issuer, and other reliable sources of financial information.

Since the semi-strong form of efficiency considers all publicly available information of an issuing company and not only historical information on the price and trading volume of its shares, there are additional complications to empirically test this form of market efficiency. That is why event studies that examine the speed at which investors react to an important announcement are the basis for semi-strong efficiency research (Fama, 1970). Event studies

⁷ Although there are several methods to determine serial correlation, the Breusch–Godfrey Lagrange multiplier test is one of the most frequently used.

imply that abnormal returns of an asset should only include new information since historical information is already incorporated in the price of the asset (Aleknevičienė, Kviedaraitienė, & Aleknevičiūtė, 2018; Derdas, 2009).

2.4.1.3 The Strong Form of Market Efficiency

A market is efficient in the strong form if all the information, publicly available or else, is reflected in current asset prices. A company's majority shareholders and senior managers likely have access to privileged information that allows them to attain higher than normal returns by buying or selling securities before such information is known to the general public. The strong form of efficiency implies that, even if an investor can obtain privileged information, such information is quickly reflected in the price of the securities so that the investor cannot realize higher than normal returns (Lakonishok & Lee, 2001; Roddenberry & Bacon, 2011). Therefore, the strong form of efficiency can be tested by determining whether groups of investors that presumably have access to privileged information can systematically obtain abnormal returns.

The strong form of efficiency is also related to the possibility that investors can realize abnormal returns by skillfully using information coming from the announcements of issuing companies. Thus, to examine this aspect of this form of efficiency, some empirical studies have focused on the returns that could have been achieved by following the recommendations of securities analysts, as well as the investment performance of mutual funds and pension funds managers (Jones & Jensen, 2016).

In summary, starting in the mid-1960s, and for most of the next two decades, financial economics theory was firmly based on the trinity of a single factor pricing model, the non-predictability of the returns of securities and the idea of the three levels of market efficiency (Ilmanen, 2016).

2.4.2 Efficiency of the Mexican Stock Market

Research studies on the efficiency of the Mexican stock market have arrived at mixed results, although evidence tends to support the argument that the stock market in Mexico meets the

weak form of efficiency. The research performed by Albornoz-Arias & Castillo-Paredes (2014), concludes that the Mexican stock market does not follow a random walk, but a stationary process. On the other hand, Duarte et al., (2015), assert that such a market has evolved from being non-efficient to being efficient in the weak form sense. This result tends to confirm the conclusions reached by Bonilla, Romero, & Gutierrez (2011), who also point out that the stock market in Mexico is weak-form efficient. Coronel-Brizio, Hernández-Montoya, Huerta-Quintanilla, & Rodríguez-Achach (2007) also concluded that the Mexican Stock Exchange increasingly complies with the weak form of efficiency.

The results of a research carried out by Duarte & Mascareñas (2014), which considered data from January 2002 to August 2012, reveal that the stock market in Mexico was weak form efficient starting in 2007. The conclusion of this study regarding the Mexican Stock Exchange compliance with the weak form of efficiency seems quite robust, since the results of several procedures, such as the nonparametric signs test, the Brock–Dechert–Scheinkman (BDS) statistic, the Alexander filters with genetic algorithms test, the Ljung-Box test, and the Bartlett intervals test confirmed such results.

2.4.3 Challenges to the Efficient Markets Hypothesis

While the EMH proposals have been questioned at various times, the challenges increased since the 1980s due to the emergence of evidence concerning the predictability of stock returns, the influence of heuristics and other biases in the investors' decision-making process on the price of the assets, as well as other aspects related to inconsistencies in the behavior of investors that cause the market to be inefficient (De Bondt & Thaler, 1985; Shiller, 1981). The literature has even suggested that markets cannot be efficient due to the presence of information costs. That is, investors would have no incentives to incur the costs of acquiring information if markets were perfectly efficient (Grossman & Stiglitz, 1980).

Hong & Stein (1999) argue that not all investors have access to the same information. Furthermore, even if they had such access to information, not all of them will react the same way towards it (Daniel, Hirshleifer, & Subrahmanyam, 1998; De Bondt, 2000). Evidence has also been reported that asset prices deviate from their fundamental value, deviations that,

besides being considerable, may persist for a long time (Barberis & Thaler, 2003; De Bondt, Muradoglu, Shefrin, & Staikouras, 2008). An analysis performed by Kim, Shamsuddin, & Lim (2011) in the U.S. market concluded that, as asserted by the EMH, it is not possible to predict stock returns during stock market crashes. During periods of political and economic crisis, though, stock returns are predictable.

The EMH has also been questioned in light of the events of the so-called Great Recession, the global financial downturn that occurred between 2007 and 2009⁸ (Nowicki, 2012). Shiller (2011a) claims that the broad acceptance of the ideas proposed by the EMH favors deregulation and regulatory failures that cause “speculative bubbles that eventually burst” (p.25), as was the case of the low-quality mortgages linked to the Great Recession. Likewise, Nowicki (2012) suggests that the EMH produced overconfidence and excessive leverage in both companies and families, a circumstance frequently linked with the financial instability that gave rise to the global financial crisis (White, 2016).

In their literature review on stock market efficiency, Duarte & Mascareñas (2013) found that the research papers have informed mixed results, depending on characteristics such as the country’s economic openness and its degree of development, as well as the region under examination and the periods considered in each study. Most of the research they analyzed rejected the EMH, and in about one-third of the reports that do accept it, developed countries’ markets predominate. Most of the articles they analyzed reject the EMH, and in about one-third of the reports that do accept it, developed countries’ markets predominate. Fakhry (2016) argues that the EMH has many problems and that it gives rise to a defective view about investors’ rationality, since “market participants are *homo sapiens*, not *homo economics*”⁹ (p. 431).

⁸ This term was introduced by Reinhart & Rogoff (2009).

⁹ The correct expression would be *homo economicus* (Thaler, 2000).

Behind several of the arguments against efficient markets are the principles proposed by behavioral finance¹⁰. Contrasting with the EMH, which assumes that the investors' decision-making process is completely rational and considers all available information, behavioral finance states that people take naturally biased investment decisions and make mistakes, which can be favorably used by other people¹¹. That is, according to behavioral finance, investors frequently make irrational decisions, which translates into markets either overreacting or being sluggish in their response to new information (Jones & Jensen, 2016).

Shiller (2011b) asserts that “the Efficient Markets Hypothesis is a half-truth” (p. 3) claiming that asset prices follow a first-order autoregressive process and not a random walk and that there is convincing evidence that some investment managers have been able to systematically outperform the market.

In summary, the trinity of financial theory based on neoclassical economics prevailed and consolidated virtually without objections for several decades. However, multiple challenges have emerged that doubt the validity of such a theory. Many of such challenges relate to the ideas the EMH, which has been increasingly questioned, mainly from the 1980s on.

2.5 The Adaptive Markets Hypothesis

The adaptive markets hypothesis (AMH) tries to mediate between the conflicting views of the EMH and behavioral finance (Lo, 2004). This theory holds that individuals act in their interest, as the EMH claims, and that even though they make mistakes, as behavioral finance theory argues, they also adapt by learning from such mistakes, which contributes to creating innovation and competition.

¹⁰ In general, the ideas of behavioral economics.

¹¹ Behavioral finance claims that asset prices diverge from their fundamental values due to decision-making biases, not that investors can systematically beat the market (Jones & Jensen, 2016).

While the concepts of the AMH are based on qualitative and abstract ideas related to evolutionary psychology, it has three practical implications. The first implication is that the relationship between risk and return is not stable over time, that is, the risk premium changes according to investor demographics and market environment. The second connotation is that the AMH considers that market timing and arbitrage opportunities are possible, which contrasts with the much more inflexible proposal of the EMH concerning this issue. The third implication is that the results of investment strategies will also be favorable or unfavorable depending on market conditions. Therefore such investment approaches may cease to be successful under certain conditions, but they may be successful again if the circumstances change (Lo, 2004). So, according to the AMH, market efficiency is a matter of degrees that change over time.

Nonetheless, the AMH is not free of controversy. The results of the analysis of equity indices of several countries performed by Urquhart & McGroarty (2016) concerning this hypothesis suggest that, although the predictability of the stock market behavior varies over time, it does not do so in a way consistent with the proposals of the AMH, and that each market adapts differently to certain conditions. Consequently, they conclude that investors should examine each market independently in terms of the predictability of returns.

2.6 Market Anomalies

In addition to those mentioned above, another important challenge to the EMH is the evidence regarding anomalous return patterns in stock markets, as well as in other markets such as the foreign exchange (Santillán Salgado, Fonseca Ramírez, & Nelson Romero, 2019) and the oil markets (Auer, 2014), which conflict with weak-form efficiency in particular. Since the late 1970s, the literature has reported multiple findings concerning the performance of asset returns that differ from what is established by both the EMH and the CAPM, and that may eventually result in abnormally profitable investment opportunities. This issue regarding market anomalies, particularly the so-called seasonal effects, is particularly important for this research.

As stated earlier, when the operations carried out in a market do not produce abnormal risk-adjusted returns, the market is efficient since prices reflect all available relevant information at any point in time. Nevertheless, it is not possible to determine whether a market is efficient without using a return measurement model. Thus, any analysis to assess market efficiency involves a joint test of the assumed pricing model, along with the performance of the market itself.

Because of the joint test problem, some authors argue that the results reported in the literature regarding market anomalies constitute a challenge to the CAPM model used in that research, and not as an infringement of the EMH propositions (Dimson & Mussavian, 1998; Marshall & Visaltanachoti, 2008; Sjøtun & Lifjeld, 2015). Likewise, Fama (1998) argues that the findings regarding market anomalies do not defy the proposals of the EMH, but that they are the result of some misleading assumptions in the CAPM. According to Dimson & Mussavian (1998), “The importance of the efficient market hypothesis is demonstrated by the fact that apparently profitable investment opportunities are still referred to as ‘anomalies’.” (p. 10).

Gregoriou, Kontonikas, & Tsitsianis (2004) have suggested that the anomalies are related to the particular conditions of the markets. Moreover, other authors claim that the discovery of market anomalies is the result of data snooping, so the reports about their existence does not necessarily imply the rejection of the EMH (Bohl & Salm, 2010; Sullivan, Timmermann, & White, 2001).

On the other hand, the analyses of several market anomalies carried out by Urquhart & McGroarty (2014) for the Dow Jones Industrial Average (DJIA) in the U.S. market and by Shahid & Sattar (2017) for the KSE-100 index in Pakistan, agree that the behavior of the anomalies has changed over time according to whether market circumstances have been favorable for their presence. The conclusions of those research papers are consistent with the ideas proposed by the adaptive markets hypothesis. In fact, according to Urquhart & McGroarty (2014), through the AMH, anomalies and the EMH “can co-exist in an intellectually consistent manner” (p. 154).

2.6.1 Seasonal Effects

Besides the so-called functional anomalies such as the size effect or the value-growth anomaly, the literature has reported the existence of a considerable number of seasonal (or calendar) effects. Among these seasonal effects are the day-of-the-week effect (Fields, 1931; Zhang, Lai, & Lin, 2017), the holiday effect (Dodd & Gakhovich, 2011; Fields, 1934), the January barometer¹² (Hirsch, 1974; Wen & Li, 2016), the January effect¹³ (Rozeff & Kinney, 1976; Swinkels & van Vliet, 2012), the turn-of-the-month effect (Ariel, 1987; Caporale & Plastun, 2017), and the Halloween indicator (Bouman & Jacobsen, 2002; Lloyd et al., 2017). These anomalies are of special interest in this research, so this section focuses on describing them in more detail.

Several studies have reported the existence of numerous seasonal anomalies such as the Mark Twain effect, the week-44 effect, and the school holidays effect, among several others. The Mark Twain anomaly suggests that October average returns are lower than the average returns of the remaining months of the year¹⁴ (Aharon & Qadan, 2019; Plastun, Sibande, Gupta, & Wohar, 2020). The severe U.S. stock market crashes in 1928, 1987, and 2008 took place in October, a fact that has been deemed as evidence for this calendar anomaly. Also, several authors have reported that between October 29 and November 4, average stock returns tend to be positive and higher than those of other weeks of the year, which has been called the week-44 anomaly or the week-of-the-year effect (Levy & Yagil, 2012; Seif et al., 2017). The school holiday effect is one of the most recently reported seasonal anomalies. Seemingly, average returns during the months following the most important school holiday periods in several countries are significantly lower than average returns during the remaining months of the year (Coakley, Kuo, & Wood, 2012; Fang, Lin, & Shao, 2018).

¹² According to Cooper et al. (2006) in the 1973 advertisements for the *Stock Trader's Almanac* the January barometer was mentioned referring to 1972 and previous years.

¹³ This anomaly is closely related to the size effect (Keim, 1983).

¹⁴ “October. This is one of the peculiarly dangerous months to speculate in stocks. The others are July, January, September, April, November, May, March, June, December, August, and February” (Twain, 1894, p.166).

There is a considerable amount of evidence regarding the existence of seasonal anomalies in different markets and periods, so they have been deemed as major challenges to the assertions of the EMH (Rossi, 2015). Among such anomalies are the day-of-the-week effect, holiday, turn-of-the-month, January, Halloween, and January barometer effects, which are subject of analysis in the context of the Mexican stock market in this research.

Also, some researchers have claimed that the findings regarding seasonal anomalies might be the result of data snooping (Bohl & Salm, 2010; Zhang & Jacobsen, 2013), particularly in those markets where they have been studied more intensively as in the case of the U.S. market (Schwert, 2003), the examination of these calendar effects using data from the Mexican stock market may provide a new perspective on this issue.

2.6.1.1 The Day-of-the-Week Effect

Since the early 1980s, several empirical studies have found the presence of dissimilarities in average returns for the different days of the week in the U.S. market (French, 1980; Gibbons & Hess, 1981; Lakonishok & Levi, 1982; Linn & Lockwood, 1988). In particular, some of such studies have claimed that average returns on Fridays have been the highest of the week and that those on Mondays have been the lowest, and even negative. This phenomenon has been called the day-of-the-week effect. It is also known as the weekend effect, the Monday effect, the Monday seasonal, and the turn-of-the-week effect (Levy & Yagil, 2012) and, according to Gregoriou et al. (2004), this calendar anomaly has been the most persistent.

The day-of-the-week effect was originally reported by Fields (1931), who found that there was a significant difference between Monday and Friday average returns for the DJIA between 1915 and 1930. However, one of the most influential studies on this anomaly was performed around 50 years later by French (1980), who found that between 1953 and 1977, Monday average returns of the S&P 500 were significantly negative and that Friday average returns were statistically positive. These findings go against two premises. First, since the data generating process for stock returns is continuous over time, Monday average returns should be three times the average returns on other days of the week, because there is no market trading in the two previous days corresponding to the weekend. Second, the remaining

days of the week should have the same average returns, considering the continuity of trading activity in the market, as well as the random nature of the arrival of new information.

In a related research work that covered the period from 1993 to 2011, Dzhabarov & Ziemba (2012) examined the day-of-the-week in the United States for the Russell 2000 stock index and the S&P 500 futures market index. The authors found that for the S&P 500 futures index, every day of the week had positive average returns, even though returns on Tuesdays were close to zero. The Russell 2000 index showed positive average returns every day of the week, except on Mondays, while the highest average daily returns were those on Tuesdays.

Several studies on the day-of-the-week effect have been carried out in numerous financial markets, both developed and emerging, although to a lesser extent in the latter. By analyzing the FTSE 100 index average daily returns of the London Stock Exchange using OLS regressions, as well as generalized autoregressive conditional heteroskedasticity (GARCH) specifications, Gregoriou et al. (2004) found that the day-of-the-week effect was statistically present in the U.K. market between December 1986 and December 1997, but that it was not economically significant once the transaction costs were considered. This conclusion is consistent with the findings reached by Steeley (2001), who suggests that this anomaly disappeared from the U.K. market during the 1990s.

Chukwuogor-Ndu (2006) carried out an analysis in 15 European markets with data from January 1997 to December 2004. Considering the results of the nonparametric Kruskal-Wallis test, the author concluded that average returns on Friday were positive in all markets under analysis. She also determined that average returns on Monday were negative for some markets and positive for others, and Tuesday and Thursday average returns were positive for most markets. However, the statistical significance of these results was weak, a result that the author attributes to the high volatility of returns. Using the Levene (1960) test, Chukwuogor-Ndu (2006) also analyzed the standard deviations of the series and found that such test rejected the null hypothesis that the standard deviations of the returns were equal for all days of the week in all markets examined, except in the case of the Italian market.

Alt, Fortin & Weinberger (2011) conducted a study of the S&P 500, FTSE 30, and DAX 30 indices of the U.S., British, and German markets, respectively, between January 1970 and December 2008 using closed test procedures¹⁵. They found that the Monday effect prevailed during the seventies and eighties, but disappeared between 1990 and 2010. So, the conclusion of this research tends to confirm the evidence about the fading of the day-of-the-week effect in the U.S. market that had been previously reported by Connolly (1989).

Seif et al. (2017) carried out analyses in nine advanced emerging stock markets¹⁶ on various seasonal anomalies. The study covered from 1994 to 2004 and, for some of the markets, a longer period. In that research, the authors applied OLS regressions when the conditional heteroskedasticity autoregressive – Lagrange multiplier (ARCH-LM) test did not reject the null hypothesis of constant variance of the random error over time. However, when the results rejected the null hypothesis of constant variance, they used GARCH models. In all cases, models included dummy variables to consider the corresponding calendar effect under analysis.

In the same research, Seif et al. (2017) also gathered evidence that average returns were significantly different across the days of the week. Likewise, they found that in eight of the nine markets considered in the study, average returns on Friday were positive and higher than the average returns for other days of the week. In contrast, Monday average returns were lower than the mean for the rest of the days, and even negative, in six of the nine markets they studied.

¹⁵ These procedures have the feature that the probability of incurring in a Type I error is equal to or less than the established significance level for each combination of null hypotheses. One of the best known of procedures of this type is Bonferroni's (1936) test.

¹⁶ Following FTSE's country classification, the markets under analysis were Brazil, Hungary, Malaysia, Mexico, Poland, Czech Republic, South Africa, Taiwan, and Turkey.

A research work that examined the performance of eleven Eastern Europe emerging markets¹⁷, from the inception of each market's major index to early September 2002 using OLS regression, concluded that the markets in Estonia and Lithuania exhibited negative Monday average returns throughout the nineties and up to 2002, while Monday average returns were positive during the same period in the Russian market (Ajayi, Mehdian, & Perry, 2004).

In another related study of five South-Eastern Europe countries¹⁸ that covered the period 2006 – 2011, a significant day-of-the-week effect was found in only two of them. More specifically, average returns on Mondays were significantly lower in the Bulgarian and Croatian stock markets. That research used OLS regressions with dummy variables, as well as the Wald test to perform the analyses (Tevdovski, Mihajlov, & Sazdovski, 2012).

Kristjanpoller (2009) examined the six main Latin American markets, namely, Argentina, Brazil, Chile, Colombia, Mexico, and Peru, using OLS regression with dummy variables, and considering the period between 1993 and 2007. Such research found that each of these markets showed at least one day with abnormal average returns and that average returns on Mondays were lower than average returns on other days of the week in four of the six markets, so those markets displayed a Monday effect. The same study also identified the presence of the Friday effect in four of the six markets, given that average returns on Fridays were higher than average returns on other days of the week. However, only the stock markets of Brazil and Chile showed both anomalies.

The results reported by Kristjanpoller & Muñoz (2012) confirmed the presence of the day-of-the-week effect also in the six most important markets in Latin America using the robust nonparametric test suggested by Cho, Linton & Whang (2007). Similarly, the results of the ARMA–GARCH models used by Kristjanpoller (2012a) to examine the day-of-the-week

¹⁷ The markets under study were Croatia, Slovakia, Slovenia, Estonia, Hungary, Latvia, Lithuania, Poland, Czech Republic, Romania, and Russia.

¹⁸ The countries were Bosnia and Herzegovina, Bulgaria, Croatia, Macedonia, and Serbia

anomaly in the same Latin American stock markets, arrived at significant evidence of lower than expected Monday returns and higher than expected Friday returns in several instances in such markets.

By applying Bonferroni's (1936) adjustment to the market indices of the six most important Latin American, and considering the period from January 1991 to August 2013, Rojas & Kristjanpoller (2014) found no evidence of the day-of-the-week effect. Nevertheless, the authors identified mixed evidence of the presence of such an anomaly when they used conventional regression analysis. It is worth mentioning, however, that there is considerable debate regarding the pros and cons of using adjustments such as Bonferroni's (1936). Gelman & Loken (2013) claim that statistical significance adjustment procedures are necessary because the degrees of freedom used in the research can create problems related to multiple comparisons. On the other hand, Nakagawa (2004) argues that using this statistical significance adjustment procedure increases the possibility of incurring a Type II error to inappropriate levels, and Perneger (1998) states that such adjustments are harmful to sensible statistical inference.

In another analysis that used numerous statistical tests were used and included the same six major Latin American markets between 1995 and 2014, Winkelried & Iberico (2018) show that Monday average returns were significantly negative in the six markets, while Friday average returns were the highest, with statistical significance in five markets, with the Mexican market being the only exception.

Zhang, Lai, & Lin (2017) also examined the day-of-week effect in 28 indices corresponding to 12 developed and 13 emerging markets¹⁹ in a study where they used both the GARCH model and the rolling sample method with data from 1990 to 2016. This study concluded that

¹⁹ The 13 emerging countries were those of Argentina, Brazil, Chile, China, the Philippines, India, Indonesia, Malaysia, Mexico, Poland, the Czech Republic, Russia, and Turkey. The 12 developed countries were those of Germany, Australia, Canada, Spain, the United States, France, Hong Kong, Italy, Japan, New Zealand, Singapore, and Switzerland.

the day-of-week effect was present in all markets under analysis. It is noteworthy, however, that in the U.S. market, the DJIA exhibited a Monday effect, while the S&P 500 index a Tuesday effect.

According to Philpot & Peterson (2011), despite the first studies on the weekend effect consistently found negative average returns on Mondays and positive average returns on Fridays, the most recent empirical research reveals that this effect has been reversed, changed towards other days, or disappeared, particularly from 2003 on. These authors argue that this is because the discovery of the weekend effect has caused investors to include it as part of the information for their decision-making process. On the other hand, Dicle & Levendis (2014) claim that, although arbitrage activities have caused the weekend effect to fade to the point that it cannot be detected in stock market indices, this anomaly still exists in many markets at the individual stocks level.

2.6.1.1.1 The Day-of-the-Week Effect in the Mexican Stock Market

A research that examined the IPC of the Mexican Stock Exchange, from January 1986 to December 2001, compared the index's average returns of different days of the week, for the full period under study and several subperiods. The returns of the index were computed in nominal and real terms, both in local currency and U.S. dollars. The results showed that average returns on Mondays were statistically the lowest of the week, whereas average returns on Thursdays were the highest (Cabello & Ortiz, 2003).

Kristjanpoller (2009) points out the existence of a Monday effect in the Mexican stock market in view that the analysis carried out in the corresponding study found that the IPC showed significantly negative average returns on Mondays. In another related research, Kristjanpoller & Muñoz (2012) found no presence of the weekend effect in Mexico, since no clear evidence of stochastic dominance of Fridays average returns over those of other days of the week was detected. Nevertheless, that study also reported the presence of the Monday effect in the Mexican stock market. On the other hand, the results of the mean equation of the GARCH model used by Kristjanpoller (2012a) suggest no evidence of the Monday or Friday effects in the returns of the IPC. The results of such analysis, though, also revealed that Tuesday

average returns were positive and statistically different from zero. Furthermore, the results showed that volatility on Fridays was significantly lower than on other days of the week, according to the results of the variance equation of the model.

An analysis also performed in the Mexican stock market, using the corresponding index published by Datastream, and applying the nonparametric Wald test, concluded that Monday average returns were different from those on other days of the week based. Similarly, another research found evidence that average returns on Friday were different from those on other days, and, according to the results of the parametric tests that were also applied, Friday average returns were the highest (Seif et al., 2017). Moreover, the research performed by Winkelried & Iberico (2018) concluded that the Mexican stock market experienced a Monday effect between 1995 and 2014, but that the Friday effect was not present during that period.

Torres & Alonso (2010) performed an examination on the weekend effect in four Latin American stock markets²⁰ from 2001 to 2009 using the GARCH in mean (GARCH-M) parameterization. The authors did not find statistically significant evidence of the day-of-the-week effect in the Mexican stock market. In an analysis of the performance of the IPC and the three most important individual stocks that comprise that index²¹, and using the trading time test proposed by French (1980) for a time series between January 2002 and April 2013, Duarte et al. (2013) did not find a significant presence of the Monday effect in the index or in the individual stocks they examined.

Vogelaar, Pimenta, Lima, & Gaio (2014), carried out a study using OLS regression and mean difference tests between January 2004 and December 2012 to IBOVESPA, DJIA and INMEX RT indices of the Brazilian, U.S. and Mexican markets, respectively. The authors highlight that they did not find differences were found in average returns on different days

²⁰ The markets studied were Brazil, Chile, Colombia, and Mexico.

²¹ The individual stocks were America Movil, Fomento Economico Mexicano, and Walmart de Mexico.

of the week in any of the three markets, so this research also rejects the presence of the day-of-the-week effect in the stock market in Mexico.

According to the results reported by Rojas & Kristjanpoller (2014), the IPC exhibited a Monday effect from 1991 to 1994, but the corresponding regression coefficient displayed low statistical significance. The IPC also showed a positive Wednesday effect between 1997 and 2008. Conversely, the same research did not find the day-of-the-week anomaly through the Bonferroni's (1936) test when examining the entire period from 1991 to 2013.

The analyses carried out by Zhang et al. (2017) concluded that the IPC (called MEXBOL in that research paper) did not exhibit the Monday or Friday anomalies, but it displayed a significant Wednesday effect when the authors examined samples of 1,000 and 1,500 observations. That research used GARCH specifications and rolling sample tests to returns data from January 1994 to July 2016.

In brief, several studies have concluded that average returns on Mondays differ from those of other days of the week in the Mexican stock market. Moreover, average returns on Monday have been reported to be the lowest and even negative (Cabello & Ortiz, 2003; Kristjanpoller & Muñoz, 2012; Winkelried & Iberico, 2018). However, the evidence concerning average returns on other days of the week, particularly on Fridays, is considerably mixed (Cabello & Ortiz, 2003; Seif et al., 2017; Zhang et al., 2017). On the other hand, some studies have even pointed out the absence of the day-of-the-week effect in the Mexican stock market (Rojas & Kristjanpoller, 2014; Torres & Alonso, 2010; Vogelaar et al., 2014).

2.6.1.2 The Holiday Effect

Several research papers have concluded that stock average returns are higher the day before a holiday, a return pattern known as the holiday effect. This anomaly was initially reported by Fields (1934) in an analysis of the DJIA index, and today is more accurately called the pre-holiday effect. Several decades later, Lakonishok & Smidt (1988) reported a related post-holiday effect also in the DJIA that existed since the 1950s. Around that same period, the results of Ariel (1990) showed that before a holiday, average stock returns were up to

fourteen times higher than on other days of the year in the indices published by the Center for Research in Security Prices (CRSP).

Other research papers have also revealed the existence of the holiday effect in stock exchanges other than the United States', such as the stock markets of Portugal (Gama & Vieira, 2013), the Middle East (Bley & Saad, 2010), and Central and Eastern Europe (Dodd & Gakhovich, 2011). Moreover, Bergsma & Jiang (2016) concluded that average returns are higher during the days around New Year by using data from eleven important markets that celebrate such a holiday on dates other than January 1. Also, Meneu & Pardo (2004) reported a significant pre-holiday effect between January 1990 and December 2000 in the stocks of Spanish companies that were traded simultaneously in Madrid, Frankfurt, and New York during that period.

An analysis conducted using returns from 1973 to 2003 in the stock exchanges of Hong Kong, the United Kingdom, and the United States concluded that the pre-holiday effect declined in those three markets, although the weakening of the anomaly turned out to be statistically significant only in the U.S. market. The outcomes of this analysis, which applied mean difference t-tests and OLS with dummy variables, also suggested that there was a reversal of the pre-holiday anomaly between 1991 and 1997 when pre-holiday average returns were negative (Chong, Hudson, Keasey, & Littler, 2005).

According to Seif et al. (2017), the holiday effect was also present in advanced emerging stock markets. The authors concluded that post-holiday average returns were 20 times higher than average returns on the remaining days, and 13 times higher than pre-holiday average returns in such markets. The pre-holiday anomaly was statistically significant in three of the nine markets under analysis, and the post-holiday effect was significant in six of them. The study also concluded that the holiday effect was present in the stock markets of countries that commemorate very diverse holidays.

The study carried out by Kristjanpoller (2012b) from 1990 to 2009 in the six main Latin American stock markets found significant evidence of the pre-holiday effect in three of them,

while the post-holiday anomaly was significantly present also in three of such markets. However, only the Brazilian and Peruvian markets showed significant evidence of both calendar effects.

In another research of the six most important stock markets in Latin America, which considered the period from 2002 to 2012, Marques (2014) concluded that in three of such markets, average returns were positive the day before the break of market operations during a holiday and negative during the first day after the holiday. Nevertheless, the Peruvian market exhibited an opposite pattern, while the markets of Argentina and Mexico did not reveal the existence of any holiday effects. A feature of this research was that it used two variables to control for the interval between two consecutive sessions of market operations. According to the author, this approach had two advantages over OLS with dummy variables models commonly used to examine calendar anomalies. The first advantage was that the coefficients of the interval variables considered the length of the pauses in trading operations, and the second is that it provided very consistent results in all the cases under analysis.

In an outcome that García Blandón (2010) considers surprising, his analysis found no evidence of the holiday effect²² in the LATIBEX and LATIBEX TOP²³ Latin American stock indices. In that research, the author applied GARCH specifications from December 1999 to December 2008 to the LATIBEX returns, and from January 2002 to December 2008 to the LATIBEX TOP returns, respectively. Nevertheless, the author argues that this outcome may be related to the unusual features of the indices considered for the analysis.

2.6.1.2.1 The Holiday Effect in the Stock Market in Mexico

Kristjanpoller (2012b) found a highly significant presence of the post-holiday anomaly in the stock market in Mexico, with average daily returns of more than 3.5 times that on other days.

²² The model used in this study simultaneously incorporates the day-of-the-week, holiday, turn-of-the-month, and turn-of-the-year effects, none of which was significant.

²³ The LATIBEX comprises company stocks from Argentina, Brazil, Chile, Mexico, Panama, Peru, Puerto Rico, and Venezuela. The LATIBEX TOP includes the 15 most liquid stocks from the LATIBEX.

This research also concluded that the pre-holiday effect was not statistically significant in the Mexican stock market. The results of this study also showed that pre-holiday and post-holiday trading volume averages are smaller in the Mexican Stock Exchange as compared to other days, although such findings were statistically significant only in the post-holiday case.

The analyses carried out by Duarte et al. (2013) found no evidence of the post-holiday effect in the IPC or the three individual stocks of the Mexican market they analyzed when considering the full period under examination from January 2002 to April 2013. However, they found evidence of the existence of the post-holiday effect in the first bullish subperiods under analysis, except in the case of one of the individual stocks they examined. In the last bullish subperiod, the authors found no evidence of the post-holiday effect, an outcome they interpreted as an increase in the efficiency of the Mexican market.

The research carried out by Tennyson (2009) between 1980 and 2004, using the mean difference test and OLS regression with dummy variables, concluded that the IPC daily returns exhibited a significant positive pre-holiday effect during the full period under analysis, as well as in the subperiod from 1980 to 1989. Even so, the author argues that this anomaly was offset by negative post-holiday returns, which he considers as evidence in favor of the EMH in the Mexican stock market. In contrast, other studies have reported the nonexistence of the holiday effect in the Mexican Stock Exchange (Seif et al., 2017; Winkelried & Iberico, 2018).

In short, the evidence on the holiday effect in Mexico is mixed. The literature has pointed out both the significant presence of the post-holiday effect (Kristjanpoller, 2012b), as well as its absence (Duarte et al., 2013; Tennyson, 2009). Also, there is research that concludes the significant presence of the pre-holiday effect (Tennyson, 2009), while other studies point at its nonexistence (Kristjanpoller, 2012b; Winkelried & Iberico, 2018). Finally, some studies have concluded the complete absence of the holiday effect in the Mexican stock exchange (Seif et al., 2017; Winkelried & Iberico, 2018).

2.6.1.3 The Turn-of-the-Month Effect

Historically stocks have produced higher than average returns a few days before and a few days after the turn of the month. This pattern is known as the turn-of-the-month effect, and it was initially reported in the late 1980s. Ariel (1987), for example, found the existence of this anomaly in the performance of the CRSP index in the United States between 1963 and 1981. In a study spanning a period of 90 years, Lakonishok & Smidt (1988) also found the presence of the turn-of-the-month effect in the DJIA.

A research paper that examined the behavior of the S&P 500, between 1960 and 2017, concluded that there were positive excess returns in any of the investment combinations that began between zero and four days before the end of the month and finished between zero and four days after the end of the month (Hull, Bakosova, & Kment, 2018). Also, using the mean difference *t*-tests and GARCH models, McConnell & Xu (2008) concluded that between 1926 and 2005 the turn-of-the-month anomaly was very strong in the CRSP index of the U.S. market because, on average, investors did not receive returns that offset the assumed risk except at turns of the month.

In a study carried out for the S&P 500 futures index from 1982 to 1999, Maberly & Waggoner (2000) concluded that the turn-of-the-month anomaly disappeared in the early 1990s, considering the outcomes of the mean difference test applied in that research. The results of the OLS models with dummy variables used in another study of the performance of the DJIA suggest that despite the turn-of-the-month anomaly showed a tendency to decline in such stock index between 1960 and 2003, no evidence seemed to indicate that it had disappeared (Marquering, Nisser, & Valla, 2006).

The literature has recently argued that the turn-of-the-month anomaly is highly dependent on the sample period under analysis. In an examination of the U.S. market between 1926 and 201, which considered data from several sources, Robins & Smith (2017) applied the Bai & Perron (1998, 2003) test to identify structural breaks and then used OLS with dummy variables to determine the possible presence of the turn-of-the-month effect. The authors concluded that, after 1978, such an anomaly was not statistically significant in the value-

weighted or the high-size portfolios they formed for research purposes. The turn-of-the-month effect was not significant either in the medium-sized portfolios after 1997 or in the low-size portfolios after 1998.

There is a very considerable number of research papers on the turn-of-the-month anomaly in different countries, but many of the analyses correspond to developed markets, while for emerging markets, the number of studies is considerably smaller. Kunkel, Compton & Beyer (2003) examined 19 developed and emerging markets using a variety of statistical procedures such as the mean difference *t*-test, three-way ANOVA test, and nonparametric Wilcoxon tests, as well as OLS regression with dummy variables. The study concluded that, on average, 87% of monthly returns were concentrated in the four days around the turn of the month. Furthermore, such an anomaly turned out to be significant in 15 of the stock markets considered for the research. Also, the analysis carried out by McConnell & Xu (2008), that included 34 international markets, in addition to the U.S. market, found that the turn-of-the-month effect was present in 30 of them.

A research paper of the stock market in India carried out between April 2003 and February 2011, found that the presence of the turn-of-the-month was independent of other calendar anomalies for several indices in that market. However, that effect was present only during bull market periods, but not under bear market conditions (Maher & Parikh, 2013). These results were significant according to the GARCH and exponential GARCH (EGARCH) specifications used, as well as to the results of the Wilcoxon test.

In a study carried out in the Ukrainian stock market between November 2001 and December 2015, Caporale & Plastun (2017) did not find any statistically significant evidence of the turn-of-the-month anomaly. This research used several statistical tests such as mean analysis, mean difference *t*-test, ANOVA, Kruskal-Wallis, and OLS with dummy variables.

Kristjanpoller & Arenas (2015) used several GARCH parameterizations to examine the six most important Latin American stock markets between January 1993 and November 2011. The results of the analysis showed the presence of the turn-of-the-month anomaly not only

in the stock market indices of all markets considered in that research but also in the most liquid stocks traded in those markets. The analysis carried out by Winkelried & Iberico (2018), considering the same Latin American markets for the period 1995 – 2014, found significant evidence of the presence of the turn-of-the-month in all of the markets, except in the Argentinean. In general, these results agree with the findings reported by Kristjanpoller & Arenas (2015).

2.6.1.3.1 The Turn-of-the-Month Effect in the Mexican Stock Market

Several studies report significant evidence on the turn-of-the-month effect in the Mexican stock market. Kunkel et al. (2003) found a significant presence of this calendar anomaly in the Mexican stock market five and six trading days before and two trading days after the end of the month. McConnell & Xu (2008) claim that the average returns from one trading day before to three trading days after the end of the month were significantly higher than the average returns on the remaining trading days of the month in the Mexican Stock Exchange and that the difference between average returns of the days considered within the turn of the month and the returns of the remaining days was also significantly positive. Similarly, Winkelried & Iberico (2018) point to a significant and robust presence of the turn-of-the-month anomaly according to the results of the different methods they used in the analysis of the Mexican market from 1995 to 2014.

Kristjanpoller & Arenas (2015) used three different time intervals to assess the presence of the turn-of-the-month effect. Specifically, from one trading day before to 3 trading days after the turn of the month (-1, 3), from 4 trading days before to 4 trading days after the turn of the month (-4, 4), and following Ariel (1987), from one trading day before the turn of the month to 9 trading days after (-1, 9). According to the results of that research, the Mexican Stock Exchange displayed a significant turn-of-the-month anomaly during the first three trading days of the month. Also, the authors identified a significant return differential on the ninth trading day after the turn of the month, and the authors attributed this finding to the temporary asset allocation decisions made by institutional investors and pension fund managers (Kristjanpoller & Arenas, 2015).

In their analysis of the IPC and the three main stocks included in that index, Duarte et al. (2013) concluded that as of 2008, the turn-of-the-month effect has switched from a single day to being distributed over several days. The authors also argue that from 2002 to 2007, the anomaly was present in each of the assets examined since all of them showed significantly higher than zero average returns on the first trading day of the month during bullish periods. Likewise, during bearish periods, the third and fourth trading days following the turn of the month exhibited significantly lower average returns as compared to the returns on other days of the month. That research also concludes that this seasonal effect disappeared during the last subperiod examined, both in the IPC and in two of the three individual stocks under analysis, a result that they interpret as evidence of the correction of the turn-of-the-month anomaly in the Mexican market.

In short, there is a substantial amount of evidence in favor of the existence of the turn-of-the-month effect in the stock market in Mexico, since several studies report the statistically significant existence of that anomaly in such a market (Kristjanpoller & Arenas, 2015; Kunkel et al., 2003; McConnell & Xu, 2008; Winkelried & Iberico, 2018). However, Duarte et al. (2013) assert that the turn-of-the-month anomaly is vanishing from the Mexican stock market.

2.6.1.4 The January Effect

The January effect, or turn-of-the-year effect, refers to an irregular behavior of the stock markets characterized by higher returns and trading volumes during January. In an influential research paper, Rozeff & Kinney (1976) concluded that during the period from 1904 to 1974, the equally weighted indices of all NYSE stocks exhibited considerably higher average returns in January than in any other month of the year.

The literature has also reported that this seasonal anomaly is closely related to the higher than average risk-adjusted returns of small-company stocks (Keim, 1983) since a considerable proportion of these anomalous returns took place during the last trading day in December and the first five days in January (Roll, 1983). Dzhavarov & Ziemba (2012) define the

January effect as “the tendency of small cap stocks to outperform large cap stocks in the month of January” (p. 19).

The results of the OLS regressions with dummy variables used by Mehdian & Perry (2002) revealed that the Dow Jones, NYSE composite, and S&P 500 stock indices exhibited significantly positive January returns between 1964 and 1998. They also discovered that January returns were positive but not significantly different from zero after the October 1987 stock market crash, a result that the authors interpret as evidence that this anomaly disappeared from those U.S. stock indices starting on that date.

The analysis of the DJIA’s returns between 1970 and 2005 carried out by Moosa (2007) concluded that the importance of the January anomaly diminished in the U.S. market after 1990. However, the results of the OLS models with dummy variables and the rolling regressions, also showed that the January effect was replaced by a July anomaly. Likewise, another study that included the monthly return differentials of the Russell 2000 and the S&P 500 futures indices, between 1993 and 2011, found that the turn-of-the-year effect persisted in the U.S. market, but that it shifted from January to December (Dzhabarov & Ziemba, 2012).

The evidence regarding the presence of the January effects in international markets is mixed. A study that included the stock indices of three regions of the world²⁴, besides the U.S. market from 1997 to 2014, found that the January effect is no longer present in any of such indices (Patel, 2016). Spoor & Rodriguez (2015) applied ARMA – GARCH models to examine the most important stock indices of three developed and three emerging countries²⁵ and concluded that there was a significant presence of the turn-of-the-year effect in all of them. However, they also found that such an anomaly did not occur in January, but in December.

²⁴ The regions were Asia-Pacific, Europe, and Latin America. The research also considered the Russell Developed and Russell Emerging stock indices.

²⁵ The developed countries were: Germany, Japan, and the United Kingdom. The emerging countries were: Brazil, India, and Russia.

Another research that used OLS and GARCH with dummy variables specifications to examine the markets of 34 countries from January 1988 to December 2010, also concluded that the January effect disappeared in 31 of them. However, this study also found the presence of a December effect and an April effect in the vast majority of the examined markets (Darrat, Li, Liu, & Su, 2011). Zhang & Jacobsen (2013) performed a comprehensive analysis of market returns in the United Kingdom for a period that spanned over 300 years²⁶ and found that the observed monthly return patterns were specific to the samples under analysis.

Cabello & Ortiz (2004) examined the presence of the January effect in seven Latin American markets²⁷ between January 1986 and December 2001. That research concluded that the January anomaly was not present in the Brazilian, Colombian, Peruvian, and Venezuelan markets. Moreover, the authors assert that the lowest monthly average returns in the Peruvian market occurred in January.

López & Rodríguez (2010) considered the same stock markets as Cabello and Ortiz (2004), except for Venezuela, between December 1992 and January 2009²⁸. The authors found mixed evidence about the turn-of-the-year effect since only four of the six markets showed significant evidence of that anomaly when they computed the returns in each country's respective local currency. Also, the results of the Wald test suggest what the authors call a weak condition²⁹ presence of the anomaly. Only the Argentinian and Chilean markets showed significant evidence of the January anomaly when examining the returns measured in U.S. dollars. In the case of the Peruvian market, the results were very consistent because the analyses found no evidence of the turn-of-the-year or any other calendar anomaly.

²⁶ The period analyzed was from 1693 to 2009.

²⁷ Argentina, Brazil, Chile, Colombia, Mexico, Peru, and Venezuela.

²⁸ For Argentina, Brazil, Chile, and México the period under study was from December 1987 to January 2009.

²⁹ According to the authors, this condition means that the January average return coefficient is significant, but at the same time, the coefficients of the average returns of the rest of the months are not statistically different from zero.

2.6.1.4.1 *The January Effect in the Mexican Stock Exchange*

Rojas & Kristjanpoller (2014) found very significant evidence of the turn-of-the-year effect in Mexico when they applied Bonferroni's (1936) correction to the IPC returns, even though the anomaly was not observed in January but in December. Similarly, Seif et al. (2017) report a significant presence of the turn-of-the-year effect in Mexico, according to the results of both parametric and nonparametric tests. However, that study also found such an anomaly in December, not in January, a result that the authors interpret as evidence of the disappearance of the January effect in the Mexican stock market, as has also been reported for other markets (Darrat et al., 2011).

On the other hand, Cabello & Ortiz (2003) concluded the existence of a positive January effect in Mexico between 1986 and 2001, but the authors assert that this outcome is attributable to the market returns corresponding to the 1986 – 1989 subperiod of their analysis. In a related research paper, Cabello & Ortiz (2004) found the presence of a May effect for nominal average returns. Nevertheless, when they considered inflation-adjusted returns, the authors confirmed the occurrence of a May effect, but not the existence of a January effect. Also, in the examination of the returns measured in U.S. dollars, the study found that the mean return in January was negative, while April's monthly average returns were the highest.

The research performed by López & Rodríguez (2010) identified a significant January anomaly in the stock market in Mexico when they computed the returns in Mexican pesos, although the effect disappeared for U.S. dollar-denominated returns. Furthermore, the results of the OLS models applied in the same study revealed that the Mexican stock market did not exhibit any seasonal effects when returns were measured in U.S. dollars. However, for U.S. dollar-denominated returns, a GARCH specification also used in that research revealed the presence of a significant May effect. In general, these results agree with the conclusions reached by Cabello & Ortiz (2004).

In her analysis of the IPC returns using several ARCH family tests between January 1992 and March 2013, Rojo (2013) did not find any evidence of the existence of the January effect

in the Mexican stock market. In that study, an integrated GARCH (IGARCH) parameterization identified the presence of the January effect, but such an anomaly turned out to be not statistically significant. Likewise, the mean difference tests and the GARCH analysis conducted by Darrat et al. (2011) revealed that there were no January or month-of-the-year effects in the Mexican Stock Exchange between January 1988 and December 2010.

In brief, some research studies have reported significant evidence regarding the presence of a turn-of-the-year effect in Mexico that occurs in December (Rojas & Kristjanpoller, 2014; Seif et al., 2017). López & Rodríguez (2010) also identified the January effect when they computed the returns in Mexican pesos, but the anomaly disappeared when they used U.S. dollars to estimate such returns. Similarly, the literature has reported the existence of the January effect when considering nominal returns, although not so when taking into account returns computed in real terms (Cabello & Ortiz, 2004). In contrast, according to Rojo (2013), this anomaly is absent from the Mexican market. So, the evidence about the presence of the January effect in Mexico is inconclusive.

2.6.1.5 The Halloween Indicator

Year by year, the European financial press refers to an old saying: “Sell in May and go away.”
30 The financial media also alludes to an investment strategy that is arguably applicable in the U.S. market (Arendas, Malacka, & Schwarzova, 2018; Bouman & Jacobsen, 2002). This seemingly profitable investment strategy originates in the idea that stock market average returns from May to October (i.e., summer months) are presumably lower than the average returns from November to April (i.e., winter months). The recently reported evidence supporting the existence of this anomaly revived and intensified the academic debate regarding market efficiency.

30 The full saying goes something like “Sell in May and go away, and come on back on St. Leger’s Day” (Stevenson, 2015), although there are several versions of this adage. The Festival of this saint of the Catholic Church is on October 2.

Bouman & Jacobsen (2002), in their very influential seminal paper regarding the Halloween indicator, examined the stock market returns of 37 countries from January 1970 to August 1998, applying OLS regression models with dummy variables. The authors found that market average returns from May to October were significantly lower than from November to April in 36 of the countries considered in their research. Also, Kaepfel (2009) concluded that after 1950 the U.S. market had a considerably higher average return from the first trading day in November to the third trading day in May than during the rest of the year.

The study by Galai, Kedar-Levy & Schreiber (2008) found a significant Halloween effect on the daily returns of the S&P 500 between January 1980 and August 2002 using the method proposed by Bouman & Jacobsen (2002) but controlling for outliers. Another research carried out by Haggard & Witte (2010) examined the CRSP index returns between 1926 and 2008 by applying OLS regressions, along with the M-estimation techniques put forward by Huber (1964) and Hampel (1974). The authors concluded that the Halloween effect was significant between 1954 and 2008 and that it was robust to the consideration of the January effect. Moreover, the results of that research revealed that the Halloween anomaly was robust to the presence of outliers in the U.S. market, as well as in other markets also examined. Finally, the study found that it was possible to design profitable investment strategies based on the Halloween indicator, which is not necessarily feasible for other calendar anomalies.

Recently Shen (2017), also following Bouman & Jacobsen (2002), concluded that the Halloween effect was present in the DJIA, S&P 500, and Russell 3000 indices from 1987 to 2017 after controlling for the January effect. The only U.S. index that did not show a significant presence of this anomaly was the National Association of Securities Dealers Automated Quotations (NASDAQ). Moreover, Arendas et al. (2018) examined 35 individual stocks of the largest U.S. companies (blue-chip stocks) included in the DJIA at some point between 1980 and 2017. They found that the Halloween effect had existed in the vast majority of such stocks and that the anomaly was significant in 18 of them. Moreover, since the binomial test, the two samples *t*-test, and the Wilcoxon test confirmed these results, the conclusions of this study regarding the Halloween indicator seem robust.

According to the literature, the Halloween effect influences diverse sectors and industries differently (Jacobsen & Visaltanachoti, 2009). To be precise, this effect is nonexistent in consumer consumption sectors and industries, but its presence is significant in production-related sectors and industries. Moreover, Andrade, Chhaochharia, & Fuerst (2013) found that the strategies related to the Halloween indicator can be used in several financial markets such as the equity risk premium, currency carry trade, equity volatility, and corporate and sovereign debt volatility risk premia.

Lloyd et al. (2017) studied whether the Halloween effect persisted after the 2008 financial crisis in several stock markets around the world. They considered the period from May 2007 to October 2015 and included 35 of the 37 markets originally examined in the research by Bouman & Jacobsen (2002), and followed the method proposed in that study. Only the Spanish market did not show any evidence of the anomaly. However, the results regarding the presence of the Halloween indicator were statistically significant only in six of the 35 markets under analysis. Likewise, Zhang & Jacobsen (2013) carried out a comprehensive research concerning the existence of the Halloween effect in the stock market of the United Kingdom and concluded that such an anomaly existed in that market over a period of 300 years.

Despite there are some studies related to the Halloween indicator in Eastern Europe, Latin America, and other less developed markets, this calendar anomaly has been less examined than others in emerging markets. Caporale & Plastun (2017) examined the Ukrainian stock market and stock futures market and found that the mean analysis of the corresponding indices showed evidence that the average cumulative returns are higher in the winter months than in the summer months. Nevertheless, the results of the OLS regressions and other statistical tests performed by the authors suggested that the anomaly was significant only in one of the indices considered in the research.

Also following Bouman & Jacobsen (2002), Almeida, Almeida, & Bergmann (2017) consider all the stocks listed in the Brazilian stock market's BOVESPA stock index from August 1994 to June 2014. The study found that the Halloween indicator was statistically

and economically significant in such a market. However, the authors also concluded that the anomaly showed a slight tendency to fade away in the last six years of the analysis. The research also determined that an investment strategy based on the Halloween indicator offers higher returns than a simple buy-and-hold approach.

On the other hand, Alshimmiri (2004) examined the general, large-capitalization, and small-capitalization indices of the Kuwaiti stock market between February 1984 and December 2000. The research found that, according to the results of the OLS models with dummy variables, the average cumulative returns between October and April tend to be lower than those from May to September in such a stock market. So, the author concludes that there was an inverse Halloween anomaly in that market.

2.6.1.5.1 The Halloween Effect in the Mexican Stock Market

Bouman & Jacobsen (2002), in their analysis performed in 37 international stock markets, found that in the Mexican Stock Exchange the average cumulative returns from November to April were 15 percentage points higher than the average cumulative returns from May to October, with a very similar standard deviation in both cases, although slightly higher during the summer months. Nevertheless, the authors concluded that the Halloween indicator was not statistically significant in any of the ordinary least squares regressions used in the research.

The research by Lloyd et al. (2017), also included Mexico as part of the analysis of 35 countries and determined that in the Mexican stock market the monthly average returns between November and April was 0.39 percentage points higher than the monthly average returns between May and October, but that such difference was not significant. Additionally, the authors point out the further reduction of the statistical significance of the anomaly after the financial crisis of 2007 – 2009.

Takki (2017) researched the Halloween indicator in 35 countries from 1991 to 2017 using the Morgan Stanley Capital International (MSCI) general index, as well as the small-, mid-, and large-capitalization MSCI indices. The study applied two OLS models with dummy

variables: one of them controlled for the January effect, and the other did not. In the case of the Mexican stock market, the analyses did not find any statistically significant evidence of the Halloween anomaly in the general, large-, and mid-capitalization indices. Nevertheless, there was a substantial positive difference between average returns from November to April and those from May to October. In contrast, the study found a significant Halloween effect in the small-capitalization MSCI index. These results seem robust since the two OLS models used in the study arrived at the same conclusion.

Jacobsen & Zhang (2018) examined the same 37 countries previously researched by Bouman & Jacobsen (2002). The authors concluded that in the first subperiod of the study, from January 1970 to August 1998, the average returns in the winter months in the Mexican stock market were 3.6 percentage points higher than those during the summer months. The corresponding difference for the second subperiod, from September 1998 to April 2017, was 5.4 percentage points. The value of the *t*-statistic was 0.58 in the first subperiod and 1.43 in the second. Therefore, none of these differences was statistically significant, and the results rejected the hypothesis concerning the presence of the Halloween indicator in the Mexican stock market. While the results of the *t*-statistic imply that the anomaly was not significant, its value increased in the most recent subperiod considered in that research. This tendency opposes the argument that the Halloween indicator has faded in Mexico in recent years, as suggested by the research carried out by Lloyd et al. (2017).

In brief, the research conducted in the Mexican market has not generally found significant evidence of the Halloween indicator presence, despite considerable differences in average returns between the summer and winter months (Bouman & Jacobsen, 2002; Lloyd et al., 2017). There is some evidence, though, that this calendar effect existed in the smaller Mexican company stocks index (Takki, 2017). However, it is also worth remarking the limited number of studies on this seasonal anomaly in Mexico.

2.6.1.6 The January Barometer

The literature has reported that the returns in January are a signal of how the stock market will perform during the rest of the year. According to Dzhavarov & Ziemba (2012), if January

return is negative, the average return during the rest eleven months is also negative five out of ten times in the U.S. market. On the other hand, if the market return in January is positive, the average return of the rest of the remaining months of the year is positive nine out of ten times in that market. In other words, as January goes, so goes the year. This stock market anomaly is known as the January barometer or the other January effect (Cooper et al., 2006; Dzhabarov & Ziemba, 2012; Hirsch, 1974).

In an examination of NYSE data using OLS regression, Cooper et al. (2006) found the presence of the January barometer³¹ between 1940 and 2006 and also verified the robustness of their results considering data starting in 1825. Furthermore, they found that the other January effect had a predictive capacity for small and big company stocks, as well as for value and growth stocks. Another study examined the returns of the U.S. market between 1941 and 2003 by applying unconditional and conditional evidence approaches. That research concluded that the January barometer existed in different subperiods, the anomaly was found to be a good predictor of bearish markets, but not as much of bullish markets (Brown & Luo, 2006). Moreover, according to Sun, Stivers, & Kongera (2013), the predictive capacity of the January barometer decreased since the 1970s, when the anomaly began to be studied. However, according to their results, this seasonal anomaly remained a good market timing technique between 1975 and 2006.

Marshall & Visaltanachoti (2010) used several statistical techniques, including the seemingly unrelated regression (SUR) method, to determine whether the January barometer was present in the CRSP index returns between 1940 and 2007. They concluded that it was not possible to use the January barometer to arrive at statistically and economically significant risk-adjusted excess returns. The authors assert that investors should be careful in considering the use of the January barometer as part of their decision-making process and that the academic community should not take the reports regarding the alleged existence of this anomaly as

³¹ In their research Cooper, et al. (2006) call this anomaly “the other January effect” (p. 315).

evidence against the EMH, since it is unable of creating economically significant risk-adjusted excess returns investment strategies.

Several studies have explored the presence of the January barometer in stock markets other than the United States'. The results of the mean difference *t*-tests applied by Wen & Li (2016) found no evidence of such a calendar anomaly in five of the six Central and Eastern European markets considered in their research. However, they found significant January barometer-type anomalies in months other than January.

Bohl & Salm (2010) examined the presence of the January barometer in 19 developed countries using data starting in 1970. The analysis applied OLS regression with dummy variables and two vectors: one that controlled for the Halloween effect and the other that controlled for the ex-ante variables related to the dependencies with the international stock market and the business cycle. In that research, the January barometer was significant in only 2 of the markets under analysis. The study also found evidence that the January barometer's predicting power depends on the selection of the stock market or the sample period. Based on these results, the authors claim that the anomaly is not an international phenomenon and that its reported presence in some markets can be attributed to data snooping.

A research paper that included stock market data of 23 individual countries, as well as MSCI World Index data, concludes that 19 of the indices analyzed exhibited higher average returns after the months of January with positive returns, but that these results were significant only in three of them³². However, such statistical significance faded away when adjusting the data for dummy variable persistence and data mining biases (Marshall & Visaltanachoti, 2008). Moreover, according to Seif et al. (2017), none of the advanced emerging markets they analyzed, except the Brazilian market, presented a statistically significant return spread between the months following negative and positive January returns. Thus, in general, the

³² Spain, Switzerland, and the MSCI.

results of these studies agree with the findings reported by Bohl & Salm (2010) for developed countries.

2.6.1.6.1 The January Barometer in the Mexican Stock Market

The research carried out by Seif et al. (2017) examined the possible presence of the January barometer in the Mexican stock market from October 1989 to February 2014, as part of their set of advanced emerging stock markets. The authors did not find a significant average return spread between the eleven months following the months of January with positive returns and the eleven months that followed the months of January with negative returns, so the study did not find the presence of the January barometer in the Mexican stock market.

It is worth remarking that, of the six calendar anomalies examined in this research, the January barometer is the most scarcely studied in the Mexican stock market, since as far as it has been possible to determine, there are no specific studies on this subject.

In brief, the review of the literature on the six seasonal effects examined in this section reflects mixed results for different markets and periods studied. The case of the Mexican stock market is not dissimilar because the outcomes of the analyses concerning the calendar effects are also mixed. Furthermore, the number of studies regarding some of the seasonal anomalies in the Mexican stock market is considerably limited, particularly for the Halloween indicator and the January barometer.

2.7 Seasonal Effects Analysis Methods Used in the Literature

Researchers have applied a wide variety of statistical tests and econometric models to examine calendar anomalies. These include descriptive statistics, parametric and nonparametric inference methods, regression models, as well as some more sophisticated econometric models recently developed. This section presents a general description of the most frequently used procedures to examine seasonal anomalies, as well as their most relevant characteristics.

2.7.1 Graphical Representations and Descriptive Statistics

Frequently, research papers on calendar effects show the results of descriptive statistics, such as the mean, the standard deviation and the variance, which are related to the anomaly under examination, and then compare the results with those corresponding to other points in time that do not belong to the period of the anomaly. Similarly, these studies use graphs as an aid to show anomalous behavior in asset returns.

Descriptive statistics, however, are frequently used as a background to the anomaly under examination, only to offer a starting point for other formal and specific analyses (Caporale & Plastun, 2017; Darrat et al., 2011; Jacobsen & Zhang, 2018; Kristjanpoller & Arenas, 2015; Marques, 2014; Sun et al., 2013; Zhang et al., 2017).

2.7.2 Mean Difference t -Test

This test proposed by Student (1908) determines whether the mean of the distribution of differences of the paired data sample is zero. In other words, this procedure is used to determine whether the means of two different groups of observations are the same. More specifically, to test the population mean of the distribution of differences, μ_d , the hypotheses are:

$$\begin{aligned} H_0: \mu_d &= 0 \\ H_1: \mu_d &\neq 0 \end{aligned}$$

The test statistic is computed from the t distribution, assuming that the population of differences follows the normal probability distribution:

$$t = \frac{\bar{X}_d}{s_d/\sqrt{n}} \quad (2)$$

In equation (2) there are $n - 1$ degrees of freedom, $\bar{X}_d$ is the mean difference between paired (i.e., related) observations, n is the number of paired observations, and s_d represents the standard deviation of the paired data. The standard deviation is computed as:

$$s_d = \sqrt{\frac{\sum_{i=1}^n (X_{di} - \bar{X}_d)^2}{n-1}} \quad (3)$$

Where X_{di} is the difference between each pair of related observations (Lind, Marchal, & Wathen, 2012).

When the test fails to reject H_0 , that is, when the absolute value of t is lower than the corresponding critical value given a previously established level of significance and the number of degrees of freedom, there is not enough evidence to assert that the means of the paired data are different. In the case of the analysis of calendar anomalies, failing to reject the null hypothesis denotes that there is not enough evidence to support that the average returns at different moments of the year are not the same.

2.7.3 Analysis of Variance

The analysis of variance (ANOVA) determines whether two samples have the same variance and compares two or more means at the same time. The hypotheses to test equal variances are:

$$\begin{aligned} H_0: \sigma_1^2 &= \sigma_2^2 \\ H_1: \sigma_1^2 &\neq \sigma_2^2 \end{aligned}$$

The ANOVA test is useful when comparing more than two means since it prevents the accumulation of Type I error³³ that is produced by the t -test when contrasting more than two differences in means (Lind et al., 2012). The hypotheses used to compare whether the means of n populations are equal are:

$$\begin{aligned} H_0: \mu_1 &= \mu_2 = \dots = \mu_n \\ H_1: &\text{At least one of the means is different from the others} \end{aligned}$$

³³ A Type I error is produced when true a null hypothesis is rejected and is also known as a false positive finding.

However, when ANOVA is used to compare the means, it is assumed that the populations (1) are independent, (2) are normally distributed, and (3) have the same standard deviations (Lind et al., 2012).

2.7.4 Wilcoxon Test

The signed-rank test proposed by Wilcoxon (1945) is a nonparametric method frequently used in the literature concerning calendar anomalies (Arendas et al., 2018; Kunkel et al., 2003; Maher & Parikh, 2013; Marshall & Visaltanachoti, 2010). The Wilcoxon test is an alternative to Student's mean difference *t*-test, but it does not require the assumptions of normality in the data distribution and equality in the data variances. Another difference between Student's *t*-test and Wilcoxon's test is that the latter focusses on the difference of the medians of the observations, not on the difference of their means, based on the argument that the sum of the ranks of the samples below and above the median should be approximately the same (IHS Global Inc., 2016).

Wilcoxon's test translates the observations into ranks (i.e., to an ordinal scale) and uses the sum of such ranks to determine whether the data come from the same population. The null and alternative hypotheses of this test are, respectively:

$$\begin{aligned}H_0: Me_d &= 0 \\H_1: Me_d &\neq 0\end{aligned}$$

Where Me_d represents the median of the data differences. When both paired samples include more than 25 observations, the distribution of the sum of the ranks approximates a normal probability distribution, so such a theoretical distribution can be used to test for the difference between the distributions of the sample medians (Galindo, 2015; Kachigan, 1986).

2.7.5 Kruskal-Wallis Test

The ranks test proposed by Kruskal & Wallis (1952) is the nonparametric equivalent to a one-way ANOVA and is a generalization of the Mann-Whitney test (Mann & Whitney, 1947)

for more than two subgroups. The test involves combining the samples, ordering the values from lowest to highest, and replacing the categorized values by ranks, starting from 1 for the lowest value.

The probability distribution of the statistic for this test is very similar to a chi-squared (χ^2) distribution with $k - 1$ degrees of freedom for samples when there are at least 5 observations. The hypotheses to contrast in the Kruskal-Wallis test are:

H₀: The population distributions are all equal

H₁: The population distributions are not all equal

2.7.6 Comparison Between Parametric and Nonparametric Tests

Most parametric tests have their nonparametric counterparts. However, both parametric and nonparametric tests have pros and cons that must be taken into consideration when making use of them (Kachigan, 1986).

When the data follow a normal distribution and have the same variance, the parametric methods offer the best alternative. These methods have superior statistical power because they reduce the possibility of incurring a type II error³⁴. These procedures also allow parameters estimation, as well as the construction of confidence intervals.

The use of nonparametric tests is adequate when the data do not meet the assumptions required by parametric models, particularly the assumption regarding normality in the distribution of the data³⁵. Moreover, extreme observations influence the value of the mean. So, when the distribution is skewed, the median is a better measure of the center of the

³⁴ Type II error means failing to reject a false null hypothesis. It is also known as a false negative finding.

³⁵ Parametric tests work correctly for any continuous distribution, even if such a distribution is not normal, provided that the sample size meets certain conditions. The requirements vary for each of the nonparametric tests (Minitab, 2015).

distribution. Median-based nonparametric tests might be convenient when examining asymmetric probability distributions³⁶.

2.7.7 Ordinary Least Squares Regressions

Many research papers on seasonal anomalies have used ordinary least squares (OLS) regression analysis. This method represents the linear relationship between one or more control (independent) variables and a response (dependent) variable through a regression equation. OLS regression is very useful for determining the value of the response variable from the values of the control variables.

The objectives of ordinary least squares specifications are to determine whether a relationship exists between two or more variables, to mathematically specify the properties of that relationship in the case it exists, to evaluate the accuracy of the description obtained from the regression, and to estimate the importance of each control variable included in the model (Kachigan, 1986).

OLS estimations with dummy (binary) variables are very frequently used in the analysis of seasonal effects. The calculation procedure with a dummy regressor is the same as with a continuous one, although its interpretation is different. More specifically, a regression that includes dummy variables is analogous to a mean difference test. The general OLS regression model with D_t as a dummy control variable is:

$$Y_t = \alpha_0 + \alpha_1 D_t + \varepsilon_t, \quad t = 1, \dots, n \quad (4)$$

Where D_t takes a value of 1 if certain condition is met and zero otherwise. Thus, if the condition is not met and $D_t = 0$, equation (4) can be written as $Y_t = \alpha_0 + \varepsilon_t$. The conditional

³⁶ Nonparametric tests are also useful when analyzing small sample sizes or when the data being examined are interval or ratio level.

expected value of Y_t is $E(Y_t|D_t = 0) = \alpha_0$, assuming that $E(\varepsilon_t|D_t) = 0$. Hence, α_0 is the value of the population mean when the condition is not met.

However, if the condition is met, then $D_t = 1$, so that equation (4) turns into $Y_t = \alpha_0 + \alpha_1 + \varepsilon_t$, and $E(Y_t|D_t = 1) = \alpha_0 + \alpha_1$, also assuming that $E(\varepsilon_t|D_t) = 0$. In other words, the value of the mean of the population when the condition is met is $\alpha_0 + \alpha_1$. Accordingly, α_1 is the difference between the population means when the condition is met ($D_t = 1$) and when the condition is not met ($D_t = 0$), that is, $(\alpha_0 + \alpha_1) - \alpha_0 = \alpha_1$.

Since α_1 is the difference between the sample means of Y_t of the two sample groups (Stock & Watson, 2011), such a parameter must have a value statistically indistinguishable from zero if the two means are equal. Thus, the hypotheses to contrast are:

$$H_0: \alpha_1 = 0$$

$$H_1: \alpha_1 \neq 0$$

2.7.8 Heteroskedasticity of the Random Errors

One of the assumptions of the OLS regression model is that the conditional mean of ε_t is homoskedastic, in other words, that the variance of its conditional distribution does not change for $t = 1, 2, \dots, n$. If, on the other hand, this condition is not met, the error is heteroskedastic (Enders, 2015; Stock & Watson, 2011). Although heteroskedasticity does not introduce inconsistency or bias in the OLS coefficients (α_i) in equation (4)³⁷, it causes the estimators of the variance to be biased and the standard errors of the OLS model to lose their validity for the determination of the t -statistic since the variance is the basis for the calculation of the errors. Moreover, this problem cannot be solved by increasing the sample size (Wooldridge, 2014). Consider the following:

$$Y_t = X_{t-1}\varepsilon_t \tag{5}$$

³⁷ Heteroskedasticity does not affect either the interpretation of goodness of fit measures R^2 and adjusted R^2 .

Where Y_t is the value of the response variable at period t , ε_t is the random disturbance with variance σ^2 , and X_{t-1} is the observation of the control variable at period $t - 1$. If X_{t-1} is constant for $t = 1, 2, \dots, n$, the variance is constant and the $\{Y_t\}$ sequence is a white noise process. Nevertheless, when the sequence of observations of $\{X_t\}$ are not all the same, the variance of Y_t is conditional to the value of X_{t-1} . Therefore,

$$\text{Var}(Y_t|X_{t-1}) = X_{t-1}^2 \sigma^2 \quad (6)$$

If X_{t-1}^2 is small, the variance of Y_t is also small and vice versa. Furthermore, if the consecutive observations of $\{X_t\}$ display serial correlation, the conditional variance of the sequence of $\{Y_t\}$ will also exhibit this characteristic (Enders, 2015; Stock & Watson, 2011).

Frequently, financial time series present heteroskedasticity in the form of clustered volatility. That is, financial data display low variance levels during certain periods and considerably higher variance levels in others (Jacobsen & Zhang, 2018; Spoor & Rodriguez, 2015; Stock & Watson, 2012; Zhang et al., 2017). Additionally, sometimes volatility clustering of financial time series also follows an asymmetric pattern, because, as reported in the literature, favorable shocks produce an increase in prices, with relatively low associated variability, while unfavorable shocks cause a decline in prices, with sizable associated variability, and there is important evidence that returns volatility tends group unevenly (Caporale & Zakirova, 2017; Enders, 2015; Rojo, 2013; Yavrumyan, 2015).

2.7.8.1 Heteroskedasticity Modeling

Conditional or clustered volatility in time series is a pattern of the error term such that, if it has a large variance in one period, its variance also tends to be large in the following period, and vice versa. Therefore, volatility clustering in time series denotes that the error term is heteroskedastic (Enders, 2015; Stock & Watson, 2011).

Autoregressive conditional heteroskedasticity (ARCH) and generalized autoregressive conditional heteroskedasticity (GARCH) estimations allow for the modeling of clustered

volatility of time series. Moreover, some methods of this family, such as the exponential GARCH (EGARCH) and the threshold GARCH (TGARCH), allow for the modeling of asymmetrical volatility clustering (Enders, 2015; Kang, 2011). The ARCH, GARCH, EGARCH, and TGARCH models are particularly important for this research, and the following sections explain them in more detail.

2.7.8.2 Autoregressive Conditional Heteroskedasticity (ARCH)

The autoregressive conditional heteroskedasticity (ARCH) model of order p , proposed by Engle (1982), and many other models that have their origin in that econometric approach, are widely used in the analysis of volatility clustering in financial time series. According to the ARCH (p) model, the conditional variance (σ_t^2) of the error term depends on the lagged squared values of the error term itself. That is:

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 \quad (7)$$

Since σ_t^2 is the conditional variance, its value must be positive. The squared errors are positive by definition; however, the coefficients ω and α_i have to meet the nonnegativity constraint for the model to be valid (Brooks, 2008). The ARCH model can be used to represent the error variance of any time series regression model that has a conditional error with a mean equal to zero (Stock & Watson, 2011).

2.7.8.3 Generalized Autoregressive Conditional Heteroskedasticity (GARCH)

Ever since the introduction of the ARCH model, a sizeable number of variants have emerged. One of the most important of such adaptations is the GARCH (p, q) model proposed independently by Bollerslev (1986) and Taylor (1986)³⁸. This model is similar to the ARCH(p), but it adds moving average terms. That is, the GARCH approach considers that,

³⁸ An ARCH specification is a special case of a GARCH model, which does not include variance lags in the conditional variance equation, that is, an ARCH model is a GARCH (0, 1) model.

at any point in time, the variance depends not only upon the lagged squared values of the error term but also upon the variance's own lagged values (Engle, 2001). The model states that:

$$\sigma_t^2 = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \quad (8)$$

The conditional variance of the error term for period t in equation (8) is represented by σ_t^2 , while ω , α_i , and β_j are the unknown parameters of the model, which must all be nonnegative and are determined using the maximum likelihood estimator³⁹.

Because GARCH (p, q) estimations consider autoregressive and moving average components in the heteroskedastic variance, they may allow for a more parsimonious and easier to estimate representation of high-order ARCH (p) estimations. The main characteristic of GARCH models is that the conditional variance of the errors works as the autoregressive moving average (ARMA) processes, so their residuals display the distinctive pattern of such processes when the series is heteroskedastic (Enders, 2015).

Also, the GARCH approach is suitable because it reasonably considers heteroskedasticity and can also distinguish between conditional and unconditional normal errors. Furthermore, one of the advantages of the model is that it can be expanded to consider other effects in the conditional variance (Connolly, 1989). This feature of the GARCH estimation is particularly important for the regression specifications used in this research.

³⁹ As suggested by Gregoriou et al. (2004) and Kiymaz & Berument (2003), the analyses in this study used the quasi-maximum likelihood estimation proposed by Bollerslev & Wooldridge (1992) when the distribution of the residuals was not normal.

2.7.8.4 Exponential GARCH (EGARCH)

A characteristic of the exponential GARCH (EGARCH) proposed by Nelson (1991) is that it acknowledges asymmetries between volatility and return. A way to represent the conditional volatility through an EGARCH (p, q) model is:

$$\log(\sigma_t^2) = \omega + \sum_{i=1}^p \alpha_i \left| \frac{\varepsilon_{t-i}}{\sigma_{t-i}} \right| + \sum_{k=1}^r \gamma_k \frac{\varepsilon_{t-k}}{\sigma_{t-k}} + \sum_{j=1}^q \beta_j \log(\sigma_{t-j}^2) \quad (9)$$

The γ_k coefficient is related to asymmetry, since if there is greater volatility after negative shocks, this leverage coefficient should be significantly negative⁴⁰, so the existence of leverage effects is tested by the hypothesis that $\gamma_k < 0$. Also, there will be an asymmetric impact whenever $\gamma_k \neq 0$ (IHS Global Inc., 2016).

The logarithm of the variance as the response variable in equation (9) implies that leverage is exponential, and not quadratic. Additionally, given that the logarithm of the conditional variance is parameterized, rather than the conditional variance itself, the implied value of σ_t^2 cannot be negative, which prevents the need to include artificial nonnegativity constraints on the model parameters. A limitation of this model, however, is that the log-linear specification imposes difficulties in constructing unbiased forecasts for the level of future variances (Brooks, 2008; Enders, 2015; Kang, 2011).

2.7.8.5 Threshold GARCH (TGARCH)

The threshold GARCH (TGARCH) model, proposed independently by Glosten, Jagannathan, & Runkle (1993) and Zakoian (1994), allows for the conditional variance to

⁴⁰Asymmetry was originally associated with financial leverage, so it was known as the leverage effect. Nowadays, however, there is a consensus that asymmetry and financial leverage are unrelated (Kang, 2011). In this context, thus, leverage is the tendency of volatility to increase when returns decrease and to decrease when returns increase (Enders, 2015).

depend on the sign of the lagged innovations. More specifically, the conditional variance in the TGARCH (p, q) model is:

$$\sigma^2 = \omega + \sum_{i=1}^p \alpha_i \varepsilon_{t-i}^2 + \sum_{k=1}^r \gamma_k \varepsilon_{t-k}^2 \bar{I}_{t-k} + \sum_{j=1}^q \beta_j \sigma_{t-j}^2 \quad (10)$$

Equation (10) is subject to the following restrictions: $\omega \geq 0$, $\alpha_i \geq 0$, $\beta_j \geq 0$, and $\alpha_i + \gamma_k \geq 0$.

$\bar{I}_{t-k}$ is a dummy variable that takes the value of 1 when $\varepsilon_{t-k} < 0$ and zero otherwise, so that bad news has an impact of $\alpha_i + \gamma_k$, and good news has an impact of α_i . That is, if γ_k is statistically different from zero, the data have a threshold effect, and when $\gamma_k > 0$ negative shocks will have larger effects on volatility than positive shocks.

In brief, in the literature related to the different seasonal effects, a wide array of statistical tests and econometric models have been used. These include descriptive statistics, parametric and nonparametric methods of inferential statistics, OLS regressions, and other recently developed regression models that allow identifying heteroskedasticity and asymmetries in the conditional variance of the disturbances.

2.7.9 Stationarity

The concept of stationarity has historically been relevant in the analysis of time series (Wooldridge, 2014). Accordingly, it is necessary to verify whether the data have this characteristic before proceeding with any further analysis of the time series.

A variable X_t is said to be stationary when its unconditional mean and variance are constant, that is, $E(X_t) = E(X_{t-j}) = \mu$ and $Var(X_t) = Var(X_{t-j}) = \sigma^2$, and its covariance does not depend on the reference period, but on the time (j) that elapses between two observations, that is, $Cov(X_t, X_{t-j}) = Cov(X_u, X_{u-j}) = \gamma_j$. If the variable does not meet one or both of these conditions, that variable is said to be nonstationary. A nonstationary series has the

feature that it does not revert to any long-run mean. Moreover, the series' variance is time-dependent and tends to infinity, and its autocorrelation declines very slowly (Barajas, 2017).

A random walk process has a stochastic trend, and it is nonstationary. So, if a variable follows a random walk, as described by equation (1), the variance of such a variable increases over time, and its probability distribution function changes. The random error (ε_t) in equation (1) is uncorrelated with X_t , and for the latter to be stationary, $Var[X_t]$ cannot depend on the reference period. Given that in equation (1) $Var[X_t] = Var[X_{t-1}] + Var[\varepsilon_t]$, the only way to meet the condition of reference period non-dependency of the variance is that $Var[\varepsilon_t] = 0$ (Wooldridge, 2014).

From a statistical standpoint, a nonstationary process has two important implications. The first is that the usual confidence intervals for the autoregressive (AR) coefficients are not valid since the test statistics are not normal. The second consequence is that the coefficients are biased and, therefore, their estimation is not reliable (Barajas, 2017).

An autoregressive process of order 1, or AR(1), can be written as:

$$X_t = \alpha + \beta_1 X_{t-1} + \varepsilon_t \quad (11)$$

A random walk process, such as the one represented in equation (1), is a special case of an AR(1) process where $\beta_1 = 1$. As a result, X_t has a stochastic trend and, therefore, it is nonstationary. On the other hand, if $|\beta_1| < 1$ and ε_t is stationary, the joint distribution of X_t and its lags does not depend on t , therefore X_t is stationary. For an AR(1) process to be stationary the $|\beta_1| < 1$ condition implies that $1 - \beta_1 z = 0$, so the root is $z = 1/\beta_1$. If the root of an AR(1) process is 1 (i.e., $\beta_1 = 1$) the series is said to have a unit root and, thus, it is nonstationary.

2.7.10 Unit Root Tests

Informally, when a large sample plot of a time series does not exhibit an obvious trend, and the first autocorrelation coefficient of the series is small, such a series may be stationary (Stock & Watson, 2011). However, to determine whether the series has this feature, it is necessary to use more formal tests. The Augmented Dickey-Fuller (ADF) and the Kwiatkowski-Phillips-Schmidt-Shin (KPSS) tests are two of the most frequently used tests for this purpose. As an antecedent, the next segment summarizes the Dickey-Fuller (DF) test. Then, the following sections outline the ADF and KPSS tests.

2.7.10.1 Dickey-Fuller Test

The Dickey-Fuller (DF) test is based on the autoregressive model of order one (Dickey & Fuller, 1979). If $\beta_1 = 1$ in the AR(1) model represented in equation (11), X_t has an autoregressive unit root, that is, the model is nonstationary. Therefore, it is possible to test whether X_t has a stochastic trend by contrasting:

$$H_0: \beta_1 = 1$$

$$H_1: \beta_1 < 1$$

It is also possible to simplify this contrast by using an equivalent expression that subtracts X_{t-1} from both sides of equation (11), that is:

$$\Delta X_t = \alpha + \delta X_{t-1} + \varepsilon_t \quad (12)$$

Where $\delta = \beta_1 - 1$. In this case the hypotheses to be contrasted are:

$$H_0: \delta = 0$$

$$H_1: \delta < 0$$

The hypotheses contrast for equations (11) and (12) imply that, the series has a unit root when the test fails to reject H_0 . The test is performed considering the critical values developed by Dickey & Fuller (1979).

When the test rejects H_0 for a series in levels, that series is said to have an $I(0)$ order of integration, but if the series has to be differenced d times to be stationary, it is said to have an $I(d)$ order of integration. Nevertheless, second or higher-order differences are infrequent in economics and finance (Santillán-Salgado, 2015a), so it is commonplace that financial time series have to be differenced only once to be stationary. In other words, in the financial time series, the difference in $X_t - X_{t-1}$ usually does not have a unit root (Yavrumyan, 2015).

2.7.10.2 Augmented Dickey-Fuller Test

The Dickey-Fuller unit root test assumes that ε_t is white noise, but if the series is autocorrelated, this assumption does not hold. The Augmented Dickey-Fuller (ADF) test is a general version of the original DF test that allows for higher-order lags. The general version of the model is:

$$\Delta X_t = \alpha + \delta X_{t-1} + \sum_{i=1}^p \gamma_i \Delta X_{t-i} + \varepsilon_t \quad (13)$$

Where $\delta = -(1 - \sum_{i=1}^p \beta_i)$ and $\gamma_i = -\sum_{j=1}^p \beta_j$. That is, δ depends on the sum of the autoregressive coefficients of the residuals, therefore if $\sum_{i=1}^p \beta_i = 1$, then $\delta = 0$. Thus, as in the original DF test, the hypotheses to be contrasted in the ADF test are:

$$H_0: \delta = 0$$

$$H_1: \delta < 0$$

2.7.10.3 Kwiatkowski–Phillips–Schmidt–Shin (KPSS) Test

The Lagrange multiplier Kwiatkowski–Phillips–Schmidt–Shin (KPSS) is a stationarity test in the sense that it assumes that the series is trend stationary (Kwiatkowski, Phillips, Schmidt, & Shin, 1992), as opposed to the ADF test, which assumes that the series has a unit root. The KPSS is represented as:

$$X_t = \mu_t + \beta_0 D_t + v_t \quad (14)$$

$$\mu_t = \mu_{t-1} + \varepsilon_t \quad (15)$$

Where D_t includes a constant and a trend, v_t is a white noise disturbance, and μ_t represents a random walk component that depends on its first lag and on a further disturbance (ε_t) with a mean equal to zero. Therefore, the nonstationary feature in the series is captured by the μ_t term. More specifically, the test contrasts whether the variance (σ_ε^2) of the error term (ε_t) is equal to zero. If $\sigma_\varepsilon^2 = 0$, μ_t is a constant and the series is stationary, since the mean of ε_t is also zero (Barajas, 2017; Greene, 2012). The hypotheses of the KPSS test are:

$$H_0: \sigma_\varepsilon^2 = 0$$

$$H_1: \sigma_\varepsilon^2 > 0$$

The asymptotic results proposed by Kwiatkowski et al. (1992) are the basis for the critical values for these hypotheses.

In sum, time-series stationarity (i.e., the nonexistence of a unit root in the series) is a necessary condition for the outcomes of statistical and econometric analyses to be reliable. This study applies the Augmented Dickey-Fuller and KPSS tests since such approaches offer different perspectives to determine whether a time series is stationary.

Chapter 3: Context of the Research

3.1 Introduction

Between 2000 and 2018, the period covered in this research, there have been several important financial and economic events, both in Mexico and abroad. Two severe international stock market crashes struck during that period. The first of these crashes was the burst of the dot-com companies bubble in April 2000, and the second was the most acute financial and economic crisis since the Great Depression of the late 1920s: the global financial crisis, also known as the Great Recession, which took place between 2007 and 2009.

Section 3.2 describes such events in more detail, along with other international relevant events that occurred from 2000 to mid- 2018, such as the European sovereign debt crisis. Segment 3.3 reviews some of the most relevant aspects of the Mexican economy that took place during the same time interval. Finally, section 3.4 presents a brief historical revision of the Mexican stock market and a description of its current situation.

3.2 Major Financial and Economic Events: 2000 – 2018

The period of this study is from January 2000 to September 2018, as described in section 4.4. During that period, several important financial and economic events took place. These include the 2007 – 2009 global financial crisis, which is widely considered the most severe economic downturn since the Great Depression of the late 1920s⁴¹, as well as the European sovereign debt crisis, which began in the last quarter of 2009, just a few months after the global financial crisis was weakening.

⁴¹ While writing the final parts of this thesis, the unprecedented COVID-19 pandemic is taking place, which has made crash the stock markets around the world in extents not seen since the Great Depression, and with still uncertain economic effects. However, such an event is well beyond the temporal scope of this research.

3.2.1 The U.S. Stock Market Boom and Burst 1991 – 2001

Between April 1991 and March 2000, the NASDAQ composite index rose from less than 500 points to almost 4,600, an average annual growth of 28%. The S&P 500 and the DJIA indices also reached record highs during that period. These impressive returns of the stock market indices in the U.S., especially those of the NASDAQ, were triggered by the introduction of technology companies in such an index during the 1990s. These technology firms included the so-called dot-com companies, as well as other so-called New Economy firms from the biotechnology, electronics, and telecommunications sectors (Eiteman, Stonehill, & Moffett, 2013; Elizondo, 2015; Markham, 2006).

The roaring stock market prices, and particularly the boom of Internet companies stock prices, along with several cases of extensive financial abuse and fraud, caused worries that a market bubble was developing. Nobel laureate economist Robert Shiller warned that the stock market bubble presaged an economic catastrophe (Markham, 2006). Also, Alan Greenspan, chairman of the Federal Reserve Board at that time, suggested that the market will crash, while famously stated that the market was in a condition of “irrational exuberance” (Greenspan, 1996, p. 8). Later, Greenspan helped the prophecy to self-fulfill by increasing interest rates.

A decade long bull market ended when the NASDAQ Index plummeted 25% between April 3 and 14, 2000, and experienced severe volatility during the following months. The S&P 500 and DJIA indices also dropped 10% and 8%, respectively, during that period. These indices did not fall as much, however, because their components were mainly so-called brick and mortar companies, that is, traditional economy firms. According to Markham (2006), before the dot-com crisis, there were around 5,000 companies in the NASDAQ. Only 3,800 firms survived after the market crashed, while the total capitalization of that market decreased by 70%.

The following year, the devastating terrorist attacks on September 11, 2001, targeted the financial and military power symbols of the United States, striking the World Trade Center and the Pentagon. The American Stock Exchange (AMEX) closed for two weeks.

Furthermore, for only the third time in history, the NYSE closed from September 11 to September 17. After trading resumed, the DJIA experienced its largest weekly percentage loss since May 1940 and its all-time highest weekly decline in dollar terms. Despite the market subsequently upturned in a matter of weeks, by the end of 2001, the DJIA had fallen for two successive years (Markham, 2006).

A sequel of the burst of the dot-com bubble and the terrorist attacks in the U.S. financial markets was that capital flowed toward the real estate sector, and banks soon discovered that mortgage lending, a business activity that was rapidly growing, was also very profitable (Eiteman et al., 2013).

3.2.2 The Argentine Crisis of 2002

In 1991 Argentina moved from a managed exchange rate system of the Argentine peso to a currency board scheme. Under the currency board, the exchange rate was fixed on one Argentine peso per U.S. dollar. The Argentine economy reacted immediately: GDP average growth was over 8% per year between 1990 and 1994, and annual inflation rates plunged from 5,000% in 1989 to slightly more than 4% five years later (Santillán-Salgado, Dieck Assad, & Fonseca Ramírez, 2015).

A further characteristic of the currency board structure in Argentina was the possibility that all citizens and foreigners could hold Eurodollar accounts in local banks. However, Argentine banks normally paid slightly lower interest rates on dollar-denominated accounts than on peso-denominated accounts, even from the onset of the currency board arrangement. This interest rate premium on peso-denominated accounts reflected the market uncertainties on the reliability of the fixed exchange rate system (Eiteman et al., 2013).

The market was finally proven right. In January 2002, a ten year long try out with a strictly fixed exchange rate in Argentina finished. The Argentine currency board came to an end after almost three years of recession and several months of social, political, and economic turbulence. The exchange rate first devalued 40%, from 1.00 to 1.40 Argentine pesos per U.S. dollar, but one month later, the peso was allowed to float freely. The consequences of

the Argentine crisis were devastating for that nation. During 2002 GDP dropped 16%, the unemployment rate reached 24%, and public debt increased to 129% of GDP (Eiteman et al., 2013; Santillán-Salgado, Dieck Assad, et al., 2015).

Ahmed, Coulibaly, & Zlate (2017), though, claim that the Argentine peso's crisis was mostly a locally confined episode that did not have substantial effects on other economies, not even on emerging countries, as demonstrated by the performance of several indicators, including the major stock market indices of such countries. Moreover, according to Lagunes (2009) and Lagunes & Watkins (2009), these effects were limited as a result of investors' appropriate anticipation of the Argentine financial crisis.

3.2.3 The Global Financial Crisis 2007 – 2009: The Great Recession

After the dot-com crisis in 2000 and the terrorist attacks in 2001, investment and speculation in the real estate market rose rapidly in the United States. Low-interest rates and economic growth contributed to the escalation in housing demand, which, in turn, promoted an increase in average home prices of around 42% between 2000 and 2006 (Santillán-Salgado, 2015b).

An important innovation in the housing credit market was the development of mortgage-related securities, such as mortgage-backed securities (MBS) and collateralized debt obligations (CDOs), that allowed mortgage originators to sell the loans to investors swiftly. Thus, growing home prices and the agency problem created by mortgage-related securities encouraged brokers and banks to increase the number of mortgages to very low credit quality borrowers. These mortgage agreements, known as subprime debt, involved low-income borrowers who acquired higher debt service obligations. Subprime debt, in turn, is closely related to the origins of the global financial crisis (Eiteman et al., 2013; Mishkin & Eakins, 2015; Santillán-Salgado, 2015b).

3.2.3.1 Financial Deregulation in the United States

A financial crisis can frequently be traced back to the lessening or removal of restrictions imposed on financial markets and institutions. Financial crises are also associated with the introduction of new kinds of financial products, that in the short-run, can promote a credit

boom by encouraging financial institutions to assume excessive risks from their lending activities (Mishkin & Eakins, 2015).

The Glass-Steagall Act of 1933, legislation that imposed severe barriers between investment and commercial banks, was the response of the U.S. government to the 1929 bank crisis during the Great Depression. As part of a series of financial regulation changes that began in the late 1960s, the approval of the Gramm-Leach-Bliley Financial Services Modernization Act by the U.S. Congress in 1999 canceled the last remnants of the Glass-Steagall Act (Santillán-Salgado, 2015b). This new legislation allowed commercial banks to assume more risks, including proprietary and underwriting dealing, and to participate in all kinds of loans. An outcome of the new legislation was that banks started to originate creative mortgage loans with attractively low-interest rates, at least during the first few years of these loans (Eiteman et al., 2013).

Another effect of financial deregulation in the United States was the increase in subprime lending. More specifically, subprime lending involves borrowers who have a greater default risk, which usually results from some credit record elements such as loan delinquency, default, bankruptcy, or just limited debt history. Most of these loans are entirely floating-rate structures and carry significantly higher interest rate spreads over floating rates.

The considerable growth of subprime loans in the United States resulted from legislative changes such as the one introduced by the Tax Reform Act of 1986. This legislation allowed tax deductibility on interest expenses related to a primary residence, as well as those on a second mortgage loan. The increasing demand for mortgages and other credits by subprime borrowers encouraged originators to offer credits at higher interest rates. By 2006 subprime mortgages were around 12.5% of all mortgage obligations, and this figure increased to 14% by 2007, even when subprime loans should have been no more than 8% of the mortgage obligations total (Eiteman et al., 2013; Santillán-Salgado, 2015b).

3.2.3.2 A Brief Chronology of the Subprime Crisis

The housing market crisis began in April 2007, when New Century Financial Corporation (NCFC), a real estate investment trust which specialized in subprime mortgages, filed for bankruptcy (Santillán-Salgado, 2015b). The U.S. housing market began to plummet, followed by its counterparts in the United Kingdom and many other countries. What happened over the next two years was a globally extended chain reaction of failing loans and plunging security prices, along with the collapse of investment funds and other institutions that held these financial assets as part of their portfolios.

Another crucial milestone of the mortgage crisis took place on July 31, 2007, when Bear Stearns, an investment bank that held a variety of CDOs and other mortgage-backed assets, had to immobilize its clients' resources in one of its hedge funds. Bear Stearns also announced the liquidation of two hedge funds related to mortgage-backed instruments, which had lost almost all of their value (Federal Reserve Bank of St. Louis, 2009).

Moreover, a few weeks later, the U.S. financial crisis spun towards the global economy. On September 14, the Bank of England announced that it would grant financial support to Northern Rock, a major British mortgage originator bank that experienced a bank run. Financial institutions from Germany, Switzerland, and other countries were also experiencing difficulties at that time (Eiteman et al., 2013).

During 2008 the crisis deepened. In the first semester that year, U.S. financial institutions, such as Merrill Lynch and the Carlyle Group, experienced the negative consequences of subprime mortgage failures on their operations, while similar events were taking place in Japan and other countries. In the meantime, the prices of crude oil and other commodities reached record high levels. On September 7, 2008, the U.S. government announced the protection of the Federal National Mortgage Association (Fannie Mae) and the Federal Home Loan Mortgage Corporation (Freddie Mac), meaning that the federal government was taking over and financially rescuing these institutions (Eiteman et al., 2013; Santillán-Salgado, 2015b).

Perhaps the most significant landmark of the mortgage crisis occurred one week after the U.S. government financially rescued Fannie Mae and Freddie Mac. On September 15, Lehman Brothers, with assets of 600 billion dollars, filed for bankruptcy, which turned out to be the largest bankruptcy in the history of the United States. The markets reacted immediately, and on that date, the DJIA and S&P 500 indices lost 4.4% and 4.7%, respectively. At the same time, the U.S. government announced that there would be no more Wall Street bailouts. Even so, American International Group (AIG), which had a large credit default swap (CDS) exposure, received an 85 billion dollars two-year loan from the U.S. Federal Reserve on September 16 in exchange for 80% equity ownership (Eiteman et al., 2013; Federal Reserve Bank of St. Louis, 2009; Mishkin & Eakins, 2015; Santillán-Salgado, 2015b).

The mortgage credit crisis had fully blasted during the autumn of 2008, but it deepened by the spring of 2009 when all kinds of lending around the world were close to a full stop. Moreover, mortgages with a risk level between prime and subprime loans, known as Alt-A mortgages, reached record failure levels, even higher than subprime loans, and at that point, analysts expected that at least 25% of all these credits would default (Eiteman et al., 2013).

3.2.3.3 The Financial Crisis Goes Global

The literature widely agrees that the failure of Lehman Brothers in September 2008 triggered the globalization of the U.S. financial crisis (Elizondo, 2015; Ortiz Bolaños, Hernández Henao, & Quintanilla Dieck, 2015; Prakash & Koehler-Geib, 2009). The financial shock of April 2007 was limited to a relatively small group of developed countries, but by the autumn of 2008 numerous developed and emerging countries faced considerable strain on their sovereign debt, foreign exchange, and stock markets, as reflected by the corresponding indices for industrialized and emerging market economies (EMEs) (Danninger, Balakrishnan, Elekdag, & Tytell, 2009).

As in the case of the United States, the credit crisis had even more complicated effects in many countries by the beginning of 2009. Financial markets and institutions weakened in many developed economies, and in these nations, pressure intensified to focus on local needs

and not on foreign ones. According to Eiteman et al. (2013), “the financial press categorized the credit dynamics as homeward flow” (p. 134), and in many developed countries, governments announced several local bailout programs.

3.2.3.4 Effects of the Global Financial Crisis in Emerging Market Economies

At least in part due to trade linkages with developed nations, production levels in EMEs exhibited a significant decline during the crisis. Moreover, the consequences on financial markets were a major drop in private credit and asset prices, the depreciation of the exchange rate, and an increase in risk premia. The worldwide reduction of leverage and homeward flow of capital were closely related to all of these events (Binici, 2015).

To offset the adverse effects of the global crisis, EMEs took various measures expected to calm the financial markets and revitalize the real economy. These measures included several changes in monetary and fiscal policies. As the crisis took hold within the EMEs and liquidity problems developed, central banks started to reduce interest rates, decrease reserve requirements, accept a broader range of collaterals, ease credit, and intervene more actively in the foreign exchange market.

Even though all EMEs faced economic and financial difficulties as a result of the mortgage crisis, there were substantial differences across countries and regions, and Latin American economies were comparatively resilient to the episode. Izquierdo & Talavi (2010) claim that the relative strength exhibited by these economies was the result of their robust economic fundamentals, such as a flexible exchange rate regime combined with a large stock of international reserves, a sound banking system, low inflation rates, and fiscal surpluses.

3.2.3.5 The Great Recession and the Mexican Stock Market

Between April 2007 and April 2008, the leading Mexican Stock Exchange index, the IPC, increased 10%. So, according to Prakash & Koehler-Geib (2009), the events that started the credit crisis had a limited impact on the stock market in Mexico, as was the case for other EMEs. Eventually, however, the IPC started to drop, and from May to August 2008, the market plummeted 22%, and after the collapse of Lehman Brothers in September that year,

the index declined an additional 18%. Eventually, the Mexican market plunged more than 44% between May 2008 and January 2009, when it finally began to recover.

Mexico's real GDP grew by only 1.1% in 2008 and fell by 5.3% in 2009⁴². These results contributed to intensifying the sluggish economic growth the country had experienced in previous years. Even so, the global financial crisis had relatively lesser effects in Mexico as compared to other countries (Ortiz Bolaños et al., 2015).

Elizondo (2015) argues that three factors contributed to lessening the impact of the crisis. First, as opposed to the banking systems of the U.S. and other developed countries, the Mexican banking system was financially sound, and it did not rely on mortgage-backed or other toxic assets. Second, the monetary and fiscal policy responses by the Mexican authorities were appropriate and timely. Third, the exchange rate was correctly allowed to automatically adjust, as a consequence of the managed float policy in place, and Mexico's central bank (Banxico) firmly intervened in foreign exchange market operations when necessary to maintain an orderly market.

In summary, the U.S. mortgage debt crisis that started in the spring of 2007, burst and spread during the autumn of 2008, and prolonged into the autumn of 2009, has been widely acknowledged as unparalleled since the Great Depression of the late 1920s. This financial crisis, also known as the Great Recession, produced very negative social, economic, and financial consequences around the globe. Citing Ben Bernanke, former president of the U.S. Federal Reserve, "... 'as a scholar of the Great Depression, I honestly believe that September and October of 2008 was the worst financial crisis in global history'..." (Russo & Katzel, 2011, p. 11). However, as compared to its effects on industrialized economies, the consequences of the crisis in Mexico and other EMEs were relatively less severe, due to the existing strength of economic fundamentals of such countries, the robustness of their banking

⁴² These figures were computed using data obtained from INEGI, and considering 2013 as the base year (<https://www.inegi.org.mx/temas/pib/default.html#Tabulados>).

systems, and the appropriate and timely economic policy changes implemented by their governments.

3.2.4 The European Sovereign Debt Crisis 2009 – 2012

The European sovereign debt crisis began just when the Great Recession had started to fade. The crisis in the Eurozone has been considered as a carry-over of the mortgage debt crisis (Eiteman et al., 2013), a psychological contagion resulting from the expectations effect, as well as the result that a large number of financial institutions of the European Union (EU) had heavily invested in mortgage-related instruments in the United States (Santillán-Salgado, Fonseca Ramírez, & Ortiz Arango, 2015).

As a response to the effects of the Great Recession, many central banks around the world, including the European central bank (ECB), established unprecedented low-interest rates and, at the same time, banks in several developed economies severely diminished lending, decelerating all types of business activities. The result was an economic recession. Some EU countries, with growing debt levels, now faced slowing economic activity, diminished tax revenues, growing fiscal deficits, and increasing debt burdens.

The highest quality debt in any nation is sovereign debt, that is, local currency-denominated debt issued by the country's government, since, unlike any other economic agent, the government has the faculty to print money or levy additional taxes to service its debt. With the adoption of the euro as a common currency, however, EU member countries gave up the possibility to print money and, even though those nations maintain a certain degree of freedom on their economic policies, they have to keep their fiscal deficit within specific limits. Nevertheless, by 2009, three members of the Eurozone had incurred large fiscal deficits: Greece, Ireland, and Portugal. These countries were confronting substantial sovereign debt problems, with Greece representing the most challenging case (Eiteman et al., 2013).

3.2.4.1 Greece and Public Deficit

A new socialist government took office in Greece in October 2009 and made known that the country's finances were considerably worse than the previous administration had reported. The country's deficit was between 12.7% and 15.4% of GDP, at least four times the limit established by the EU, while Greece's debt was 298.5 billion euros. Specialists immediately questioned whether Greece would be capable of servicing its massive debt, and rating agencies rapidly downgraded Greek bonds (Nelson, Belkin, & Mix, 2010).

A factor that contributed to reducing investors' confidence was that the recently appointed Greek Prime Minister acknowledged that officials of the preceding government made-up fiscal information and tried to conceal the actual level of Greece's sovereign debt through complex financial instruments. Before the crisis, Greek 10-year bonds yields used to be between 10 to 40 basis points above their German counterparts. However, as the crisis developed and investors' certainty on the Greek government and the country's economy severely diminished, this spread raised to a historically high 400 basis points by January 2010 (Nelson et al., 2010).

On May 2, 2010, the EU and the International Monetary Fund (IMF), granted Greece 110 billion euros bailout credits which narrowly allowed the Greek government to pay its debt service obligations due less than three weeks later. In exchange, the government pledged to reduce its budget deficit to less than 3% of GDP by 2014. Still, to face further financial problems that developed during 2010 and 2011, the Greek authorities agreed to receive a second EU – IMF bailout on February 12, 2012. Greece received 130 billion euros more, but the government promised to reduce the country's debt-to-GDP ratio from 160% to 120.5% by 2020 (Council on Foreign Relations, 2019; Eiteman et al., 2013; Santillán-Salgado, Fonseca Ramírez, et al., 2015).

3.2.4.2 Ireland and the Mortgage Crisis

Ireland's financial and economic conditions differed from Greece's, despite they both had a large amount of sovereign debt by 2008. Ireland crisis had features similar to the U.S. credit crisis. Following many years of continuous economic growth, accompanied by financial

deregulation, Ireland was the first EU economy that suffered the effects of the U.S. subprime crisis, experiencing a short recession in 2007, followed by another two-year-long recession episode between 2008 and 2009, and undergoing immense losses when the bubble of the Irish real state sector burst.

By the end of 2008, the Irish banking system was at risk, with banks suffering capital flight and confidence failures. The country's largest banks had incurred vast mortgage-related losses, so the government had no alternative but to provide bailout funds to prevent the breakdown of the financial sector. While financial stress for Irish banks momentarily lessened in May 2010 as a result of the Greek bailout, problems resumed and deepened during the second half of 2010. The United Kingdom, Sweden, Denmark, the EU, and the IMF put forward an elaborate scheme, and the Irish government received an 85 billion euros bailout in November 2010 (Eiteman et al., 2013; Santillán-Salgado, Fonseca Ramírez, et al., 2015).

3.2.4.3 Portugal and the Misallocation of Capital

Between 2000 and 2012, the rate of economic growth in Portugal was below that of the U.S. economy during the Great Depression. Reis (2013) claims that the sources of this sluggish economic growth were Portugal's low average educational achievement, the country's low productivity level, a large increase in government size and spending, labor market rigidity, an inefficient legal system, and the lack of productive competitiveness due to the concentration of Portugal's economic activity in low-value-added goods and low-wage labor market. These factors were also the background of Portugal's financial crisis in 2009 – 2010.

Starting in 2000, Portuguese debt to GDP ratio increased around 2.4% per year on average, reaching a level of more than 68% by 2007, with state-owned companies acquiring a large portion of such debt (Eiteman et al., 2013). During that period, Portugal received considerable capital inflows, but such resources were largely misallocated (Reis, 2013).

In 2009, Portugal's debt burden was close to 84% of GDP, and by the second quarter of 2010, as the Eurozone debt crisis escalated, credit rating agencies downgraded Portuguese sovereign debt, weakening investors' confidence in the country's economic and financial

conditions. On April 7, 2011, following Greece and Ireland, Portugal became the third EU member to apply for financial assistance to prevent default on its sovereign debt obligations. One month later, the EU and the IMF approved a 78 billion euros bailout plan for Portugal (Eiteman et al., 2013; Santillán-Salgado, Fonseca Ramírez, et al., 2015).

After three years of financial and economic difficulties, the Eurozone crisis was finally over by the end of 2012. Restored economic growth in Europe enabled governments to start tapering their budget deficits, which contributed to investors recovering confidence in the Eurozone troubled countries' sovereign debt sustainability (Eichengreen & Wyplosz, 2016).

A study carried out by Cabello, Moncarz, & Ortiz (2015) concluded that because of the important financial and economic ties between European and Latin American countries, these were not immune to the perhaps adverse effects of a recession in the Eurozone rising from the sovereign debt problems. Also, Ahmed et al. (2017) found that economic fundamentals have been increasingly important in describing variations in financial stress across EMEs during recent financial crisis episodes and that the Eurozone sovereign debt crisis influenced such emerging economies differently, depending on the strength of their economic fundamentals.

3.3 The Mexican Economy in the Twenty-First Century

The year 2000 witnessed the last eleven months of Ernesto Zedillo's presidential tenure in Mexico. Six years earlier, in December 1994, Zedillo had started his administration with the burst of an acute economic crisis his government inherited from the previous administration. This event, known as the Tequila Crisis, was so profound that it produced international consequences through a contagion effect, and it was the first financial contagion episode that had its origins in an emerging country. In around five weeks, from December 20, 1994, to January 30, 1995, the Mexican peso depreciated 65% to the U.S. dollar. The plummeting effects of the Mexican currency rapidly spread to other EMEs in Latin America, Eastern Europe, and Southeast Asia (Eiteman et al., 2013; Lagunes, 2009; Santillán-Salgado, Dieck Assad, et al., 2015).

In July 2000, Vicente Fox was elected Mexico's new president and took office five months later. Pastor & Wise (2005) argue that at the time Fox assumed power, Mexico immediately required an increase in its productivity and competitiveness and a microeconomic restructuring, focusing on the country's profound income disparities. Even so, all over Fox's tenure from 2000 to 2006, economic reforms stalled. Although during that period the exchange rate of the Mexican peso to the U.S. dollar was reasonably stable, with the peso depreciating an average of only 2.5% per year against the U.S. currency, Mexico's GDP scarcely grew around 1.9% annually on average. In contrast, the IPC average return was 28.5% per year between 2000 and 2006.

A controversial general election took place in July 2006, and, after two months of political disputes and turbulence, Felipe Calderón was declared president-elect by the Electoral Court. It was during Calderón's tenure that the Great Recession and the Eurozone debt crisis occurred and, while Mexico's economy performed relatively well as compared to other EMEs and most developed countries during these crises, the country's economic structure did not improve between 2006 and 2012. Throughout Calderon's presidential tenure little was achieved to define an industrial policy, or to design and introduce economic structural reforms. From 2006 to 2012, average GDP growth was a modest 1.7% per year. However, in the second half of Calderon's administration, between 2009 and 2012, GDP average growth was 4.1% per year, due to the upturn after the subprime debt crisis of consumer spending on durable goods that Mexico exported to the United States, and a competitive Mexican peso exchange rate to the U.S. dollar (Rozental, 2012). In the 2006 – 2012 period, the IPC annual average return was 8.8%, but this figure includes the declines in the Mexican stock market linked to the global financial crisis and the Eurozone's sovereign debt episodes.

In July 2012, Enrique Peña was elected president and, after a twelve-year break during Fox and Calderón's administrations, the Institutional Revolutionary Party (PRI) took back the political power such party maintained in Mexico during most of the twentieth century. Peña proposed a series of structural reforms that were passed by the Mexican Congress between 2012 and 2014. Such reforms involved several strategic aspects such as the labor market,

education, economic competitiveness, and fiscal policy, and also encompassed the financial, telecommunications, and energy sectors (Valenzuela, 2016). According to Peña's government officials, these structural reforms were capable of producing an average annual GDP growth of at least 5% (Saldaña, 2018). Nevertheless, from 2012 to 2018, GDP average annual growth was only 2.4%. In that period, the Mexican peso depreciated an average of 7.9% per year to the U.S. dollar and, despite the bullish stock market in the U.S., the IPC annual average return was close to zero, due to internal and external economic concerns, as well as to political uncertainty (Imagen Radio, 2018).

In July 2018, in his third attempt to win the presidency, Andrés M. López obtained a landslide difference in the general elections. Even before López formally took office on December 1 that year, he announced several measures his government would implement as soon as he began his tenure. On October, 29 the forthcoming government made one of its most important announcements: it had decided to stop the construction of a 13-billion-dollar new airport in Mexico City, a project that started two years earlier (Harrup, 2018). Financial markets immediately reacted to this statement, and the IPC plunged 4.2% on that day, while the Mexican peso depreciated 3.5% against the U.S. dollar.

This section depicted a summary of some of the most important economic and financial events in Mexico from 2000 to mid- 2018, which corresponds to the period covered by this research. The recapitulation of these events followed the timeline of the corresponding Mexican presidents' tenure periods.

3.4 The Stock Market in Mexico

This section presents a brief history of the stock market in Mexico and then reviews some of the most relevant aspects of the current circumstances that prevail in that Mexican market.

3.4.1 History of the Mexican Stock Market

The first stock trading operations in Mexico date back to the 1850s. Over 40 years later, on October 31, 1894, a group of stockbrokers founded a formally organized stock exchange, and

the next year, on June 14, 1895, another group of brokers created a second stock market called Bolsa de México (Mexico Stock Exchange). These two groups of brokers joined in September 1895 and decided to maintain the name Bolsa de México to create a new stock exchange in Mexico City.

Two other stock exchanges were created in Mexico in the 1950s. The Monterrey Stock Exchange was established in 1950 in the northern industrial city of Monterrey, while the Occident Stock Exchange was founded in Guadalajara City in 1956. However in 1975, the three existing stock exchanges in Mexico merged, and the name Bolsa de México (Mexico Stock Exchange) changed to its current name: Bolsa Mexicana de Valores (Mexican Stock Exchange) or BMV (BMV Group, 2015; Pérez Rojas & Ramírez Galindo, 2009). The broadest and most important index of the BMV, the Price and Quotations Index (IPC), was first published on October 30, 1978 (Sánchez, 2018).

In 2001, the Mexican congress passed a reform to the Stock Market Law, which included the demutualization of the stock market. This new legislation implied that the BMV was allowed to become a widely held company, and its stocks could trade in the market. Seven years later, on June 13, 2008, the BMV accomplished an initial public offering of its equity shares (BMV Group, 2015; Gutiérrez, 2015).

Also, on July 25, 2018, a new stock exchange, Bolsa Institucional de Valores (Institutional Stock Exchange) or BIVA, started operations in Mexico. This new exchange is said to offer a more advanced trading technology than the BMV. BIVA's general index, known as the FTSE BIVA, was designed in collaboration with FTSE Russell, a London Stock Exchange Group company (FTSE Russell, 2019).

3.4.2 The Mexican Stock Exchange Today

Since the main focus of this research is on four of the Mexican Stock Exchange stock indices, as described in section 4.4, it is appropriate to review some relevant aspects of the stock market in Mexico. As of September 2018, the BMV, with a total market capitalization of over 474 billion dollars, was the second-largest stock exchange in Latin America only after

the São Paulo Stock Exchange (BOVESPA) in Brazil, and it was the twentieth largest in the world by the end of that year (Knoema, 2018; Stock Market Clock, 2019). Mexico's stock market capitalization to GDP ratio was 33.5% as of December 2018, although the corresponding figure one year earlier was close to 39% (Banco de México, 2019).

The Mexican Stock Exchange is a public organization that operates observing the Stock Market Law and under a concession conferred by the Ministry of Finance. Considering this legal framework, the BMV performs several functions, such as providing the means and facilities to support securities supply and demand activities, and supervising that the operations carried out at the exchange follow the pertinent regulations. The Mexican Stock Exchange also releases guidelines that set up standards, as well as operational and conduct directives, to promote fair market practices, disclosing the pertinent information of the securities listed in the market and continuously providing access to such information to the general public.

In summary, the Mexican stock market can be traced back around 160 years, to the mid-nineteenth century. During that period, a considerable number of important political, economic, and financial events have taken place, both locally and abroad, which have influenced the Mexican stock market. Presently, there are two stock exchanges in Mexico, the recently founded Institutional Stock Exchange (BIVA) and the Mexican Stock Exchange (BMV). The main focus of this research is on four of the indices published by the latter.

Chapter 4: Research Methodology

4.1 Introduction

This chapter describes the methodological aspects of the research presented in this document. Section 4.2 discusses the features of the research. Segment 4.3 puts forward the research questions and hypotheses of construct developed from the literature review. Section 4.4 describes the data examined and provides a framework of the indices and the periods and subperiods considered. Finally, part 4.5 presents, explains and justifies the different methods of analysis used in the research.

4.2 Characteristics of the Research

In this research, the performance of daily and monthly historical returns of four indices of the Mexican stock market is observed and measured concerning six seasonal or calendar patterns that have been identified in the stock markets of several countries, as reported in the literature.

Thus, according to the taxonomy proposed by Kothari (2004) and Saunders, Lewis, & Thornhill (2009), this is a quantitative, longitudinal, non-experimental research, that correlates certain times of the week, month, or season of the year with the predictable performance of the returns of four Mexican Stock Exchange's indices.

4.3 Research Questions

Taking into consideration the mixed results, as well as the relatively scarce research carried out in the Mexican stock market on the day-of-the-week, holiday, turn-of-the-month, and January effects, as well as on the Halloween indicator and the January barometer, some questions arise that are worth researching:

- Did any of these six calendar anomalies exist in the Mexican stock exchange during the time intervals under examination? If so, to what extent?

- Do seasonal effects tend to fade, remain, or increase over time in the stock market in Mexico?
- Considering the answers to the previous questions, is there evidence against the Efficient Markets Hypothesis in the Mexican stock market?

4.3.1 Hypotheses of Construct

The review of the literature and the research questions led to the following hypotheses of construct for this research:

H_{1A}: Average stock returns are not the same across different days of the week in the Mexican Stock Exchange.

H_{1B}: There are dissimilarities in the volatility of stock returns across different days of the week in the Mexican stock market.

H_{1C}: The inequalities in average stock returns across different days of the week are fading in the stock market in Mexico.

H_{1D}: The differences in volatility across different days of the week are vanishing in the Mexican Stock Exchange.

H_{2A}: Average returns on trading days before and after holidays are not the same as those on other days in the Mexican stock market.

H_{2B}: In the Mexican stock market, there are differences in volatility on the days before and after holidays and the volatility on other days.

H_{2C}: The differences in average stock returns on the days before and after holidays and other days have faded away in the Mexican Stock Exchange.

H_{2D}: The disparities in volatility on the days before and after holidays and other days have disappeared in the BMV.

H_{3A}: Average stock returns on the days around the turn of the month and those on the remaining days of the month, are different in the stock market in Mexico.

H_{3B}: Volatility of stock returns on the days around the turn of the month is not the same as volatility on the remaining days of the month in the Mexican stock market.

H3C: The inequalities in average returns on the days around the turn of the month and those on other days have vanished in the Mexican Stock Exchange.

H3D: The differences in volatility on the days around the turn of the month and those on other days have disappeared in the Mexican stock market.

H4A: Average stock returns in January are higher than those on other months in the stock market in Mexico.

H4B: In the Mexican stock market, the volatility of stock returns in January is higher than that of other months.

H4C: Dissimilarities in average returns in January and those of other months have disappeared in the Mexican Stock Exchange.

H4D: Differences in volatility in January and those of other months have faded away in the stock market in Mexico.

H5A: Average stock returns are higher from November to April than from May to October in the Mexican Stock Exchange.

H5B: Volatility of stock returns from November to April is higher than that from May to October in the stock market in Mexico.

H5C: Divergences in average returns from November to April and average returns from May to October have faded away in the Mexican stock market.

H5D: Differences in November to April volatility and May to October volatility have disappeared in the Mexican stock market.

H6A: There is a direct relationship between the performance of stock returns in January, and the stock returns performance of the following eleven months in the Mexican stock market.

H6B: The direct relationship between stock returns in January and those of the remaining months of the year is disappearing in the Mexican stock market.

4.4 Data

This research considers the performance of the Mexican stock market through the Price and Quotation Index (S&P/BMV IPC) of the Mexican Stock Exchange, as well as the large-capitalization (S&P/BMV IPC LargeCap), medium-capitalization (S&P/BMV IPC MidCap) and small-capitalization (S&P/BMV IPC SmallCap) stock indices. As section 4.5.1 discusses in more detail, this study used a daily continuous return frequency to examine the day-of-the-week, holiday, and turn-of-the-month effects. Also, the study employed a monthly return frequency for the January, Halloween, and January barometer anomalies. The sample period under analysis included the continuous returns from January 3, 2000, to September 28, 2018, for the IPC, and from October 26, 2006, to September 28, 2018, for the LargeCap, MidCap, and SmallCap indices⁴³.

The data of the daily and monthly closing prices of the stock indices came from the Bloomberg and Economatica databases. The return series of the one-month Federation Treasury Certificates (CETES), used to compute the excess returns of the indices, were downloaded from the online database published by Banxico, Mexico's central bank.

4.4.1 The Price and Quotation Index

The population of the Price and Quotation Index, or IPC for short, are all stocks listed on the Mexican Stock Exchange and traded in the equity market, except mortgage trusts and Real Estate Investment Trusts (FIBRAS, its acronym in Spanish). However, the index includes only those stocks that satisfy the criteria about trading history, volume-weighted average price float-adjusted market capitalization, and investable weight factor. The composition of the IPC, which comprises a total of 35 stocks, is re-formed two times per year, applicable after the market close on the third Friday of March and September (S&P Dow Jones Indices, 2018).

⁴³ The publication of the three indexes by capitalization began as of October 16, 2006.

4.4.2 The IPC LargeCap, IPC MidCap, and IPC SmallCap Indices

The index population includes all stocks in the S&P/BMV IPC CompMX Index⁴⁴. When a company has more than one share class, the most liquid of them is chosen, based on the median traded value ratio over the previous 12 months. The division by size considers the cumulative market capitalization within the S&P/BMV IPC CompMx. The first step is to rank issuing companies by total market capitalization, and then float-adjusted market capitalization for each stock is summed up to 75% generating the S&P/BMV IPC LargeCap, the next 20% producing the S&P/BMV IPC MidCap, and the final 5% making up the S&P/BMV IPC SmallCap. Each index is rebalanced twice per year, applicable after the market close on the third Friday of June and December, and the respective rebalancing reference dates are the last day of April and October (S&P Dow Jones Indices, 2018). The IPC LargeCap and the IPC SmallCap include 17 stocks each, while the IPC MidCap comprises 22 stocks.

The literature has reported the presence of the turn-of-the-month effect on stock indices representing different market capitalization sizes (Maher & Parikh, 2013; McConnell & Xu, 2008), while the January effect is closely related to small company stocks (Keim, 1983; Roll, 1983). Thus, it is important to examine whether such findings are valid to these and other calendar anomalies in the stock market in Mexico, so the sample represented by the broad index and size-related indices of the Mexican Stock Exchange is useful for studying this issue.

4.4.3 Periods and Subperiods

Mishkin & Eakins (2015), Ortiz Bolaños et al. (2015), Russo & Katzel (2011), and Santillán-Salgado (2015b), among several other authors, have stressed the vast influence of the Great Recession on numerous social, economic, financial, and political aspects in many countries around the globe, as described in section 3.2.3. This event had considerable global

⁴⁴ This index is a broad benchmark for the Mexican stock market (S&P Dow Jones Indices, 2018).

consequences not only in financial markets but in production activity and employment, among many other variables.

As described in section 3.2.4, the European sovereign debt crisis, which almost immediately followed the Great Recession, began in the autumn of 2009, when the global financial crisis was fading. Such an event stretched out for three years, up to late 2012, and involved considerable economic and financial consequences, not only in the Eurozone but also internationally (Cabello et al., 2015; Eiteman et al., 2013; Elizondo, 2015).

Therefore, it is of research interest to identify the presence of the calendar anomalies before, during, and after these financial crises. To this end, previous studies have considered periods between 2003 and 2015 (Lloyd et al., 2017; Maher & Parikh, 2013). Nonetheless, this research examines a longer period to avoid spurious results due to a small sample size related to short subperiods (Andrade et al., 2013).

The study considered the daily returns of the IPC during a period of 18 years and 9 months to examine the day-of-the-week, holiday, and turn-of-the-month effects. Thus, it was possible to divide the full period in four subperiods: one before the financial crises, one during the Great Recession, another during the Eurozone sovereign debt crisis, and one more after these two crises. More precisely, these four subperiods are (1) from January 2000 to March 2007, (2) from April 2007 to September 2009, (3) from October 2009 to December 2012, and (4) from January 2013 to September 2018, respectively. The dates of these subperiods were determined based on the literature about the global financial crisis (Cabello et al., 2015; Dua & Tuteja, 2016; Eiteman et al., 2013; Elizondo, 2015; Russo & Katzel, 2012). Additionally, these subperiods are long enough to avoid the loss of the inference power of the statistical tests that were applied.

In contrast, because of the more limited number of observations, only two subperiods were considered for the January, Halloween, and January barometer effects: one before and one after the Great Recession. More specifically, the subperiods were from January 2000 to September 2009, and from October 2009 to September 2018, because these calendar

anomalies are based on monthly data and the number of observations is considerably less than in the case of daily-returns-based seasonal effects.

Similarly, since the number of observations of the capitalization size indices considered in this study is smaller than for the IPC due to the reasons explained at the beginning of this section, only two subperiods were considered for such indices: from October 2006 to September 2009 and from October 2009 to September 2018. The latter subperiod corresponds to the post- Great Recession interval. As in the case of the IPC analysis mentioned earlier, the selection of the post-crisis dates was based on the literature.

4.5 Methodology

In addition to using graphical representations and descriptive statistics as a starting point for data analysis, the analysis of the data considered OLS regression models with dummy variables when Engle's (1982) ARCH–Lagrange Multipliers (ARCH–LM) test did not reject the null hypothesis of constant variance of ε_t across time. However, in view of the extensive evidence that stock returns time series frequently exhibit volatility clustering as well as volatility asymmetry, when the ARCH–LM test revealed the presence of non-constant variance, the GARCH (p, q) model proposed by Bollerslev (1986) and Taylor (1986) was used to determine the conditional variance.

More specifically, the study used GARCH (1, 1) models as the basis for the econometric analysis. Besides the widespread use of such models in the financial time series analysis literature, there is also evidence that for certain financial time series these specifications are not outperformed by other more sophisticated ones (Hansen & Lunde, 2005). Moreover, according to Engle (2001), “the GARCH (1, 1) is the simplest and most robust of the family of volatility models” (p. 166). Similarly, TGARCH and EGARCH parameterizations were used in this research to examine the asymmetric volatility of the return series.

Section 4.5.1 presents the return calculation method. The rest of the chapter reviews and specifies the different statistical and econometric methods used in this research.

4.5.1 Returns Calculation

The random walk model represented by equation (1) can be applied to asset prices. More specifically, the dependent variable is the natural logarithm of the asset price, $\ln(P_t)$. Thus, the expression that denotes that the logarithm of the asset price follows a random walk can be written as:

$$\ln(P_t) = \alpha + \ln(P_{t-1}) + \varepsilon_t \quad (16)$$

Equation (16) implies that the return of an asset is related to the continuous random change in its price between a period (t) and the previous one ($t - 1$). Particularly, for the analysis of the return series of the Mexican stock market indices, this study used daily and monthly data to compute the logarithmic (i.e., continuous) returns of the four indices, depending on the seasonal anomaly under examination. The first-order difference of the logarithm of index prices in equation (16) is the logarithmic return on the index. That is:

$$r_t = \ln\left(\frac{P_t}{P_{t-1}}\right) = \alpha + \varepsilon_t \quad (17)$$

In other words, logarithmic returns are independent and identically distributed (i.i.d.) increments with a mean equal to α . Thus, equation (17) is equivalent to the difference of the price logarithms defined in equation (16):

$$r_t = \ln(P_t) - \ln(P_{t-1}) = \alpha + \varepsilon_t \quad (18)$$

In equation (18) r_t is the close-to-close continuous return corresponding to period t of the Mexican Stock Exchange index under analysis, P_t is the index closing price in period t , P_{t-1} is the index closing price the previous period, $t - 1$, α is a constant or intercept, and ε_t is the random error i.i.d. This computation considered daily or monthly periods, as appropriate, according to the calendar effect examined. Equations (17) and (18) denote that the average rate of return of the index is the same for any period t , and that it follows a random walk without drift.

4.5.2 Unit Root – Stationarity Tests

The analysis of each of the stock indices return series took into consideration both the ADF and KPSS tests to determine the presence of a unit root (i.e., non-stationarity). As described in section 2.7.9, the ADF test examines for the presence of a unit root, whereas the KPSS test assumes that the series is stationary, so the null hypotheses for each of these tests are specified accordingly.

The ADF test has a low power to reject H_0 when the series is close to a unit root (i.e., when the value of δ in equation (13) is close to zero), and when the series is trend-stationary (Barajas, 2017). The KPSS test tries to deal with these issues and, therefore, the corresponding analyses in this study used such a test as a stationarity robustness assessment.

4.5.3 Ordinary Least Squares Regression with Dummy Variables

To analyze the performance of the calendar anomalies examined in this research during the full period and the subperiods that were considered, the study used the following OLS regression model was used:

$$r_t = \alpha_0 + \sum_{i=1}^n \alpha_i D_{i,t} + \sum_{j=1}^p \eta_j r_{t-j} + \varepsilon_t \quad (19)$$

Where r_t is the continuous return from period $t - 1$ to period t , i goes from a value of 1 through n , where n is the number of periods in the year considering the data frequency corresponding to the calendar effect studied. $D_{i,t}$ is the dummy variable for period t that is equal to 1 if the time unit (day or month) corresponds to the moment in which the calendar effect is assumed to be present and zero otherwise. r_{t-j} relates to the p lags of the return necessary to circumvent autocorrelation. Section 4.5.4.2 further reviews the motives for the inclusion of these autoregression terms

The OLS regression with dummy variables method is widely used in the literature related to the analysis of calendar anomalies. However, the regression must include as many dummy variables as the number of time units corresponding to the calendar effect under study, less one (Caporale & Plastun, 2017; Lakonishok & Smidt, 1988; Urquhart & McGroarty, 2014; Vogelaar et al., 2014; Winkelried & Iberico, 2018). This procedure, known as dummy coding, is designed to avoid the dummy variable trap, in other words, perfect collinearity due to saturation in the regression (i.e., $\sum_{i=1}^n D_{i,t} = 1$). So, it is necessary to remove one dummy variable from each group of seasonal anomalies and allow the intercept to reflect its effects (Stock & Watson, 2011; Winkelried & Iberico, 2018; Wooldridge, 2014). This goal is achieved by selecting a calendar reference date (c') and setting $\alpha_{c'} = 0$. Upon recognizing this restriction, equation (19) becomes:

$$r_t = \alpha_0 + \sum_{i \neq c'}^n \alpha_i D_{i,t} + \sum_{j=1}^p \eta_j r_{t-j} + \varepsilon_t \quad (20)$$

Coefficient α_0 corresponds to the average return when $D_{i,t} = 0$, while coefficient α_i is the difference between α_0 and the return for each period $i = 1, 2, \dots, n$, and ε_t is the error term which is independent and identically distributed (i.i.d.). The error term is white noise, because its mean is zero ($E[\varepsilon_t] = 0$), its variance (i.e., the expected value of its squares) is constant ($Var[\varepsilon_t] = E[\varepsilon_t^2] = \sigma^2$), and the covariance between any pair of different observations is equal to zero ($Cov[\varepsilon_t, \varepsilon_s] = 0$) whenever $t \neq s$ (Barajas, 2017).

4.5.4 ARCH and GARCH Models

In this research, the OLS regression model was used to estimate equation (20) when the ARCH-LM test did not reject the null hypothesis of constant variance of ε_t over time. Because of the extensive evidence that financial time series variance clusters over time (Bekaert & Harvey, 2002; Rojo, 2013; Stock & Watson, 2011; Urquhart & McGroarty, 2016; Winkelried & Iberico, 2018; J. Zhang et al., 2017), when the ARCH-LM test suggested the presence of non-constant variance, a GARCH model, such as the one described by equation

(8), was used as the basis to determine the conditional variance of the error term (Caporale & Zakirova, 2017; Seif et al., 2017).

4.5.4.1 ARCH Testing Procedure

The analyses follow Brooks (2008) to determine whether the series have non-constant variance. The residuals (ε_t) corresponding to equation (20) were regressed on their p lags to test for the presence of an ARCH (p) process:

$$\varepsilon_t^2 = \lambda_0 + \sum_{i=1}^p \lambda_i \varepsilon_{t-i}^2 + v_t \quad (21)$$

Where v_t is a random error term, as usually defined. After computing the coefficient of determination (R^2), the test statistic was determined by multiplying the number of observations (T) by such a coefficient of determination, that is, $T \cdot R^2$, which follows a $\chi^2(p)$ probability distribution. The hypotheses to be tested are:

$$\begin{aligned} H_0: \lambda_1 &= \lambda_2 = \dots = \lambda_p \\ H_1: &\text{At least one } \lambda_i \text{ coefficient is different from the others} \end{aligned}$$

When the test fails to reject the null hypothesis, that is, when the value of the test statistic is lower than the critical value from the χ^2 distribution, there is not a significant ARCH process in the series.

4.5.4.2 GARCH Specifications with Dummy Variables

The GARCH (1, 1) model is extensively used in the literature related to the analysis of financial time series. Engle (2001) argues that such a model is the simpler and most robust of all volatility models and that it can be adapted and broadened in numerous ways. There is also evidence that, for some financial time series, the GARCH (1, 1) model is not outperformed by other more sophisticated models (Hansen & Lunde, 2005). Following Caporale & Zakirova (2017) and Kristjanpoller & Arenas (2015) and, more specifically, Auer (2014) and Kristjanpoller (2012a), the version of the ARMA – GARCH (i.e., AR(m) – GARCH (p, q)) specification used in this research is:

$$r_t = \psi_0 + \sum_{i=1}^m \phi_i r_{t-i} \quad (22)$$

$$r_t = \gamma_0 + \sum_{i \neq c'}^n \zeta_i D_{i,t} + \sum_{j=1}^p \eta_j r_{t-j} + \varepsilon_t \quad (23)$$

$$\sigma_t^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \beta_1 \sigma_{t-1}^2 + \sum_{i \neq c'}^n \delta_i D_{i,t} \quad (24)$$

In expression (23), which represents the mean equation of the GARCH (1, 1) model, r_{t-i} denotes the p lags of the return. The number of lags was initially established considering the results of the AR(p) model described by equation (22), and only those lags that turned out to be significant and that contributed to minimizing the Akaike information criterion (AIC) were considered in the final version of the model.

In equation (24) α_1 and β_1 represent the variance equation's coefficients for the lags of the error and the variance, respectively. Also, δ_i is the i -th period average variance of the BMV stock index under study, that is, such a coefficient captures the impact of the calendar effect in volatility, both in direction and size, in comparison to a certain calendar reference date (c') to avoiding the dummy variable trap.

4.5.4.3 EGARCH and TGARCH Models with Dummy Variables

EGARCH and TGARCH models can be revised to include exogenous variables, such as dummies, following an approach similar to the procedure described in section 4.5.4.2 for GARCH models (Begiazi & Asteriou, 2015; Cagli, Mandaci, & Kahyaoğlu, 2011; Malik,

2011). Equations (26) and (25), respectively, represent the TGARCH (1, 1) and EGARCH (1, 1) models used to examine asymmetrically clustered volatility⁴⁵:

$$\sigma^2 = \omega + \alpha_1 \varepsilon_{t-1}^2 + \gamma_1 \varepsilon_{t-1}^2 \bar{I}_{t-1} + \beta_1 \sigma_{t-1}^2 + \sum_{i \neq c'}^n \delta_i D_{i,t} \quad (25)$$

$$\log(\sigma_t^2) = \omega + \alpha_1 \left| \frac{\varepsilon_{t-1}}{\sigma_{t-1}} \right| + \gamma_1 \frac{\varepsilon_{t-1}}{\sigma_{t-1}} + \beta_1 \log(\sigma_{t-1}^2) + \sum_{i \neq c'}^n \delta_i D_{i,t} \quad (26)$$

Where α_1 , β_1 , and γ_1 are the EGARCH and TGARCH usual coefficients, as described in sections 2.7.8.4 and 2.7.8.5. In equation (25), $\bar{I}_{t-1}$ represents a dummy variable that takes the value of 1 when $\varepsilon_{t-1} < 0$ and zero otherwise, while δ_i denotes the impact of the seasonal effect in volatility as compared to a reference date.

In summary, considering the extensive evidence on the presence of volatility clustering in financial time series, GARCH models were used in this research, where appropriate, to examine volatility in the stock indices under analysis. Likewise, because of the evidence regarding asymmetries in returns volatility, EGARCH and TGARCH specifications were applied to analyze this feature of the series. Such models were also used to check for the robustness of that feature.

4.5.5 Calendar Effects Regressions

This section presents and explains the specific OLS regression models used for each of the calendar anomalies studied in this research. The basis for all of such regressions is the general model described in equation (20).

⁴⁵ The mean equation for the TGARCH and EGARCH models is determined in a similar way than the GARCH model mean equation.

4.5.5.1 Day-of-the-Week Regression Model

The regression model used for the day-of-the-week anomaly is:

$$r_t = \alpha_0 + \alpha_1 D_{1,t} + \alpha_2 D_{2,t} + \alpha_3 D_{3,t} + \alpha_4 D_{4,t} + \sum_{j=1}^p \eta_j r_{t-j} + \varepsilon_t \quad (27)$$

Where r_t is the index daily return at period t , α_0 is the intercept that captures the average Monday return. In other words, the reference date (c') for this model is Monday. Coefficients α_1 , α_2 , α_3 , and α_4 represent the differences between the average return on Monday and the average returns on Tuesday, Wednesday, Thursday, and Friday, respectively, $D_{i,t}$ is the dummy variable corresponding to the i -th day of the week from Tuesday ($i = 1$) to Friday ($i = 4$), and ε_t is the random error term.

4.5.5.2 Pre-Holiday and Post-Holiday Regression Model

Two additional dummy variables and their respective regressors are added to equation (27) to examine the pre-holiday and post-holiday effects in the Mexican stock market:

$$r_t = \alpha_0 + \alpha_1 D_{1,t} + \alpha_2 D_{2,t} + \alpha_3 D_{3,t} + \alpha_4 D_{4,t} + \alpha_5 D_{PRH,t} + \alpha_6 D_{POH,t} + \sum_{j=1}^p \eta_j r_{t-j} + \varepsilon_t \quad (28)$$

As the names of the additional dummy variables imply, $D_{PRH,t}$ is equal to one for the days before holidays in the Mexican Stock Exchange and zero otherwise, while $D_{POH,t}$ is equal to one for the days after holidays and zero otherwise. Table 1 displays the holidays observed in the Mexican Stock Exchange.

Holidays Calendar for the Mexican Stock Exchange	
New Year's Day	January 1st.
Constitution Day	First Monday of February
President Juarez's Birthday	Third Monday of March
Maundy Thursday and Good Friday	March or April
Labor Day	May 1st.
Mexican Independence Day	September 16th.
Day of the Death	November 2nd.
Revolution Day	Third Monday of November
Presidential Inauguration	December 1st.
Banking Day	December 12th.
Christmas Day	December 25th.

Table 1. Official Holiday Calendar of the BMV⁴⁶

Source: Own elaboration with data of the BMV.

4.5.5.3 Turn-of-the-Month Regression Model

For the analysis of the turn-of-the-month effect, different studies have used diverse day period specifications to define when the turn of the month occurs. Such period specifications have been anywhere from ten days before ($i = -10$) to ten days after ($i = +10$) the month changes (McConnell & Xu, 2008). However, the literature has frequently defined the period of the turn-of-the-month anomaly as the last trading day of a given month and the first three trading days of the following month (i.e., from $i = -1$ to $i = +3$) (Caporale & Plastun, 2017; Kristjanpoller & Arenas, 2015; Lakonishok & Smidt, 1988; McConnell & Xu, 2008).

⁴⁶ Before 2006 Constitution Day was celebrated on February 5, President Juarez's Birthday on March 21, and Revolution Day on November 20. Maundy Thursday and Good Friday can be, respectively, as early as the 19 and 20 of March, and as late as the 22 and 23 of April. Presidential inaugurations are observed once every six years. For the purposes of this research the Presidential Inauguration holidays were relevant in 2000, 2006, and 2012.

To test for the presence of the anomaly in the stock market in Mexico, in this research the turn of the month definition included the usual period from $i = -1$ to $i = +3$, and the period from $i = -4$ to $i = +4$, that is, from the last four trading days of a given month to the first four trading days of the following month. The first array of days has been widely used in the literature, and the second has been used in research studies related to the turn-of-the-month effect in the Mexican stock market with conflicting results (Duarte et al., 2013; Kristjanpoller & Arenas, 2015). Accordingly, the models used to examine this anomaly were model 1, as described by equation (29), and model 2, which is represented by equation (30):

$$r_t = \alpha_0 + \sum_{i=-1}^3 \alpha_i D_{i,t} + \sum_{j=1}^p \eta_j r_{t-j} + \varepsilon_t \quad (29)$$

$$r_t = \alpha_0 + \sum_{i=-4}^4 \alpha_i D_{i,t} + \sum_{j=1}^p \eta_j r_{t-j} + \varepsilon_t \quad (30)$$

In both models, r_t denotes the daily return of the index, α_i represents the difference between the average return of the days considered as part of the turn of the month interval and the daily average returns of the rest of the month, $D_{i,t}$ is a dummy variable for each of the trading days considered as part of the turn of the month in models 1 and 2, α_0 is the intercept that represents the daily average return of the rest of the month, and ε_t is the random disturbance.

4.5.5.4 January Effect Regression Model

The OLS regression model used to examine the January effect was similar to the specification used for the day-of-the-week, as described by equation (27). Specifically, the OLS specification used for the January effect was:

$$r_t = \alpha_0 + \sum_{i=1}^{11} \alpha_i D_{i,t} + \sum_{j=1}^p \eta_j r_{t-j} + \varepsilon_t \quad (31)$$

Where r_t is the monthly return of the index. Given that, in this case, the reference calendar date is the month of January, the intercept, α_0 , captures that month's average return. Coefficients α_i represent the difference in average returns between January and each of the remaining eleven months, from February ($i = 1$) to December ($i = 11$), respectively, $D_{i,t}$ is a dummy variable corresponding to each of these months, and ε_t is the usual error term.

4.5.5.5 Halloween Effect Regression Model

Following the model proposed by Bouman & Jacobsen (2002) in their research on the Halloween indicator, the first regression model used to examine the existence of this anomaly in the Mexican stock market in this study is:

$$r_t = \alpha_0 + \alpha_1 D_{1,t} + \sum_{j=1}^p \eta_j r_{t-j} + \varepsilon_t \quad (32)$$

Where r_t is the stock market index for a particular month t , α_0 is the intercept which denotes the average return from May to October (i.e., the summer months) and ε_t is the residual. Also, α_1 is the Halloween indicator coefficient, and $D_{1,t}$ is a dummy variable that is equal to one for the six months corresponding to the Halloween indicator, that is, from November to April (i.e., the winter months), and zero from May to October.

Haggard & Witte (2010) suggest that the Halloween effect is just the January effect in disguise. Therefore, to control for the influence of the January anomaly, equation (32) is extended to a second model to include that possibility:

$$r_t = \alpha_0 + \alpha_1 D_{1,t} + \alpha_2 D_{2,t} + \sum_{j=1}^p \eta_j r_{t-j} + \varepsilon_t \quad (33)$$

Coefficient α_2 represents the average monthly return difference between January and the summer months, and $D_{2,t}$ is a dummy variable which is equal to one in January and zero otherwise.

4.5.5.6 January Barometer Regression Model

Following Cooper et al. (2006), the OLS model applied in this research to examine the January barometer is:

$$r_{Feb-Dic,t} = \alpha_0 + \alpha_1 D_t + \sum_{j=1}^p \eta_j r_{t-j} + \varepsilon_t \quad (34)$$

Where $r_{Feb-Dic,t}$ is the average monthly return from February to December in year t , α_0 is the average return from February to December following Januarys with negative returns, α_1 represents the difference between 11-month average returns following Januarys with positive returns and those following Januarys with negative returns. Also, D_t is a dummy variable that is equal to one when the average return in January is positive and zero otherwise, and ε_t is the random disturbance.

This research applied two versions of the model in equation (34). The first version, or model 1, considers raw monthly February to December returns. The second version, or model 2, takes into account February to December excess returns, computed as the difference between the monthly raw return less the corresponding one-month Federation Treasury Certificates (CETES).

In brief, chapter 4 described the characteristics of the study, the examined data, the research questions, and the hypotheses of construct. The same section also reviewed the models used to analyze each of the six seasonal effects of interest for this study. Next, chapter 5 presents the statistical and econometric results of the research.

Chapter 5: Empirical Results

5.1 Introduction

This chapter presents the empirical results of the econometric and statistical analyses performed to attain the objectives of this research. The chapter also reviews the most important findings. In this study, results are relevant when they show significance levels up to 5%. Chapter 6 focuses on the discussion and conclusions of the research within the context of the literature.

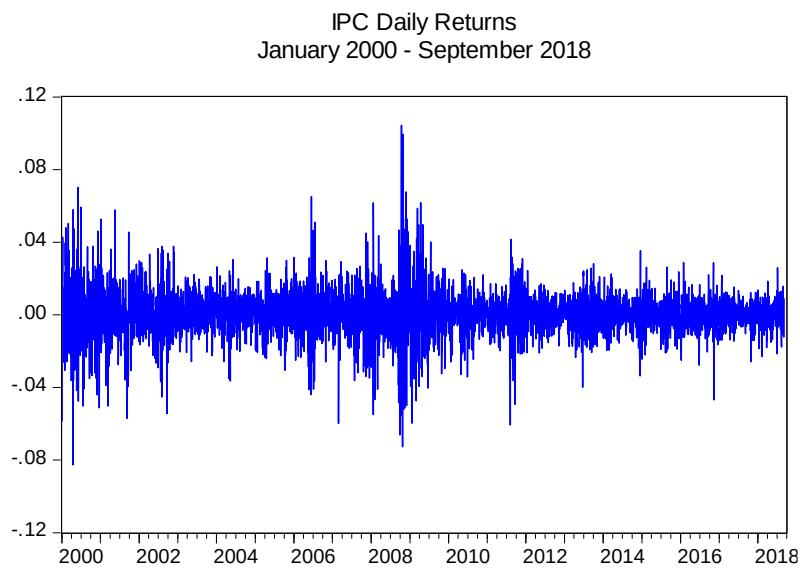


Figure 5. IPC Daily Returns: Full Period

5.2 Descriptive Statistics

Figure 5 and Figure 6 display, respectively, the return patterns of the IPC during the full period and the four subperiods under analysis. The vertical axes of the four graphs in Figure 6 were adjusted to the same scale to make their comparison easier. The graphs show that volatility increased during the subperiod corresponding to the Great Recession (2007 – 2009), whereas during the most recent subperiod (2013 – 2018), which followed the Eurozone crisis, volatility seems to be noticeably less than in the other three subperiods. The returns displayed in the graphs also hint at the presence of volatility clustering. In other words, the return patterns in the diagrams seem to show that low volatility periods follow intervals of low

volatility and vice versa. Likewise, the return time series depicted in both figures seem to display stationarity around the mean.

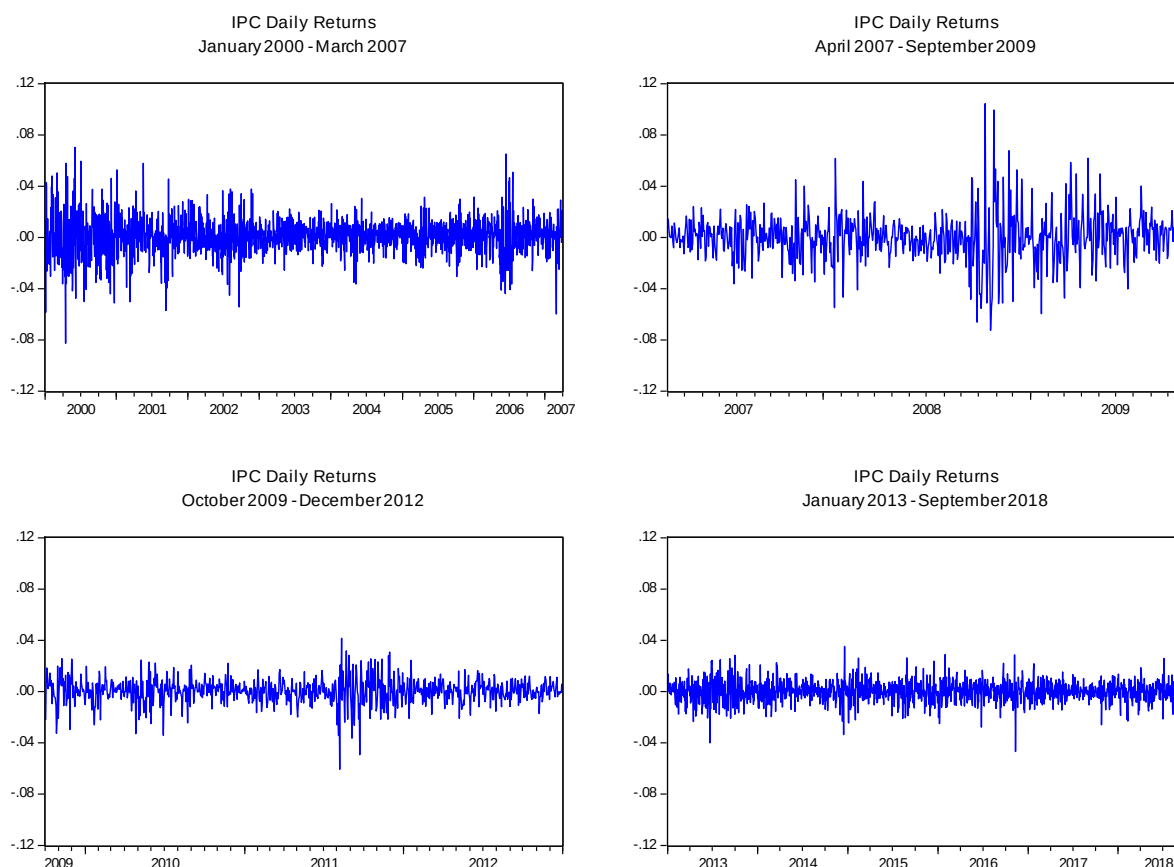


Figure 6. IPC Daily Returns: Four Subperiods

The charts corresponding to the IPC LargeCap, IPC MidCap, and IPC SmallCap exhibited in Figure 7 display a similar pattern than those for the IPC, that is, stationarity around the mean and volatility clustering⁴⁷. It also seems that the IPC SmallCap has the lowest volatility of these indices, followed by the IPC MidCap and then by the IPC LargeCap. However, the graphs also seem to suggest that the volatility of the latter two indices was not very different.

⁴⁷ The graphs corresponding to monthly data display similar patterns than those shown in Figure 5, Figure 6, and Figure 7.

These graphical results very likely imply that ARCH family regressions are the best fit for modeling these daily return series and that the presence of non-stationarity in the data will not be an issue for further analyses, except of course, that more formal statistical tests indicate otherwise.

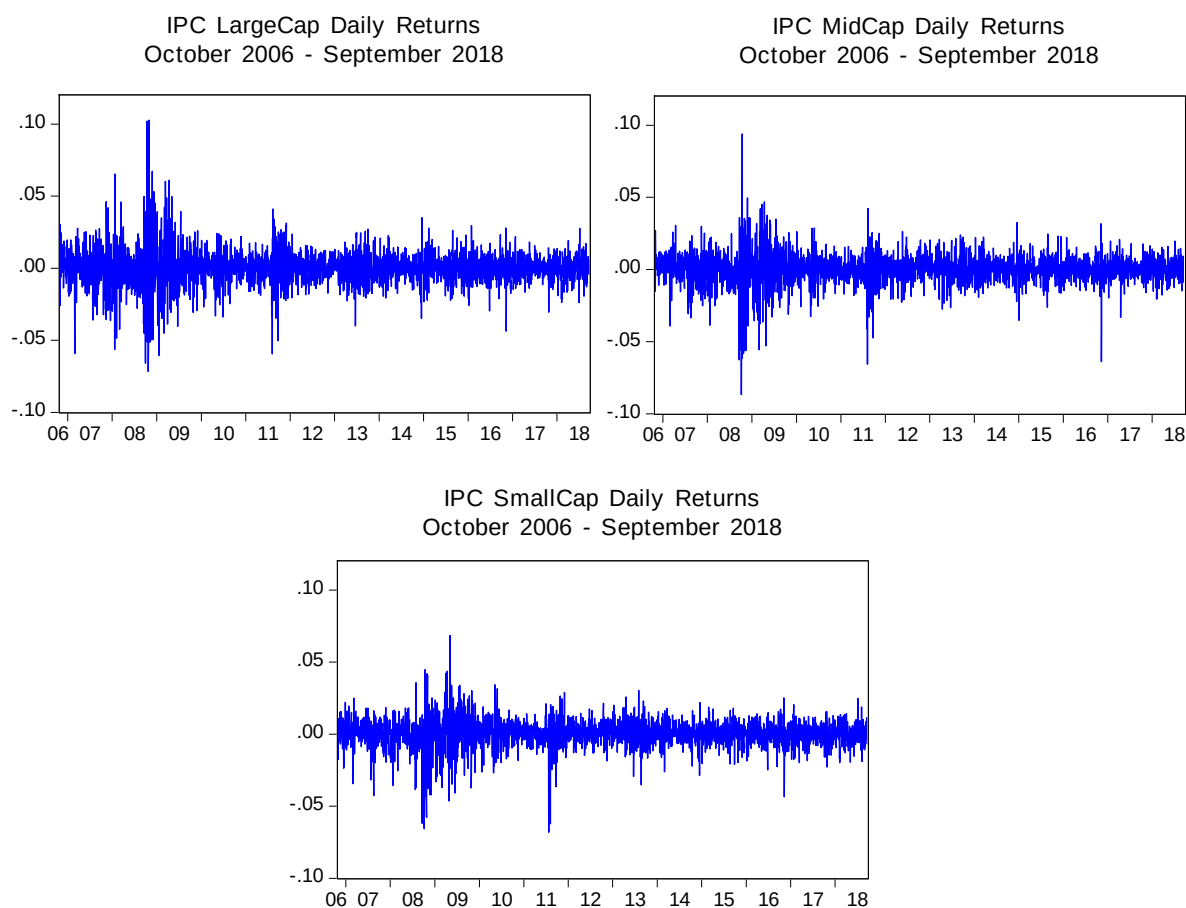


Figure 7. IPC LargeCap, MidCap, and SmallCap Indices Daily Returns

Table 2 displays some relevant descriptive statistics along with the ADF and KPSS unit root (stationarity) tests results for the IPC, while Table 3 shows the corresponding information for the IPC LargeCap, the IPC MidCap, and the IPC SmallCap indices.

Table 2 reveals that the IPC returns exhibited skewness and excess kurtosis throughout the full period, as well as during each of the four subperiods under examination. Therefore, such

returns did not follow a normal probability distribution, a conclusion confirmed by the results of the Jarque-Bera test. The largest standard deviation and the highest daily return emerged during the Great Recession. The lowest return observation, though, was recorded during the subperiod preceding the Great Recession⁴⁸.

Descriptive Statistics for the IPC					
	Full Period	Pre-crises	Great Recession	European Crisis	Post-crises
	Jan/03/2000 - Sep/28/2018	Jan/03/2000 - Mar/31/2007	Apr/01/2007 - Sep/30/2009	Oct/01/2009 - Dec/31/2012	Jan/01/2013 - Sep/28/2018
Descriptive Statistics:					
Mean	0.0396%	0.0738%	0.0026%	0.0474%	0.0083%
Median	0.0308%	0.0778%	0.0354%	0.0397%	0.0000%
Maximum	10.4407%	7.0199%	10.4407%	4.1672%	3.5251%
Minimum	-8.2673%	-8.2673%	-7.2661%	-6.0620%	-4.6789%
Standard deviation	1.2546%	1.3764%	1.8832%	0.9778%	0.8130%
Skewness	0.02839	-0.10756	0.31270	-0.55201	-0.19315
Kurtosis	8.81	6.21	6.88	6.70	5.02
Jarque-Bera	6,882.78	816.93	421.13	526.07	264.26
<i>p</i> -value	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
Observations	4,890	1,890	653	848	1,499
Unit Root/Stationarity Tests:					
ADF					
<i>t</i> statistic	-31.081	-30.989	-23.470	-18.279	-19.032
<i>p</i> -value	< 0.01	< 0.01	< 0.01	< 0.01	< 0.01
KPSS					
<i>t</i> statistic	0.160	0.022	0.178	0.044	0.046
<i>p</i> -value	> 0.10	> 0.10	> 0.10	> 0.10	> 0.10

Table 2. IPC Descriptive Statistics: Daily Data

The findings in Table 3 suggest that the daily returns of the size indices did not follow a normal distribution either since the Jarque-Bera test *p*-values were well below the 1% significance level⁴⁹. The returns of the IPC SmallCap exhibited the highest daily mean and

⁴⁸ More precisely, for the 2000 – 2018 interval of this research, the lowest daily return took place on April 14, 2000.

⁴⁹ The results of the Jarque-Bera test, which are not shown here for the sake of brevity, imply that the monthly returns of all four indices were normally distributed during the October 2009 – September 2018 subperiod. This was also the case for the IPC LargeCap and the IPC SmallCap monthly returns during the October 2006 – September 2009 subperiod.

median but also had the lowest standard deviation⁵⁰. On the other hand, the IPC LargeCap showed the highest standard of the three size indices, and that index also exhibited the maximum single daily return.

Descriptive Statistics for the IPC LargeCap, MidCap, and SmallCap Indices			
	IPC LargeCap	IPC MidCap	IPC SmallCap
Oct/26/2006 - Sep/28/2018			
Descriptive Statistics:			
Mean	0.0270%	0.0242%	0.0321%
Median	0.0206%	0.0368%	0.0478%
Maximum	10.2629%	9.3894%	6.8350%
Minimum	-7.1685%	-8.6734%	-6.8070%
Standard deviation	1.1835%	1.0389%	0.9644%
Skewness	0.14122	-0.73202	-0.76078
Kurtosis	11.01	11.87	9.81
Jarque-Bera	8,321.10	10,475.63	6,309.82
<i>p</i> -value	< 0.01	< 0.01	< 0.01
Observations	3,112	3,112	3,112
Unit Root/Stationarity Tests:			
ADF			
<i>t</i> statistic	-25.234	-11.325	-14.017
<i>p</i> -value	< 0.01	< 0.01	< 0.01
KPSS			
<i>t</i> statistic	0.074	0.070	0.089
<i>p</i> -value	> 0.10	> 0.10	> 0.10

Table 3. Size Indices Descriptive Statistics: Daily Data

Average daily returns were positive for the four indices during the corresponding full period under examination. The same was true for the IPC in each of the four subperiods analyzed, but the average daily returns of this index were close to zero during the Great Recession. As can be seen in Table 2, the IPC pre-crisis average return was around 28.4 times the average return during the Great Recession and 1.6 times that in the European debt crisis. However, the mean during the most recent 2013 – 2018 subperiod was 3.2 times as high as that during the Great Recession, 1.8 times as high as the average return corresponding to the European crisis. The mean return in the 2013 – 2018 subperiod was only 0.11 times that corresponding to the pre-crisis subperiod.

⁵⁰ These findings did not hold for the monthly data of the size indices. Even though the returns of the IPC SmallCap displayed the highest monthly mean and median, they also showed the highest standard deviation.

Not surprisingly, the IPC's highest volatility, as measured by the standard deviation, was by far the one observed during the Great Recession. In contrast, the subperiod following the crises presented the lowest standard deviation.

The premise based on the idea of the overvaluation of the IPC before the Great Recession and the market slowly correcting its previous overreaction might explain the index's average returns and volatility between 2013 and 2018. Such an explanation, though, is decidedly in conflict with market efficiency theory. The performance of the IPC during the 2013 – 2018 subperiod might also be related to the economic and political events in Mexico during that time interval, as described in section 3.3.

The high daily returns of the IPC SmallCap shown in Table 3 might be viewed as an expected result, as long as the argument that small company stocks usually have higher idiosyncratic risk is valid. The low standard deviation exhibited by the small-capitalization index, on the other hand, is counterintuitive because such a dispersion level was the smallest of the three size-related indices, a result that could be evidence in favor of the size effect reported in the literature (Fama & French, 1992). Additionally, the IPC MidCap had a lower average return but also a smaller risk level than the IPC LargeCap. Nonetheless, both indices had a similar coefficient of variation (i.e., the ratio of the standard deviation to the mean).

There was a large number of outliers in the series, which is not unusual for stock returns, as demonstrated by the high kurtosis of the return distributions. Also, all return series exhibited asymmetry. Throughout all subperiods, except during the Great Recession episode, the IPC had frequent small losses and sporadic substantial gains, so the index showed negative skewness in those time intervals. The same was true for the IPC MidCap and the IPC MidCap between 2006 and 2018.

Contrarily, in the full period and during the subperiod from 2007 to 2009, small gains were frequent in the IPC. The index, though, also displayed considerable losses in that time interval, as a consequence of the contagion from the mortgage debt crisis in the United States. The large-capitalization index displayed a similar pattern from 2006 to 2018, quite possibly

also influenced by the Great Recession, as well as by the European debt crisis episode, since these crises spanned from 2007 to 2012. This pattern is reflected by the positive skewness of the IPC and the IPC LargeCap during such intervals.

Considering the results regarding excess kurtosis and positive (negative) skewness of the series, as well as the results of the Jarque-Bera test, non-parametric central tendency comparison procedures, such as the Kruskal-Wallis test, were more suitable than parametric tests, such as the ANOVA. So, in view that the returns generally were not normally distributed, non-parametric tests were frequently more suitable.

Finally, Table 2 and Table 3 show that all the series displayed the absence of a unit root (i.e., the series are stationary). The results of the ADF test for the returns of all four indices strongly reject the null hypothesis of a unit root in the series, with p -values well below the 1% significance level. Likewise, the results of the KPSS test strongly fail to reject the null hypothesis of stationarity. Similar results were obtained for the returns of the size indices when divided into two subperiods, as well as for the monthly returns of all indices under analysis. As discussed earlier, non-stationarity in the series may lead to spurious regressions and may cause that the t statistics of the regressors to be non-valid. The results of the unit root (stationarity) tests strongly suggest that these problems are nonexistent in the analyses presented in the following sections.

5.3 Day-of-the-Week Effect Results

As described in section 4.5.4, the analyses of the calendar anomalies began with OLS regression models with dummy variables and $AR(p)$ terms, but when the ARCH-LM test rejected the null hypothesis of homoskedasticity, GARCH, TGARCH, and EGARCH specifications were used to examine the time series.

The day-of-the-week OLS regression models for the IPC corresponding to the full period and the four subperiods under study exhibited ARCH effects, except for the model related to the European debt crisis subperiod, from October 2009 to December 2012. Likewise, the OLS

specifications corresponding to the large, mid-, and small-capitalization indices exhibited ARCH effects. When such effects were found, the EGARCH (1, 1) model turned out to be the most suitable parameterization in all cases and was selected over the GARCH (1, 1) and TGARCH (1, 1) specifications to examine the day-of-the-week effect.

More precisely, EGARCH specifications produced the lowest values for the Akaike (AIC), Schwarz (SIC), and Hannan-Quinn (HQ) information criteria and, very importantly, their post-estimation results did not present autocorrelation or ARCH effects in the residuals. In contrast, GARCH and TGARCH parameterizations showed one or both of these econometric issues. The residuals of all EGARCH models, though, were not normally distributed, so quasi-maximum likelihood (QML) estimation was used (Bollerslev & Wooldridge, 1992).

Price and Quotations Index (IPC)					
	Full Period	Pre-crises	Great Recession	European Crisis	Post-crises
	Jan/03/2000 - Sep/28/2018	Jan/03/2000 - Mar/31/2007	Apr/01/2007 - Sep/30/2009	Oct/01/2009 - Dec/31/2012	Jan/01/2013 - Sep/28/2018
	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>					
Monday (Constant)	0.00062 **	0.00061	0.00010	0.00138 ***	0.00032
Tuesday (D ₁)	-0.00046	0.00029	-0.00086	-0.00138	-0.00019
Wednesday (D ₂)	-0.00041	0.00055	-0.00066	-0.00023	-0.00056
Thursday (D ₃)	-0.00050	0.00061	0.00059	-0.00157	-0.00098 ***
Friday (D ₄)	-0.00048	-0.00030	0.00036	-0.00134	-0.00029
<i>Variance Equation</i>					
Monday (Constant)	-0.03385	-0.20210	0.26922	----	-0.16896
Tuesday (D ₁)	-0.06618	-0.03109	-0.73815 **	----	0.06134
Wednesday (D ₂)	-0.28219 **	-0.15355	-0.43786 *	----	-0.11495
Thursday (D ₃)	-0.20536 *	-0.16385	-0.69780 ***	----	0.02398
Friday (D ₄)	-0.36264 ***	-0.47659 **	-0.44262	----	-0.12709
$ \epsilon_{t-1}/S_{t-1} $	0.12654 ***	0.11371 ***	0.10458 ***	----	0.03731 *
ϵ_{t-1}/S_{t-1}	-0.08157 ***	-0.11858 ***	-0.09995 ***	----	-0.10184 ***
$\log(S_{t-1}^2)$	0.98668 ***	0.96842 ***	0.98620 ***	----	0.98226 ***

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 4. Day-of-the-Week: IPC

Table 4 shows that, according to the results of the mean equation of the EGARCH model for the full period under analysis, average returns on Monday were positive and significantly

different from zero. Contrasting with the results widely reported in the literature, Monday average returns of the IPC were higher than the returns on the remaining days of the week between 2000 and 2018, which implies a positive Monday effect in that period. The Kruskal-Wallis tie-adjusted test⁵¹, on the other hand, strongly failed to reject the null hypothesis of equal returns on different days of the week.

The day-of-the-week anomaly was absent from the IPC returns in the first two subperiods examined, also according to the results of the EGARCH mean equations shown in Table 4. Nevertheless, the IPC Monday average returns were significantly positive during the European sovereign debt crisis episode, as reflected in the results of the corresponding OLS regression model.

Moreover, there was a significant Thursday effect in the most recent subperiod, where the negative value of the coefficient of the related dummy variable (i.e., D_3) implies that Thursday average returns were the lowest of the week and that this difference was highly significant.

The variance equations of the EGARCH models exhibited the presence of day-of-the-week effects in the IPC during the full period, as well as in the pre-crisis and Great Recession subperiods. To be more specific, from 2000 to 2018, the full period considered for this index Wednesdays and Fridays displayed significantly lower volatility. Fridays also exhibited statistically reduced volatility between 2000 and 2007, and Tuesdays and Thursdays showed significantly less volatility from 2007 to 2009.

It is worth reminding that, according to the ARCH-LM test, there were no ARCH(1) effects in the OLS model for the IPC during the subperiod corresponding to the European crisis and, therefore, there was no day-of-the-week effect in volatility during that time interval.

⁵¹ The analyses included the Kruskal-Wallis test for all periods and subperiods of the IPC and the IPC size-related indices. These results do not appear in this document for the sake of brevity.

Moreover, the outcomes of the volatility equation of the EGARCH model corresponding to the post-crises subperiod do not show any evidence of the anomaly. So, according to such results, volatility was not significantly different for each day of the week during the two most recent subperiods, that is, from 2009 to 2012, and from 2012 to 2018.

Furthermore, the results of the variance equations of the EGARCH models reveal that the IPC returns showed significant volatility clustering, and exhibited significant shocks to the conditional variance, as evidenced by the significance of the coefficients of the ARCH (i.e., $|\varepsilon_{t-1}/\sigma_{t-1}|$) and GARCH (i.e., $\log(\sigma_{t-1}^2)$) terms, respectively. Additionally, the large size of the conditional variance term suggests that it was persistent and that it changed slowly through time. These results also imply that the IPC returns exhibited negative leverage, as shown by the highly significant negative sign of the asymmetry coefficient (i.e., $\varepsilon_{t-1}/\sigma_{t-1}$), which reveals that bad news had a larger impact than good news on the performance of the index volatility.

	IPC Sizes Indices								
	Full Period (Oct/26/2006 - Sep/28/2018)			Sub-period 1 (Oct/26/2006 - Sep/30/2009)			Sub-period 2 (Oct/01/2009 - Sep/28/2018)		
	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap
	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>									
Monday (Constant)	0.00070 **	0.00042	0.00017	-0.00026	-0.00017	0.00028	0.00074 **	0.00040	0.00008
Tuesday (D ₁)	-0.00084 *	-0.00050	-0.00026	-0.00009	-0.00008	-0.00086	-0.00089 *	-0.00043	-0.00007
Wednesday (D ₂)	-0.00077	0.00021	0.00044	0.00075	0.00111	0.00078	-0.00077	0.00009	0.00054
Thursday (D ₃)	-0.00095 **	-0.00022	0.00029	0.00131	0.00124	0.00071	-0.00119 **	-0.00043	0.00027
Friday (D ₄)	-0.00071	-0.00029	0.00124 ***	0.00018	0.00139	0.00095	-0.00061	-0.00062	0.00120 **
<i>Variance Equation</i>									
Monday (Constant)	-0.03903	-0.16733	-0.00145	0.21026	0.12121	0.15090	-0.27844 **	-0.81756 ***	-0.29558
Tuesday (D ₁)	0.01200	-0.01181	-0.39271	-0.40861	-0.52748	-0.56579	0.15135	0.19869	-0.29508
Wednesday (D ₂)	-0.30711 **	-0.39214 **	-0.28591	-0.64292 **	-0.45997	-0.25024	-0.16983	-0.37897 **	-0.31704
Thursday (D ₃)	-0.25187 *	-0.09789	-0.18433	-0.78070 ***	-0.56254 **	-0.55551 *	-0.04559	0.11096	-0.02538
Friday (D ₄)	-0.21770	-0.19491	-0.45520 **	-0.44629	-0.57316 *	-0.70677 **	-0.12789	-0.03334	-0.36968
$ \varepsilon_{t-1}/\sigma_{t-1} $	0.10893 ***	0.16505 ***	0.137523 ***	0.11281 ***	0.17156 ***	0.15438 ***	0.08925 ***	0.16648 ***	0.11039 ***
$\varepsilon_{t-1}/\sigma_{t-1}$	-0.09183 ***	-0.06150 ***	-0.037743 **	-0.11760 ***	-0.06838 **	-0.04778	-0.09983 ***	-0.11017 ***	-0.05782 ***
$\log(\sigma_{t-1}^2)$	0.98811 ***	0.98068 ***	0.982972 ***	0.98087 ***	0.98016 ***	0.98322 ***	0.97394 ***	0.92659 ***	0.95777 ***

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 5. Day-of-the-Week: IPC Size Indices

Table 5 displays the results for the day-of-the-week effect in the size indices of the Mexican Stock Exchange. According to the results of the mean equations of the corresponding EGARCH specifications, Thursday average return was statistically lower than Monday average return for the large-capitalization index throughout the full period and during the subperiod after the Great Recession. The outcomes in Table 5 also imply that Monday

average returns were positive and significantly different from zero at the same time intervals in that index.

The returns of the IPC SmallCap index displayed a significant positive Friday effect in the full period and the most recent subperiod. In the subperiod from October 2006 to September 2009, none of the size indices exhibited a significant presence of the day-of-the-week anomaly. That seasonal anomaly was consistently absent from the returns of the IPC MidCap throughout all time intervals under analysis. Besides, the Kruskal-Wallis test failed to reject the hypothesis of equal returns on all days of the week for the large and medium-capitalization indices in all the time intervals considered. Although the Kruskal-Wallis test failed to reject the hypothesis of equal returns on all days of the week for the IPC SmallCap during the 2006 – 2009 and 2009 – 2018 subperiods, that test rejected that hypothesis for such an index during the full period from 2006 to 2018. Thus, according to these results, the presence of the Friday effect found by the EGARCH model in the IPC SmallCap index between 2006 and 2018 seems robust.

Regarding the outcomes of the day-of-the-week analysis in the variance equations for the full period, the IPC LargeCap and the IPC MidCap indices showed significantly lower volatility on Wednesdays, and the IPC SmallCap displayed significantly less volatility on Fridays. In the first subperiod, the large- and medium-capitalization indices exhibited statistically reduced volatility on Thursdays. The IPC LargeCap also exhibited lower volatility on Wednesdays, while the IPC SmallCap exhibited less volatility on Fridays during the second subperiod, from 2006 to 2009.

Moreover, throughout the second subperiod, the IPC Large Cap and the IPC MidCap index showed evidence of the day-of-the-week effect in volatility, with significantly negative coefficients on Monday and Wednesday. Thus, all three size indices exhibited the day-of-the-week effect in volatility in all time intervals under analysis, since all of them exhibited at least one day with significantly lower volatility in most of the time intervals examined. The exception to this pattern, though, was the IPC SmallCap index in the subperiod 2009 – 2018,

after the Great Recession. This finding is evidence in favor of the vanishing of the day-of-the-week in volatility in that index.

Additionally, the results of the variance equations suggest that, in general, the returns of the size indices exhibited highly significant volatility clustering and persistence. These findings also suggest that those stock indices had significant negative leverage, except in the case of the IPC SmallCap index during the first subperiod, where despite the leverage coefficient was negative as in the rest of the subperiods, it turned out to be not significant.

So, the IPC mean returns exhibited evidence of the presence of the day-of-the-week effect, considering that Monday and Thursday returns were statistically different from those on other days of the week. Furthermore, these return patterns appeared, respectively, in the two most recent subperiods studied, which is contrary to the vanishing tendency reported for this anomaly in the stock markets of several countries.

The day-of-the-week effect also emerged in the IPC variance equations coefficients, but such an anomaly disappeared from volatility in recent years. Most of the day-of-the-week anomalies in the IPC volatility appeared during the Great Recession episode since two of the three statistically different volatility coefficients surfaced during such a subperiod and none subsequently.

The returns of the IPC size indices also displayed evidence of the day-of-the-week effect, mainly in the IPC LargeCap index, because two significantly different than expected returns appeared in the full period and the second subperiod in that index. It is not surprising that there were several concurrences in the results of the IPC and the IPC LargeCap, since of the three size indices, the large-capitalization index is the closest related to the broad index considering the methodology applied to select its components, as described in section 4.4.2.

Interestingly, no significantly different than expected coefficients appeared in the IPC between April 2007 and September 2009, the subperiod corresponding to the Great Recession. The same was true for the size indices from October 2006 to September 2009, a

time interval that closely matches the period of the Great Recession. The reason for this finding remains an open question. The financial turmoil throughout this severe crisis episode increased the standard deviation of daily returns. As can be observed in Table 2, the IPC daily standard deviation was almost 0.83 percentage points higher during the 2007 – 2009 subperiod than the average of the other three subperiods. So, the high level of volatility may have caused the lack of statistical significance of the day-of-the-week coefficients.

The day-of-the-week anomaly in the variance equations of the size indices displayed a tendency to diminish, as was also the case for the broad index. Also, there is consistent statistical evidence of the existence of volatility clustering and persistence, as well as evidence for the presence of leverage in all four stock indices.

To sum up, the regression models found significant evidence regarding the existence of the day-of-the-week effect in the returns of the IPC, the IPC LargeCap, and the IPC SmallCap in the corresponding full periods examined. Furthermore, that seasonal anomaly did not fade away from the returns of such indices. In contrast, the regression analysis and the Kruskal-Wallis test did not find any evidence that the day-of-the-week effect existed in the returns of the IPC MidCap.

The day-of-the-week anomaly was also present in the volatility of the four stock indices examined in this research. Despite this calendar effect did not disappear from the large- and medium-capitalization indices' volatility, it faded away from the volatility of the IPC and the IPC SmallCap.

5.4 Holiday Effect Results

To examine the holiday effect in the Mexican Stock Exchange, the model described by equation (28) was used for the IPC, as well as for the three size-related stock indices. Where applicable, the models specified in equations (24), (25), and (26) were also used.

The residuals of all OLS regression models for the IPC displayed heteroskedasticity, except for the model used for the Eurozone debt crisis subperiod, a finding that matches the results of the day-of-the-week examination for the same time interval. Therefore, for the full period and the pre-crises, Great Recession, and post-crises subperiods, the analyses included the testing of GARCH, TGARCH, and EGARCH specifications. The residuals of the GARCH and TGARCH models exhibited serial correlation, heteroskedasticity and, in several instances, both econometric issues. That was not the case for the EGARCH models since all postestimation results were satisfactory. However, in all cases, the residuals turned out to be not normally distributed, so the analysis included QML estimation. Table 6 and Table 7 present the results of the EGARCH models for the IPC and the IPC size-related indices, respectively.

As the results in Table 6 show, the mean equations of the EGARCH specifications suggest that the broad stock index of the Mexican stock market did not display significant abnormal returns before or after the holidays in any of the time intervals examined. Also, the corresponding Kruskal-Wallis tests for the full period and the four subperiods failed to reject the null hypothesis that the returns of the pre-holiday, post-holiday and other days were the same, so the absence of the holiday anomaly in the IPC seems robust.

The constant of the mean equation of the EGARCH models displayed in Table 6 The constant of the mean equation of the EGARCH models displayed in Table 6 represents the non-pre-holiday Monday average returns. The results corresponding to the full period imply that the average return on a non-pre-holiday Monday was 0.053% and that it was statistically different from zero. This finding tends to confirm the presence of a positive Monday effect in the IPC during the 2000 – 2018 interval, as described in section 5.3⁵².

⁵² For example, according to the results shown in Table 6, a typical return on a Thursday after a holiday was $(0.00053 - 0.0004 + 0.00089) \times 100 = 0.182\%$ during the full period.

Price and Quotation Index (IPC)					
	Full Period	Pre-crises	Great Recession	European Crisis	Post-crises
	Jan/01/2000 - Sep/28/2018	Jan/01/2000 - Mar/31/2007	Apr/01/2007 - Sep/30/2009	Oct/01/2009 - Dec/31/2012	Jan/01/2013 - Sep/28/2018
	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>					
No post-holiday Monday (Constant)	0.00053 **	0.00059	-0.00018	0.00128 *	0.00033
Tuesday (D_1)	-0.00044	0.00022	-0.00037	-0.00147	-0.00023
Wednesday (D_2)	-0.00039	0.00033	0.00008	-0.00017	-0.00055
Thursday (D_3)	-0.00040	0.00062	0.00032	-0.00149	-0.00091
Friday (D_4)	-0.00034	-0.00013	0.00068	-0.00122	-0.00023
Pre-holiday (D_{PRH})	-0.00090	-0.00120	-0.00520	-0.00066	-0.00058
Post-holiday (D_{POH})	0.00089	0.00197	0.00542	0.00274	-0.00048
<i>Variance Equation</i>					
No post-holiday Monday (Constant)	-0.11771	-0.17150	0.14930	----	-0.25676
Tuesday (D_1)	-0.00162	-0.03408	-0.59150 **	----	0.11209
Wednesday (D_2)	-0.20674 *	-0.12944	-0.40356	----	-0.07197
Thursday (D_3)	-0.15420	-0.15899	-0.63645 **	----	0.07837
Friday (D_4)	-0.22301 *	-0.43211 **	-0.27425	----	-0.03391
Pre-holiday (D_{PRH})	-0.61945 ***	-0.70218 ***	-0.85285 **	----	-0.35240 *
Post-holiday (D_{POH})	0.77557 ***	0.78186 ***	0.98297 ***	----	0.45299 **
$ e_{t-1}/S_{t-1} $	0.13333 ***	0.11036 ***	0.11681 ***	----	0.05444 **
e_{t-1}/S_{t-1}	-0.08611 ***	-0.11120 ***	-0.10270 ***	----	-0.10119 ***
$\log(S^2_{t-1})$	0.98585 ***	0.97351 ***	0.98326 ***	----	0.97990 ***

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 6. Holiday Effect: IPC

In contrast, the positive Monday effect found during the European debt crisis, as well as the negative Thursday anomaly identified during the post-crises subperiod in the respective day-of-the-week analyses, faded away from the IPC when controlling for the pre- and post-holiday returns. More precisely, when including these two variables in the full model, the statistical significance of the day-of-the-week coefficients disappeared, although their association (i.e., their sign) with the returns of the index remained. It is also worth stating that, despite the coefficients of the pre- and post-holiday returns were not significant, the inclusion of these variables was statistically relevant since the AIC diminished in all cases, except for the model corresponding to the last subperiod.

The results of the variance equations denote that there was significantly lower pre-holiday volatility in the IPC throughout the full period under analysis, as well as in the pre-crises and Great Recession subperiods. Likewise, post-holiday volatility was significantly higher

throughout each of the time intervals under examination, except during the European debt crisis episode.

The presence of lower pre-holiday and higher post-holiday volatilities in the BMV's broad index was accompanied by lower than average pre-holiday and higher than average post-holiday returns, although the differences in returns were not statistically significant. Nevertheless, during the 2009 – 2012 and 2013 – 2018 subperiods, this pattern of higher return associated with higher volatility, and vice versa, did not hold for the IPC. Moreover, the significantly negative pre-holiday volatility was offset by statistically positive post-holiday volatility throughout the full period, as well as during the pre-crisis and Great Recession subperiods.

The variance equations reveal that there was significantly lower Friday volatility in the pre-crises subperiod, a result that agrees with the outcomes of the day-of-the-week analysis. According to the results displayed in Table 6, significantly lower Tuesday and Thursday volatility irregularities replaced the lower Friday volatility between 2007 and 2009.

All these effects in volatility weakened during the most recent 2013 – 2018 subperiod. Furthermore, an examination of the holiday anomaly in the IPC using OLS regression models, which do not include the day-of-the-week dummy variables, found that the ARCH-LM test failed to reject the null hypothesis of homoskedasticity in the residuals from 2013 to 2018. Hence, considering this evidence, the pre-holiday and post-holiday effects in volatility seem to have disappeared from the IPC after the Great Recession⁵³.

In general, there were highly significant clustering and leverage effects in the volatility of the IPC during the full period and the four subperiods studied. There was also statistically

⁵³ The results of these models do not change the conclusions presented in this document. These analyses are not shown here for the sake of brevity but are available upon request.

significant volatility persistence, with variance changing slowly over time, as reflected by the results of the corresponding coefficients of the EGARCH models' variance equations.

	IPC Sizes Indices								
	Full Period (Oct/26/2006 - Sep/28/2018)			Sub-period 1 (Oct/26/2006 - Sep/30/2009)			Sub-period 2 (Oct/01/2009 - Sep/28/2018)		
	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap
	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>									
No post-holiday Monday (Constant)	0.00063 *	0.00021	0.00025	-0.00063	-0.00068	0.00040	0.00071 **	0.00030	0.00018
Tuesday (D_1)	-0.00086 *	-0.00051	-0.00027	-0.00015	-0.00034	-0.00119	-0.00090 *	-0.00050	-0.00015
Wednesday (D_2)	-0.00076	0.00025	0.00039	0.00103	0.00120	0.00089	-0.00080	0.00013	0.00044
Thursday (D_3)	-0.00084 *	-0.00003	0.00013	0.00130	0.00162	0.00031	-0.00108 **	-0.00032	0.00012
Friday (D_4)	-0.00055	-0.00006	0.00101 **	0.00091	0.00183 *	0.00029	-0.00054	-0.00026	0.00098 *
Pre-holiday (D_{PreH})	-0.00098	-0.00004	-0.00045	-0.00234	-0.00059	-0.00115	-0.00061	0.00011	-0.00026
Post-holiday (D_{PostH})	0.00079	0.00277 **	-0.00080	0.00617 **	0.00348	-0.00114	0.00009	0.00222 *	-0.00027
<i>Variance Equation</i>									
No post-holiday Monday (Constant)	-0.15709	-0.33999 **	-0.08612	0.13417	0.09264	0.06238	-0.40231 ***	-1.08476 ***	-0.33605 *
Tuesday (D_1)	0.11098	0.07818	-0.32410	-0.30888	-0.49617	-0.68668 *	0.25698	0.311049	-0.19816
Wednesday (D_2)	-0.20252	-0.33539 **	-0.23187	-0.56606 **	-0.46941	-0.39520	-0.06628	-0.289248	-0.21805
Thursday (D_3)	-0.17287	-0.00075	-0.12739	-0.70391 ***	-0.53160 **	-0.45898 *	0.02587	0.207132	0.01082
Friday (D_4)	-0.02897	-0.02191	-0.32494 *	-0.31725	-0.54378	-0.74515 **	0.05388	0.153934	-0.21720
Pre-holiday (D_{PreH})	-0.61224 ***	-0.71981 ***	-1.05028 ***	-1.01605 ***	-0.98411 ***	-1.43130 ***	-0.47674 **	-0.590328 ***	-0.88869 ***
Post-holiday (D_{PostH})	0.73907 ***	0.96209 ***	1.09206 ***	1.00807 ***	1.01547 ***	1.61033 ***	0.62674 ***	0.983767 ***	0.88415 ***
$ \hat{\epsilon}_t /S_{t-1}$	0.11446 ***	0.19433 ***	0.14311 ***	0.11124 ***	0.17679 ***	0.21063 ***	0.09976 ***	0.20354 ***	0.10737 ***
$\hat{\epsilon}_t/S_{t-1}$	-0.09790 ***	-0.07164 ***	-0.04275 **	-0.11927 ***	-0.07960 **	-0.06924	-0.10255 ***	-0.11317 ***	-0.06196 ***
$\log(S_{t-1}^2)$	0.98643 ***	0.97454 ***	0.98127 ***	0.98079 ***	0.97944 ***	0.97462 ***	0.97198 ***	0.91364 ***	0.96133 ***

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 7. Holiday Effect: IPC Size Indices

According to the results displayed in Table 7, corresponding to the IPC size indices, significantly higher than average post-holiday returns existed in the IPC MidCap between 2006 and 2018. However, there was also a significantly higher post-holiday variance in such stock index during the same time interval. A similar condition appeared in the IPC LargeCap in the first subperiod. So, although post-holiday returns were higher in these two instances, the presence of higher volatility could explain them.

While the corresponding Kruskal-Wallis tests carried out for the returns of each of the size indices, found no indication of the day-of-the-week or holiday effects, the mean equation of the EGARCH specifications discovered evidence of the day-of-the-week anomaly, as can be seen in Table 7. Friday average return of the IPC SmallCap was significantly higher than non-post-holiday Monday returns. Considering the results of the day-of-the-week model in Table 5, along with those of the full model in Table 7, the presence of the Friday effect in the small-capitalization index seems robust. The same is true for the Monday and Thursday anomalies in the IPC LargeCap after the Great Recession examined in section 5.3.

The three size-related indices exhibited significantly low pre-holiday and high post-holiday volatility, irrespective of the time interval, and in some instances, the corresponding coefficients were quite high. As was the case for the IPC, lower pre-holiday volatility was followed by higher post-holiday variance in the size indices.

Thus, in general, the results of the full model point in the same direction as the findings of the day-of-the-week analysis. Three of six statistically significant coefficients identified in the mean equation of the day-of-the-week anomaly model appeared in the results of the full model used to study the interactions between the day-of-the-week and holiday anomalies. Furthermore, ten significantly different volatility coefficients emerged in the model that examined the day-of-the-week effect, and seven of such coefficients turned out to be significant in the full model. So, most of the findings reported in the previous section for the size-related indices seem robust.

The results of the variance equations for the IPC size indices displayed in also reveal that volatility decayed very slowly through time. Volatility clustering and leverage effects were also significant in such indices, for the entire period and the two subperiods considered in the analysis. The only exception to this pattern was the small-capitalization index after the Great Recession. More specifically, although bad news had a larger impact than good news on that index volatility, as was the case for the other indices and periods, the IPC SmallCap index leverage coefficient was not significant during the 2009 – 2018 subperiod. Thus, in general, the findings of the full model that included the holiday anomaly for the size-related indices support the same conclusions reached in the analysis of the day-of-the-week effect regarding leverage and volatility clustering and persistence.

When bearing in mind the results of the full model for the interactions of the holiday and day-of-the-week effects, the vanishing of the day-of-the-week effect in the volatility of the IPC during the 2013 – 2018 subperiod reported in section 5.3 looks consistent. Similarly, the findings reported in that section about the presence of a Friday anomaly in the returns of the IPC SmallCap during the 2006 – 2018 period, as well as the appearance of Monday and Thursday effects in the IPC LargeCap returns in the most recent subperiod, are also robust.

In brief, the results of the regression models and the Kruskal-Wallis test found no statistical evidence concerning the existence of the holiday effect in the returns of the IPC, the IPC LargeCap, and the IPC SmallCap. This calendar anomaly, however, was found in the returns of the IPC MidCap, and it did not show evidence of vanishing from that index. Conversely, the results of the variance equations reveal that the holiday effect was consistently present in the four stock indices examined. Additionally, this seasonal anomaly did not exhibit any sign of having disappeared from the indices' variance, except in the case of the volatility pre-holiday effect that emerged in the IPC.

5.5 Turn-of-the-Month Effect Results

The analysis of the turn-of-the-month anomaly included two specifications, according to the models described in section 4.5.5.3. The first model encompassed the last trading day of a particular month and the initial three trading days of the next. The second model comprised the final four trading days of a given month and the first four trading days of the subsequent month. Equations (29) and (30), respectively, represent such specifications.

The best fit was EGARCH parameterizations with QML estimation for the four indices and each of the time intervals examined, since the residuals of the GARCH and TGARCH estimations also tested, displayed autocorrelation and heteroskedasticity. Nevertheless, an OLS regression was the most appropriate model during the European crisis episode, since the ARCH-LM test failed to reject the hypothesis of homoskedasticity, and there was no evidence of ARCH(1) effects.

Table 8 shows the results of the turn-of-the-month effect in the IPC using model 1. During the pre-crises and Great Recession subperiods, there was a significantly positive turn-of-the-month anomaly on the first trading day of each month ($i = +1$). This anomaly was strong enough during the first two subperiods as to be detected for the entire period analyzed, despite that it disappeared in the last two subperiods.

Price and Quotation Index (IPC)					
	Full Period	Pre-crises	Great Recession	European Crisis	Post-crises
	Jan/03/2000 - Sep/28/2018	Jan/03/2000 - Mar/31/2007	Apr/01/2007 - Sep/30/2009	Oct/01/2009 - Dec/31/2012	Jan/01/2013 - Sep/28/2018
	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>					
Rest of the month	0.00002	0.00040	-0.00047	0.00035	-0.00008
D ₋₁	-0.00007	0.00160	-0.00148	0.00007	-0.00124
D ₊₁	0.00333 ***	0.00588 ***	0.00581 ***	0.00131	0.00101
D ₊₂	0.00127 *	0.00190	0.00390	0.00057	0.00074
D ₊₃	0.00056	0.00069	0.00187	0.00077	-0.00048
<i>Variance Equation</i>					
Rest of the month	-0.23496 ***	-0.38779 ***	-0.19260 ***	----	-0.24732 ***
D ₋₁	0.08640	-0.19159	-0.21207	----	0.46707 **
D ₊₁	0.10169	0.21023	0.49195	----	-0.19854
D ₊₂	0.07289	0.17918	0.00063	----	0.25628
D ₊₃	-0.21175	-0.11026	-0.34912	----	-0.25911
e _{t-1} /S _{t-1}	0.13374 ***	0.11800 ***	0.09960 ***	----	0.04621 **
e _{t-1} /S _{t-1}	-0.08688 ***	-0.12613 ***	-0.11056 ***	----	-0.10284 ***
log (S ² _{t-1})	0.98558 ***	0.96697 ***	0.98543 ***	----	0.97938 ***

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 8. Turn-of-the-Month Effect Model 1: IPC

The results of the Kruskal-Wallis test imply that the returns during all trading days of the month were the same for the last three subperiods. For the 2000 – 2018 interval and the 2000 – 2007 subperiod, on the other hand, the corresponding Kruskal-Wallis tests strongly rejected the null hypothesis of equal returns between the days corresponding to the turn of the month and the remaining days of the month. This finding was consistent for both models used to examine the turn-of-the-month effect. Therefore, the presence of this anomaly in the IPC during the full period and the pre-crisis subperiod appears to be robust.

No evidence of the turn-of-the-month anomaly emerged in the corresponding variance equations of the IPC, except during the most recent subperiod where volatility seems to have increased significantly during the last trading day of each month ($i = -1$). The IPC volatility on days other than those corresponding to the turn of the month was significantly and consistently lower, except throughout the Eurozone debt crisis episode. According to the results shown in Table 8, there were ARCH and long-lasting GARCH effects, as well as negative leverage, which turned out to be significant during all time intervals examined.

Price and Quotation Index (IPC)					
	Full Period	Pre-crises	Great Recession	European Crisis	Post-crises
	Jan/03/2000 - Sep/28/2018	Jan/03/2000 - Mar/31/2007	Apr/01/2007 - Sep/30/2009	Oct/01/2009 - Dec/31/2012	Jan/01/2013 - Sep/28/2018
	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>					
Rest of the month	-0.00006	0.00015	-0.00068	0.00030	0.00000
D ₋₄	-0.00006	0.00210 **	-0.00121	-0.00067	-0.00068
D ₋₃	0.00079	0.00039	0.00216	0.00259 *	0.00045
D ₋₂	0.00003	0.00046	0.00388	0.00043	-0.00077
D ₋₁	0.00002	0.00196 *	-0.00121	0.00020	-0.00135
D ₊₁	0.00339 ***	0.00617 ***	0.00580 ***	0.00125	0.00093
D ₊₂	0.00134 *	0.00221	0.00455 *	0.00064	0.00066
D ₊₃	0.00068	0.00113	0.00221	0.00067	-0.00059
D ₊₄	0.00049	0.00111	-0.00076	-0.00128	-0.00006
<i>Variance Equation</i>					
Rest of the month	-0.23979 ***	-0.37135 ***	-0.16866 ***	----	-0.24706 ***
D ₋₄	0.10690	-0.12544	0.28931	----	0.07692
D ₋₃	-0.03762	0.26572	-0.79964 ***	----	-0.07071
D ₋₂	0.19121	0.33548	0.34697	----	-0.13202
D ₋₁	-0.09148	-0.56988 **	-0.19781	----	0.61931 **
D ₊₁	0.10339	0.20178	0.49471	----	-0.19972
D ₊₂	0.08044	0.18553	0.00228	----	0.26297
D ₊₃	-0.10841	0.10272	-0.14485	----	-0.41605 **
D ₊₄	-0.08664	-0.21648	-0.32351	----	0.19343
$ e_{t-1}/S_{t-1} $	0.13352 ***	0.11292 ***	0.09125 ***	----	0.04440 **
e_{t-1}/S_{t-1}	-0.08756 ***	-0.12139 ***	-0.11498 ***	----	-0.10337 ***
$\log(S_{t-1}^2)$	0.98559 ***	0.96894 ***	0.98617 ***	----	0.97960 ***

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 9. Turn-of-the-Month Effect Model 2: IPC

Table 9 presents the findings of the second EGARCH model used to examine the turn-of-the-month anomaly in the IPC. Such results reveal the presence of the anomaly since, during the full period, as well as during the pre-crises and Great Recession subperiods, average returns on the first day of each month were significantly higher than those observed on other days. These outcomes tend to confirm the findings of model 1 in this regard.

Additionally, during the pre-crises subperiod, there were significantly higher than average returns on the fourth trading day before the end of the month ($i = -4$). However, no evidence about the turn-of-the-month anomaly was found in the mean equation of the IPC in the last three subperiods studied.

As opposed to the findings reported for model 1, the second model shows that there were turn-of-the-month effects in the corresponding variance equations of the subperiods examined, except during the European crisis subperiod, since the residuals of the corresponding OLS model were homoskedastic during that time interval.

The variance was significantly lower at $i = -1$ and $i = -3$, and $i = +3$ during the pre-crises, Great Recession, and post-crises subperiods, respectively. Conversely, the variance was significantly higher at $i = -1$ also during the post-crises subperiod. So, according to these results, the last trading day of each month exhibited higher average returns along with lower volatility in the IPC throughout the 2013 – 2018 subperiod.

	IPC Sizes Indices								
	Full Period (Oct/26/2006 - Sep/28/2018)			Sub-period 1 (Oct/26/2006 - Sep/30/2009)			Sub-period 2 (Oct/01/2009 - Sep/28/2018)		
	IPC LargeCap Coefficient Value	IPC MidCap Coefficient Value	IPC SmallCap Coefficient Value	IPC LargeCap Coefficient Value	IPC MidCap Coefficient Value	IPC SmallCap Coefficient Value	IPC LargeCap Coefficient Value	IPC MidCap Coefficient Value	IPC SmallCap Coefficient Value
<i>Mean Equation</i>									
Rest of the month	-0.00004	0.00008	0.00047 ***	-0.00037	0.00030	0.00036	0.00000	0.00004	0.00041 **
D ₋₁	-0.00082	0.00103 *	0.00132 *	0.00101	0.00173	0.00259 *	-0.00094	0.00079	0.00138 *
D ₋₁	0.00228 ***	0.00119 *	0.00071	0.00358	0.00227	0.00137	0.00218 ***	0.00116	0.00060
D ₋₂	0.00153 *	0.00094	0.00006	0.00373	0.00134	0.00110	0.00139	0.00073	-0.00012
D ₋₃	0.00014	0.00149 **	-0.00043	0.00185	0.00148	-0.00246 *	-0.00007	0.00147 **	-0.00016
<i>Variance Equation</i>									
Rest of the month	-0.19537 ***	-0.32263 ***	-0.251228 ***	-0.20171 **	-0.26010 ***	-0.19417 ***	-0.34223 ***	-0.800735 ***	-0.48096 ***
D ₋₁	0.22581	-0.01539	0.05286	-0.31312	-0.16731	-0.36854	0.41132 ***	0.006979	0.13398
D ₋₁	-0.06720	0.10861	-0.15837	0.21297	0.14201	0.38833	-0.17086	0.072971	-0.33723
D ₋₂	0.03362	0.16851	0.08548	0.13254	-0.42396	-0.02508	0.00871	0.339281	0.10488
D ₋₃	-0.29378	-0.16738	-0.09367	-0.51059 *	0.17208	-0.22693	-0.17504	-0.262773	-0.00438
$ e_{i,t}/S_{i,t} $	0.11306 ***	0.17224 ***	0.13613 ***	0.09562 ***	0.16961 ***	0.13452 ***	0.10140 ***	0.17110 ***	0.10514 ***
$e_{i,t}/S_{i,t+1}$	-0.09195 ***	-0.05964 ***	-0.04337 ***	-0.13055 ***	-0.07302 **	-0.04925	-0.09770 ***	-0.09858 ***	-0.07056 ***
$\log(S_{i,t}^2)$	0.98760 ***	0.98003 ***	0.98378 ***	0.98185 ***	0.98350 ***	0.98826 ***	0.97268 ***	0.93162 ***	0.95857 ***

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 10. Turn-of-the-Month Effect Model 1: IPC Size Indices

Table 10 displays the results of model 1 for the turn-of-the-month corresponding to the size indices. As can be noticed in that table, EGARCH parameterizations turned out to be the best fit in all instances. The IPC LargeCap and the IPC MidCap exhibited evidence of significantly higher than average returns on the first and third trading days of the month, respectively, in the 2009 – 2018 subperiod. These two indices also showed evidence of the turn-of-the-month effect on the same days throughout the full period under analysis. The IPC SmallCap average returns on days other than those defined as corresponding to the turn of the month in model 1 were significantly higher than zero in the entire period and the second

subperiod, but no evidence of the turn-of-the-month effect appeared in that index. Furthermore, the anomaly was absent of the three indices during the 2006 – 2009 interval.

No significant evidence of the turn-of-the-month anomaly came up in the variance equations of the EGARCH models, although there were highly significant evidence of ARCH effects, negative asymmetry, and volatility persistence in all cases. The results also suggest that volatility persistence was slightly reduced during the post-crises subperiod, as demonstrated by the corresponding $\log(\sigma_{t-1}^2)$ term coefficient.

	IPC Sizes Indices								
	Full Period (Oct/26/2006 - Sep/28/2018)			Sub-period 1 (Oct/26/2006 - Sep/30/2009)			Sub-period 2 (Oct/01/2009 - Sep/28/2018)		
	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap
	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>									
Rest of the month	-0.00007	0.00026	0.00054 **	-0.00050	0.00056	0.00002	0.00000	0.00012	0.00050 **
D ₋₄	-0.00066	-0.00231 ***	-0.00198 ***	-0.00034	-0.00365	0.00074	-0.00083	-0.00174 ***	-0.00221 ***
D ₋₃	0.00108	-0.00035	0.00028	0.00057	-0.00321 **	0.00037	0.00097	0.00016	0.00042
D ₋₂	-0.00016	-0.00081	-0.00006	0.00085	-0.00182	0.00079	-0.00017	-0.00041	0.00003
D ₋₁	-0.00076	0.00062	0.00125 *	0.00132	0.00155	0.00288 *	-0.00092	0.00068	0.00133 *
D ₋₁	0.00225 ***	0.00112	0.00064	0.00387	0.00192	0.00149	0.00212 **	0.00110	0.00056
D ₋₂	0.00156 *	0.00078	-0.00010	0.00382	0.00099	0.00102	0.00136	0.00083	-0.00029
D ₋₃	0.00016	0.00139	-0.00053	0.00214	0.00144	-0.00219	-0.00013	0.00143 *	-0.00026
D ₋₄	0.00030	0.00071	0.00037	0.00056	0.00198	0.00163	0.00006	0.00055	0.00033
<i>Variance Equation</i>									
Rest of the month	-0.20524 ***	-0.32981 ***	-0.267421 ***	-0.18370 **	-0.26727 ***	-0.20957 ***	-0.34528 ***	-0.781383 ***	-0.49011 ***
D ₋₄	0.19716	0.15783	0.22567	0.23657	0.36589	0.37138	0.19037	0.047768	0.22020
D ₋₃	-0.26840	-0.23101	-0.221181	-0.51291	-0.79352 **	-0.15239	-0.10123	-0.004814	-0.15853
D ₋₂	0.38278	0.33896 *	0.145414	0.90612	0.88390 **	0.20187	-0.03820	0.123088	0.02014
D ₋₁	0.01174	-0.16127	0.021854	-0.82124	-0.47017	-0.52312	0.43974 **	-0.059162	0.17314
D ₋₁	-0.06095	0.12285	-0.15271	0.21304	0.09909	0.39205	-0.16581	0.084537	-0.33243
D ₋₂	0.04811	0.18795	0.11133	0.14364	-0.38670	0.00351	0.02092	0.35599	0.12054
D ₋₃	-0.27530	-0.26367	-0.27302	-0.18970	0.12223	-0.39754	-0.26284	-0.320046	-0.16537
D ₋₄	0.02440	0.16233	0.25508	-0.31927	0.13517	0.35038	0.14107	0.104668	0.23264
$ e_{1t}/S_{1,t} $	0.11445 ***	0.17219 ***	0.13659 ***	0.09587 ***	0.16453 ***	0.13479 ***	0.09910 ***	0.17481 ***	0.10543 ***
$e_{1t}/S_{1,t-1}$	-0.09369 ***	-0.06048 ***	-0.04783 ***	-0.13124 ***	-0.08713 ***	-0.06113 *	-0.09823 ***	-0.09361 ***	-0.07239 ***
$\log(S_{1,t-1}^2)$	0.98748 ***	0.98039 ***	0.98325 ***	0.98484 ***	0.98365 ***	0.98904 ***	0.97290 ***	0.93475 ***	0.95869 ***

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 11. Turn-of-the-Month Effect Model 2: IPC Size Indices

Moreover, the results of model 2 displayed in Table 11 confirm the outcomes of model 1 regarding that the IPC LargeCap exhibited significantly higher average returns on the first trading day of each month during the full period, as well as throughout the 2009 – 2018 subperiod. The IPC MidCap and the IPC SmallCap presented significantly lower than average returns on the fourth trading day before the end of the month during the same time intervals.

According to the results in model 2, though, the statistically higher than the average return on the third trading day of the month identified in the full period and the second subperiod in model 1 for the IPC MidCap was not significant. Also, average returns of the small-capitalization index on trading days other than the last four of one month and the first four of the next were significantly higher than zero in the 2006 – 2018 period and in the subperiod after the Great Recession.

Therefore, the results in Table 11 show that most of the different than average daily returns emerged four trading days before the end of the month. In particular, average returns were significantly lower in the medium- and small-capitalization indices four trading days before the end of the month. The large-capitalization index showed significantly higher than average returns on the first trading day of each month, according to the outcomes of both models 1 and 2.

The results of the corresponding Kruskal-Wallis test applied to the IPC LargeCap and IPC MidCap failed to reject the null hypothesis that daily returns were the same, irrespective of the days of the month involved in the turn of the month, as defined for models 1 and 2. On the other hand, the respective test for the small-capitalization index rejected the null hypothesis of equal return distributions during the full period and the first subperiod, but the test failed to reject the null hypothesis for the second subperiod for that index.

According to the results of the EGARCH models variance equations shown in Table 11, the IPC MidCap displayed significantly lower volatility on the third trading day before the end of the month ($i = -3$) during the first subperiod. However, higher volatility on the next day ($i = -2$) contributed to offset such a pattern to some extent. The IPC LargeCap also showed significantly higher volatility the last trading day during the most recent subperiod, which confirms the results of model 1 in this respect.

Finally, the results of model 2 confirm the presence of significant conditional heteroskedasticity, leverage, and volatility persistence based on the corresponding coefficients of the variance equations for each index and time interval considered. It is worth

noticing, however, that the leverage effect for the small-capitalization index during the first subperiod was only significant at the 10% level⁵⁴.

In short, the regression models found significant and consistent evidence regarding the presence of the turn-of-the-month anomaly in the returns of the four indices of the Mexican Stock Exchange examined in this research. This result was supported by the outcomes of the Kruskal-Wallis test, both for the IPC and the IPC SmallCap. Nevertheless, while this anomaly faded away from the IPC returns, it did not disappear from the three size indices.

In contrast, throughout the full period, the regression models did not find evidence of the turn-of-the-month effect in any of the indices' volatility. It is worth noting that the IPC and the IPC LargeCap exhibited the presence of such an anomaly in the corresponding variance equations. Hence, it is sensible to make a case that this seasonal effect has not vanished from those indices' volatility.

5.6 January Effect Results

The null hypothesis for the January effect, as the literature usually defines this anomaly, is that the constant term in equation (31) is positive and statistically different from zero. Additionally, the fact that the coefficients of the dummy variables in that equation are not significant, or that they are significant but negative, represent even more convincing evidence in favor of the January effect.

⁵⁴ The p -value of the corresponding coefficient was 0.084.

Price and Quotation Index (IPC)			
	Full Period	Sub-period 1	Sub-period 2
	Jan/03/2000 - Sep/28/2018	Jan/03/2000 - Sep/30/2009	Oct/01/2009 - Sep/28/2018
	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>			
January (Constant)	0.00275	0.01480	-0.00913
February (D ₁)	-0.00442	-0.01705	0.00761
March (D ₂)	0.02288	0.01456	0.03048 **
April (D ₃)	0.00377	-0.00272	0.01041
May (D ₄)	-0.00470	0.00043	-0.01153
June (D ₅)	0.01336	-0.00146	0.02764 *
July (D ₆)	0.00495	-0.01502	0.02431
August (D ₇)	-0.00181	-0.00589	0.00287
September (D ₈)	-0.00705	-0.02120	0.00655
October (D ₉)	0.01117	-0.00952	0.02984 *
November (D ₁₀)	0.00956	0.00488	0.01318
December (D ₁₁)	0.02410	0.02394	0.02677 *

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 12. January Effect: IPC

Table 12 displays the results of the OLS models for the IPC corresponding to the whole period studied, as well as those of the two subperiods considered in the case of monthly returns, as described in section 4.4.3. Throughout all three time intervals, the ARCH-LM tests failed to reject the hypothesis of homoskedasticity in the residuals, so OLS regressions were appropriate to examine for the presence of the January effect. No evidence of the month-of-the-year effect in the IPC volatility arose from the analyses performed.

The results of the regression models reflect no significant evidence of the January effect, or any other month-of-the-year anomaly, in the IPC returns during the full period or the first subperiod. Moreover, such outcomes appear to be robust because the corresponding Kruskal-Wallis tests strongly failed to reject the null hypothesis of equal monthly returns throughout the year.

In contrast, the IPC average returns in March were significantly higher than the average on other months after the Great Recession, and the corresponding coefficient value denotes that March's average returns were the highest of the year. Also, the returns of the IPC followed a

normal probability distribution during the post-crisis subperiod, according to the Jarque-Bera test⁵⁵. Thus, in addition to the Kruskal-Wallis test, the ANOVA test was also performed to the corresponding time series. Although both tests failed to reject the hypothesis of equal returns for all months of the year, the result of the ANOVA presented a relatively low significance level⁵⁶. So, this outcome might be considered evidence for the presence of the month-of-the-year effect in the IPC, despite that result is not as solid as the regression model findings.

	IPC Sizes Indices								
	Full Period (Oct/26/2006 - Sep/28/2018)			Sub-period 1 (Oct/26/2006 - Sep/30/2009)			Sub-period 2 (Oct/01/2009 - Sep/28/2018)		
	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap
	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>									
January (Constant)	-0.01613	-0.01024	0.00790	-0.03197	-0.01332	-0.07312	-0.00840	-0.00224	0.01247
February (D ₁)	0.00327	-0.00085	-0.00450	-0.00706	0.01329	0.04327	0.00831	-0.00672	-0.00205
March (D ₂)	0.05536 ***	0.03482	0.02053	0.12949 **	0.03894	0.08691	0.03882 ***	0.03240 **	0.02501
April (D ₃)	0.02378	0.03067	0.00359	0.06689	0.09010	0.17602 **	0.00363	0.00948	-0.00234
May (D ₄)	0.02014	0.00885	0.00005	0.11639 ***	0.10577 *	0.19229 *	-0.00885	-0.02512	-0.02244
June (D ₅)	0.02455	0.02203	0.01295	0.00063	0.02410	0.04242	0.02259 *	0.02084	-0.00538
July (D ₆)	0.02786	0.03298	-0.00110	0.05026	0.04789	0.07363	0.02200 *	0.02377	-0.00519
August (D ₇)	0.01156	-0.00061	-0.02270	0.02923	-0.00574	0.08720	0.00767	-0.00623	-0.02674
September (D ₈)	0.01333	0.00614	0.00792	0.04186	0.00229	0.05178	0.00283	0.00565	-0.00660
October (D ₉)	0.02128	-0.00628	0.00892	-0.03022	-0.11857 **	0.01266	0.03330 **	0.01842	0.00838
November (D ₁₀)	0.02288	0.00781	-0.01501	0.06197	-0.00770	0.03957	0.01350	0.00789	-0.00730
December (D ₁₁)	0.03995 *	0.04861 *	0.00924	0.07994	0.11867 *	0.10226 **	0.02339	0.02116	0.00656
<i>Variance Equation</i>									
January (Constant)	----	----	0.00229 ***	----	----	----	0.00074	----	----
February (D ₁)	----	----	-0.00321 **	----	----	----	-0.00071	----	----
March (D ₂)	----	----	-0.00231 **	----	----	----	-0.00084 ***	----	----
April (D ₃)	----	----	-0.00287 ***	----	----	----	-0.00094	----	----
May (D ₄)	----	----	-0.00021	----	----	----	-0.00062	----	----
June (D ₅)	----	----	-0.00355 **	----	----	----	-0.00031	----	----
July (D ₆)	----	----	-0.00143	----	----	----	-0.00087	----	----
August (D ₇)	----	----	-0.00199	----	----	----	-0.00036	----	----
September (D ₈)	----	----	-0.00227 *	----	----	----	-0.00024	----	----
October (D ₉)	----	----	-0.00181	----	----	----	-0.00042	----	----
November (D ₁₀)	----	----	-0.00118	----	----	----	-0.00023	----	----
December (D ₁₁)	----	----	-0.00266 *	----	----	----	-0.00092	----	----
$\hat{\epsilon}_{t-1}^2$	----	----	0.26630 ***	----	----	----	0.04532	----	----
S_{t-1}^2	----	----	0.58913 ***	----	----	----	0.59083	----	----
$\hat{\epsilon}_{t-1}^2 (\hat{\epsilon}_{t-1}^2 < 0)$	----	----	----	----	----	----	0.21189	----	----

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 13. January Effect: IPC Size Indices

The IPC size-related indices required different models to examine the presence of the January effect, as revealed by the results in Table 13. Seven of the nine models used for this purpose

⁵⁵ The Jarque-Bera test p -value for the IPC returns distribution corresponding to the second subperiod was 0.697.

⁵⁶ The p -value of the ANOVA mean equality test was 0.106.

were OLS regressions since, in such instances, the ARCH-LM test for equation (31) failed to reject the hypothesis of homoskedasticity. This was not the case, however, for the IPC SmallCap nor the IPC LargeCap in the full period and the second subperiod, respectively. That is, according to the results of the AIC, a GARCH parameterization was the most suitable model in the case of the small-capitalization index in the full period. Likewise, a TGARCH specification was the best fit for the large-capitalization index during the second subperiod. A maximum likelihood (ML) estimation was used in the corresponding models in both cases since the regression residuals followed a normal distribution.

Despite January average returns were negative for the IPC LargeCap and the IPC MidCap in all time intervals under analysis, as well as for the IPC SmallCap in the first subperiod, January returns were not significantly different from zero for any of such indices and time intervals. Therefore, no evidence of the January effect in the returns of the size indices was found. On the other hand, a significant and persistent positive March effect was identified in the IPC LargeCap throughout all time intervals examined. Average returns in October were also higher than expected in the same index between 2009 and 2018.

The results point at several different than expected average returns between 2006 and 2009. In addition to the significantly higher March average returns in the IPC LargeCap mentioned earlier, such an index also displayed higher than expected returns in May. In the case of the medium-capitalization index, October average returns were significantly lower, whereas April and December mean returns were statistically higher for the IPC SmallCap.

Table 13 reveals that, after the Great Recession, the IPC MidCap average returns in March were statistically higher. Only in this instance, both the Kruskal-Wallis or ANOVA tests determined different distributions of monthly returns. More precisely, the ANOVA test was performed in the medium-capitalization index for the second subperiod, since the corresponding returns were normally distributed⁵⁷. That test rejected the hypothesis of equal

⁵⁷ The *p*-value of the corresponding Jarque-Bera test was 0.556.

distribution of returns for all months at the 5% significance level. The Kruskal-Wallis test arrived at a similar result.

A statistically significant January effect was found in the variance equation of the IPC SmallCap GARCH model in the full period under analysis, as shown in the bottom section of Table 13. January variance coefficient was significantly positive, and at the same time, seven of the dummy variable coefficients were not significant⁵⁸, whereas the remaining four dummy variables were significant but negative. June showed the lowest level of volatility, followed by the volatility in February. The small-capitalization index also displayed significant ARCH and GARCH effects in the entire period examined, as well as relatively high volatility persistences⁵⁹.

The results of the variance equation of the TGARCH model for the IPC LargeCap in the time interval following the Great Recession suggest no evidence of the January effect in volatility. These results reveal, nonetheless, significantly lower volatility in March. The respective coefficients of the variance equation suggest that there was no significant ARCH, GARCH, or leverage effects in the large-capitalization index during that subperiod.

The analyses carried out in this research found no evidence of the month-of-the-year anomaly in the IPC in the full period or the first subperiod under examination. On the other hand, there was a month-of-the-year anomaly in that index after the Great Recession, since average returns in March were significantly higher.

Despite the January anomaly was not identified in the IPC LargeCap, IPC MidCap, or IPC SmallCap, the analyses of the month-of-the-year effect produced mixed results. During the first subperiod, the three size indices displayed evidence of different than average returns on at least one month. In the second subperiod, the large-capitalization index exhibited

⁵⁸ Among such coefficients are those corresponding to September and December, which were negative, and relevant at the 10% significance level.

⁵⁹ The sum of coefficients α_1 and β_1 corresponding to equation (24) is 0.855.

significantly higher average returns in March and October, and the returns of the IPC MidCap displayed a March effect. The small-capitalization index, though, did not show evidence of the January or month-of-the-year anomalies at all.

The results reveal that the IPC LargeCap consistently exhibited a March anomaly from 2006 to 2018. Thus, that index presented evidence of a higher average return in March. The same is true for the IPC, particularly in the most recent subperiod.

There was a significantly positive January effect in volatility in the IPC SmallCap, as well as ARCH and GARCH effects in that index from 2006 to 2009. Additionally, the large-capitalization index showed a significant negative volatility effect in March in the subperiod after the Great Recession.

In summary, the January effect did not come up in either the returns or volatility of any of the four indices examined in this research. However, a month-of-the-year anomaly appeared between 2009 and 2018 in the IPC and the IPC LargeCap. Specifically, the IPC exhibited significantly higher returns in March, and the large-capitalization index showed significantly lower volatility along with significantly higher average returns also in March.

5.7 Halloween Indicator Results

Two models were used to test for the presence of the Halloween effect in the Mexican stock market as described by equations (32) and (33). Table 14 shows the results of model 1, which does not control for the January effect in the IPC. In the full period and the first subperiod, the ARCH-LM test failed to reject the hypothesis of homoskedasticity, so OLS models were the best fit in both cases. In the subperiod after the Great Recession, however, ARCH(1)

effects were significant, and to deal with this feature of the return series, EGARCH with ML estimation turned out to be the best fitting specification⁶⁰.

Price and Quotation Index (IPC)			
	Full Period	Sub-period 1	Sub-period 2
	Jan/03/2000 - Sep/28/2018	Jan/03/2000 - Sep/30/2009	Oct/01/2009 - Sep/28/2018
	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>			
Summer months (Constant)	0.00568	0.00654	0.00254
Halloween indicator (D_1)	0.00584	0.01119	0.00113
<i>Variance Equation</i>			
Summer months (Constant)	----	----	-4.76019 *
Halloween indicator (D_1)	----	----	0.24139
$ e_{t-1}/S_{t-1} $	----	----	0.37946
e_{t-1}/S_{t-1}	----	----	-0.18828
$\log(S_{t-1}^2)$	----	----	0.37090
***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.			

Table 14. Halloween Indicator Model 1: IPC

As stated by the results of model 1 shown in Table 14, no significant difference in average returns between summer and winter months was found in the IPC in any of the time intervals examined. Thus, the Halloween indicator was nonexistent in the returns of that stock index. Moreover, no significant seasonal, ARCH, GARCH, or leverage effects appeared either in the variance equation of the EGARCH specification.

As described earlier, the second model to test for the Halloween anomaly, controls for the January effect. Table 15 displays the results of such a model for the IPC. The most suitable parameterization for all intervals involved was OLS regressions since no indication of ARCH(1) effects was found in the corresponding specifications. The results of model 2 for the Halloween indicator in the IPC tend to confirm the nonexistence of this anomaly in such

⁶⁰ GARCH and TGARCH models were also tested as in several other cases in this research. However, the coefficients of the GARCH did not meet the nonnegativity constraints of the model. The TGARCH specification did not present this problem, but its AIC was higher than that of the EGARCH.

an index. Moreover, the significance of the returns difference between the summer and winter months decreased in the most recent subperiod.

Price and Quotation Index (IPC)			
	Full Period	Sub-period 1	Sub-period 2
	Jan/03/2000 - Sep/28/2018	Jan/03/2000 - Sep/30/2009	Oct/01/2009 - Sep/28/2018
	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>			
Summer months (Constant)	0.00571	0.00582	0.00489
Halloween indicator (D_1)	0.00709	0.01531	0.00427
January (D_2)	-0.00739	-0.00784	-0.02181 **
***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.			

Table 15. Halloween Indicator Model 2: IPC

The corresponding Kruskal-Wallis and ANOVA tests strongly failed to reject the null hypothesis of equal median and mean, respectively, of the IPC returns during the summer and winter months. Therefore, according to these tests, the results of the Halloween indicator regressions seem robust.

There was, though, a significantly lower than average January average return in the subperiod after the Great Recession. This finding matches the results shown in Table 12 concerning negative returns in January, except that such returns turned out to be not significant in the month-of-the-year analysis described in section 5.6.

The outcomes of the two models used to test for the Halloween indicator in the IPC imply that such an anomaly did not exist in the returns or volatility of such stock index in any of the time intervals examined. Additionally, the results reveal that the statistical significance of the difference in average returns in the winter and summer months has decreased⁶¹.

⁶¹ The Halloween dummy coefficient p -value in model 1 was 0.327 for the first subperiod and 0.867 for the second. The corresponding p -values in model 2 were 0.192 and 0.502, respectively.

As can be seen in Table 16, different specifications turned out to be the best fitting to examine the presence of the Halloween anomaly in the case of the size indices. In most instances, the ARCH-LM test failed to reject the hypothesis of homoskedasticity, particularly in the 2006 – 2009 subperiod, where OLS estimations turned out to be the most appropriate for the three size indices. Nevertheless, EGARCH specifications were the best fit for the large-capitalization index in the full period and the second subperiod, while a TGARCH parameterization was the most adequate for the IPC SmallCap in the full period examined.

	IPC Sizes Indices								
	Full Period (Oct/26/2006 - Sep/28/2018)			Sub-period 1 (Oct/26/2006 - Sep/30/2009)			Sub-period 2 (Oct/01/2009 - Sep/28/2018)		
	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap
	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>									
Summer months (Constant)	0.00343	0.00105	0.00159	-0.00076	-0.00974	-0.00180	0.00032	0.00232	0.00281
Halloween indicator (D_1)	-0.00373	0.00967	0.01201	0.01649	0.02587	-0.01714	0.00444	0.00762	0.01298 *
<i>Variance Equation</i>									
Summer months (Constant)	-0.35078	----	0.00042	----	----	----	-11.57086 ***	----	----
Halloween indicator (D_1)	0.02137	----	0.09456	----	----	----	0.63820	----	----
$\hat{\epsilon}_{t-1}^2$	----	----	0.21194	----	----	----	----	----	----
S_{t-1}^2	----	----	0.65928 ***	----	----	----	----	----	----
$\hat{\epsilon}_{t-1}^2 (\hat{\epsilon}_{t-1}^2 < 0)$	----	----	0.09456	----	----	----	----	----	----
$ \hat{\epsilon}_{t-1}/S_{t-1} $	0.14317	----	----	----	----	----	0.57481 **	----	----
$\hat{\epsilon}_{t-1}/S_{t-1}$	-0.22581 ***	----	----	----	----	----	-0.04331	----	----
$\log(S_{t-1}^2)$	0.96470 ***	----	----	----	----	----	-0.55166 **	----	----

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 16. Halloween Indicator Model 1: IPC Size Indices

No significant evidence of the Halloween effect was identified in the returns of the size indices, as suggested by the results of model 1 shown in Table 16. No conclusive evidence of the Halloween effect was identified in the returns of the size indices, as suggested by the results of model 1 shown in Table 16. However, the IPC SmallCap exhibited larger average returns from November to April than from May to October in the subperiod after the Great Recession. Nonetheless, the corresponding coefficient was only relevant at the 10% significance level. The respective ANOVA test rejected the hypothesis of equal average returns in the winter than in the summer, but this result was also significant only at the 10% level.

The IPC LargeCap and the IPC SmallCap exhibited significant GARCH effects during the full period. According to the corresponding EGARCH model, there was also a statistically

relevant GARCH effect in the large-capitalization index during the 2009 – 2018 subperiod. Interestingly, though, the sign of the coefficient was negative in that subperiod, as opposed to the positive GARCH effect sign found in the full period. This outcome means that throughout the most recent subperiod the contemporary monthly variance was inversely related to that of the previous month.

During the 2009 – 2018 subperiod, the constant of the variance equation of the large-capitalization index was very negative and significantly different from zero. In other words, the volatility of that index was lower in the summer months than in the winter months in that subperiod. In the same interval, the mean equation value of the Halloween indicator coefficient suggests that the IPC LargeCap exhibited higher average returns in the winter months than in the summer months, although such a difference was not statistically significant. So, it is reasonable to assume that for the large-capitalization index lower average returns during the summer were related to lower volatility.

The large- and small-capitalization indices exhibited leverage in the full period, although it was significant only in the former. In other words, an asymmetry between good and bad news was identified only in the IPC LargeCap. The large-capitalization index also displayed leverage between 2009 and 2018, but the corresponding EGARCH coefficient turned out to be not significant.

	IPC Sizes Indices								
	Full Period (Oct/26/2006 - Sep/28/2018)			Sub-period 1 (Oct/26/2006 - Sep/30/2009)			Sub-period 2 (Oct/01/2009 - Sep/28/2018)		
	IPC LargeCap Coefficient Value	IPC MidCap Coefficient Value	IPC SmallCap Coefficient Value	IPC LargeCap Coefficient Value	IPC MidCap Coefficient Value	IPC SmallCap Coefficient Value	IPC LargeCap Coefficient Value	IPC MidCap Coefficient Value	IPC SmallCap Coefficient Value
<i>Mean Equation</i>									
Summer months (Constant)	0.00088	0.00137	0.00096	0.00684	-0.00712	0.00855	0.00026	0.00246	0.00281
Halloween indicator (D ₁)	-0.00147	0.01283	0.01555 **	0.02944	0.03196	-0.02171	0.00498	0.01122	0.01364 *
January (D ₂)	-0.01389	-0.02252	-0.00929	-0.10029 **	-0.06574	-0.10692 **	-0.00334	-0.02383 *	-0.00398
<i>Variance Equation</i>									
Summer months (Constant)	-0.02331	----	0.00075 ***	----	----	----	-11.9985 ***	----	----
Halloween indicator (D ₁)	-0.08837	----	-0.00122 ***	----	----	----	0.64638	----	----
January (D ₂)	0.99589	----	0.00197 ***	----	----	----	-0.17340	----	----
$\hat{\epsilon}_{t-1}^2$	----	----	0.19276 ***	----	----	----	----	----	----
S_{t-1}^2	----	----	0.68819 ***	----	----	----	----	----	----
$\hat{\epsilon}_{t-1}^2 (\hat{\epsilon}_{t-1}^2 < 0)$	----	----	----	----	----	----	----	----	----
$ a_{-1}/S_{t-1} $	-0.08687	----	----	----	----	----	0.55499 **	----	----
a_{-1}/S_{t-1}	-0.20680 ***	----	----	----	----	----	-0.01263	----	----
$\log(S_{t-1}^2)$	0.98764 ***	----	----	----	----	----	-0.61396 **	----	----
	----	----	----	----	----	----	----	----	----

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 17. Halloween Indicator Model 2: IPC Size Indices

The results in Table 17 show that the same specifications used in model 1 for the Halloween effect in the size indices were also applicable for model 2, which controls for the January effect. The only exception was the IPC SmallCap in the full period, where a GARCH specification replaced the original TGARCH as the best parameterization.

The results of model 2 imply the presence of the Halloween effect in the IPC SmallCap only since average winter returns of that index were statistically higher than summer average returns in the 2006 – 2018 interval. The significant presence of the Halloween indicator in the returns of the IPC SmallCap discovered here may conflict with the findings reported in previous research about the non-existence of this anomaly in the stock market in Mexico. It is worth remarking, however, that such studies only considered the broad index of the Mexican stock market.

The results of the variance equations in model 2 are very similar to those found in model 1. A noteworthy difference, though, is that all the coefficients of the variance equation of the GARCH model for the IPC SmallCap were highly significant in the full period. This outcome implies that there were ARCH and GARCH effects in the small-capitalization index between 2006 and 2018. Furthermore, the volatility equation intercept was positive and statistically different from zero. In this regard, a result that is particularly relevant for this research is that the IPC SmallCap volatility from November to April was significantly lower than that from May to October, despite that volatility in January was statistically higher than the summer months' volatility.

Furthermore, from 2006 to 2018, the significant Halloween coefficients corresponding to the mean and variance equations of the small-capitalization index imply that average returns were higher in the winter than in the summer, and volatility lower. Therefore, after controlling for the January effect in the IPC SmallCap discussed in section 5.6, the Halloween anomaly seems to have existed in this index during the whole period examined.

In short, no significant evidence regarding the existence of the Halloween indicator was found whatsoever in the broad index of the Mexican Stock Exchange, nor in the large- and medium-capitalization indices. In the case of the IPC SmallCap, the Halloween effect was identified in the full period when controlling for the January effect, since it emerged in the returns of that index in the most recent subperiod.

The small-capitalization index also displayed significantly lower volatility in the winter months, while the volatility in the summer months was statistically different from zero. This outcome might imply an inverse Halloween anomaly in the volatility of such an index.

5.8 January Barometer Results

As discussed in section 4.5.5.6, the analysis for the presence of the January barometer in the Mexican stock market used two versions of the model represented by equation (34): one that considered raw monthly returns and another that encompassed excess monthly returns. The purpose was to determine whether average returns from February to December following Januarys with positive returns (i.e., positive Januarys) have been higher than the 11-month average returns following Januarys with negative returns (i.e., negative Januarys).

Table 18 presents the results of the January barometer analysis for the raw returns of the IPC. As can be seen in that table, OLS estimation turned out to be the best fit for the full period and the first subperiod, while EGARCH with ML estimation was the most suitable specification for the period following the Great Recession. It is worth remarking that it was necessary to include one or more lags of the response variable in some of the regression models to avoid serial correlation. More specifically, the OLS regression for the 2000 – 2018 period included the second and fifth lags of the raw returns of the IPC.

However, as far as it could be determined, previous research papers regarding the January barometer do not explicitly specify the use of lagged values of the response variable. Furthermore, in previous studies, only OLS regressions have been used to examine the

January barometer, but GARCH family models were applied here in those instances where the ARCH-LM test rejected the hypothesis of homoskedasticity.

Price and Quotation Index (IPC)			
	Full Period	Sub-period 1	Sub-period 2
	Jan/03/2000 - Sep/28/2018	Jan/03/2000 - Sep/30/2009	Oct/01/2009 - Sep/28/2018
	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>			
Following negative Januarys (Constant)	0.00941 *	0.00943	0.00546
Following positive Januarys (D ₁)	-0.00041	0.00397	-0.00445
<i>Variance Equation</i>			
Constant	----	----	-0.78377
$ \epsilon_{t-1}/s_{t-1} $	----	----	0.06832
ϵ_{t-1}/s_{t-1}	----	----	-0.22085 *
$\log(s^2_{t-1})$	----	----	0.89442 ***

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 18. January Barometer Model 1: IPC

According to the results displayed in Table 18 during the full period and the second subperiod, February to December average raw returns were lower following positive Januarys than after negative Januarys, but the opposite occurred in the 2000 – 2009 subperiod. Nevertheless, such results do not show any evidence of statistically different average raw monthly returns between the 11 months following positive Januarys and those following negative Januarys. The results of the variance equation of the EGARCH for the second subperiod imply that there was highly significant and persistent volatility in the IPC, but no other volatility effects were statistically relevant.

Also, as Table 19 shows, when considering excess returns, the IPC did not present the existence of the January barometer either. Average February to December excess returns following positive Januarys were lower than those following negative Januarys in the full period and the first subperiod. This difference, however, was not significant, which endorses the results of model 1 in this respect.

EGARCH specifications turned out to be the best fit for the full period and the second subperiod. However, QML estimation was used in the former, since the postestimation results revealed that the residuals of the corresponding regression model did not follow a normal probability distribution. The results of the variance equation in model 2 imply that there was highly significant and persistent volatility after the Great Recession and during the full period. Also, there was a statistically relevant ARCH effect from 2000 to 2018, and the negative constant was significantly different from zero at the same time interval.

Price and Quotation Index (IPC)			
	Full Period	Sub-period 1	Sub-period 2
	Jan/03/2000 - Sep/28/2018	Jan/03/2000 - Sep/30/2009	Oct/01/2009 - Sep/28/2018
	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>			
Following negative Januarys (Constant)	0.00486	0.00262	0.00146
Following positive Januarys (D_1)	-0.00297	0.00452	-0.00431
<i>Variance Equation</i>			
Constant	-0.48225 **	----	0.02633
$ e_{t-1}/s_{t-1} $	0.24173 **	----	-0.14043
e_{t-1}/s_{t-1}	-0.06712	----	-0.12611
$\log(s_{t-1}^2)$	0.95470 ***	----	0.98522 ***
***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.			

Table 19. January Barometer Model 2: IPC

The results of models 1 and 2 agree that there was no January barometer anomaly in the IPC in any of the time intervals under analysis. Moreover, the Kruskal-Wallis test failed to reject the hypothesis that the median 11-month raw or excess returns following positive Januarys were statistically the same as the median 11-month returns following negative Januarys in the full period and the first subperiod.

The analyses uncovered similar results in the subperiod after the Great Recession. The ANOVA test used for the normally distributed monthly returns in that subperiod found no significant difference in the means between the February to December raw or excess returns after positive and negative Januarys. Additionally, the results of both models revealed that

the IPC's volatility was significantly persistent after the Great Recession and that there was a significant ARCH effect from 2000 to 2018 when considering excess returns.

Table 20 presents the results of the January barometer for the raw returns of the IPC size-related indices. OLS estimation was the best fit in most instances. In the case of the IPC SmallCap during the full period and the IPC LargeCap in the second subperiod, though, GARCH family parameterizations were the most appropriate. Particularly, the former required a GARCH specification and the latter an EGARCH model. Also, in some cases, it was necessary to include one or more lags of the raw 11-month returns following January to circumvent autocorrelation. For example, the GARCH for the IPC SmallCap during the 2006 – 2018 interval included the 8th lag of the February to December raw returns⁶².

	IPC Sizes Indices								
	Full Period (Oct/26/2006 - Sep/28/2018)			Sub-period 1 (Oct/26/2006 - Sep/30/2009)			Sub-period 2 (Oct/01/2009 - Sep/28/2018)		
	IPC LargeCap Coefficient Value	IPC MidCap Coefficient Value	IPC SmallCap Coefficient Value	IPC LargeCap Coefficient Value	IPC MidCap Coefficient Value	IPC SmallCap Coefficient Value	IPC LargeCap Coefficient Value	IPC MidCap Coefficient Value	IPC SmallCap Coefficient Value
<i>Mean Equation</i>									
Following negative Januarys (Constant)	0.01209 ***	0.00484	0.01448 **	0.00882	-0.01310	-0.01724	0.00664 *	0.00598	0.01466 **
Following positive Januarys (D ₁)	-0.01033	0.00209	-0.00870	-0.00119	0.01650	0.03442	-0.00533	0.00433	-0.00888
<i>Variance Equation</i>									
Constant	----	----	0.00054 *	----	----	----	-0.86194	----	----
ϵ_{t-1}^2	----	----	0.31849 **	----	----	----	----	----	----
S_{t-1}^2	----	----	0.46651 **	----	----	----	----	----	----
$ \epsilon_{t-1}/S_{t-1} $	----	----	----	----	----	----	0.09675	----	----
ϵ_{t-1}/S_{t-1}	----	----	----	----	----	----	-0.22589 *	----	----
$\log(S_{t-1}^2)$	----	----	----	----	----	----	0.88610 ***	----	----

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 20. January Barometer Model 1: IPC Size Indices

According to the results shown in Table 20, positive raw February to December returns following negative Januarys were significantly higher than zero for the large- and small-capitalization indices from 2006 to 2018. This was also true for the IPC SmallCap after the Great Recession. In contrast, the coefficients of the 11-month returns following positive Januarys were not significant.

⁶² The *p*-value of the ARCH-LM test of the OLS of the IPC in the full period was 0.001. The *p*-value of the coefficient of the 8th lag in the GARCH was 0.0104, and the *p*-values of the autocorrelation function up to the 8th and 12th lags were 0.199 and 0.375, respectively.

These findings mean that when January returns were negative, the average returns in the remaining months of the year were statistically positive. Thus, an inverse January barometer anomaly was present in the Mexican stock market. However, the 11-month average returns following positive and negative Januarys were statistically indistinguishable from the 11-month returns following negative Januarys.

The results in Table 20 also imply that January returns performance was, at best, an unclear signal for the performance of the indices during the rest of the year. Therefore, it is reasonable to assume that the January barometer effect was not present in the raw returns of the size indices in any of the time intervals examined.

The variance equation of the GARCH model corresponding to the IPC SmallCap during the 2006 – 2018 period reveals that there were significant ARCH and GARCH effects in that index. Similarly, the results of the EGARCH model corresponding to the IPC LargeCap after the Great Recession reveal a significant and relatively persistent GARCH effect in that index.

	IPC Sizes Indices								
	Full Period (Oct/26/2006 - Sep/28/2018)			Sub-period 1 (Oct/26/2006 - Sep/30/2009)			Sub-period 2 (Oct/01/2009 - Sep/28/2018)		
	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap	IPC LargeCap	IPC MidCap	IPC SmallCap
	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value	Coefficient Value
<i>Mean Equation</i>									
Following negative Januarys (Constant)	0.00859 *	0.00121	0.00838	0.00353	-0.01074	-0.02260	0.00080	0.00274	0.01245 **
Following positive Januarys (D ₁)	-0.01093	0.00143	-0.00632	-0.00139	0.02546	0.03421	-0.00408	0.00377	-0.00654
<i>Variance Equation</i>									
Constant	----	----	0.00055 *	----	----	----	0.14963	----	----
$\hat{\epsilon}_{t-1}^2$	----	----	0.32466 **	----	----	----	----	----	----
S_{t-1}^2	----	----	0.45900 **	----	----	----	----	----	----
$ \hat{\epsilon}_{t-1}/S_{t-1} $	----	----	----	----	----	----	-0.09687	----	----
$\hat{\epsilon}_{t-1}/S_{t-1}$	----	----	----	----	----	----	-0.18673 ***	----	----
$\log(S_{t-1}^2)$	----	----	----	----	----	----	1.00634 ***	----	----

***, **, and * denote significance levels of 1%, 5%, and 10%, respectively.

Table 21. January Barometer Model 2: IPC Size Indices

Table 21 shows the results of the January barometer analyses considering excess returns of the size-related indices. The findings previously discussed for raw returns seem robust in general, in light of the information presented in that table. Two exceptions are that the constant term of the excess returns regression models for the IPC LargeCap and the IPC SmallCap in the full period were not significantly different from zero at the 5% significance

level. In general, nonetheless, the evidence found in model 2 relating to the nonexistence of the January barometer points in the same direction as the findings of model 1.

The ANOVA test applied to in the cases of normally distributed monthly returns failed to reject the hypothesis that the distribution of February to December raw or excess returns following negative Januarys was statistically the same as that following positive Januarys. The Kruskal-Wallis tests used for non-normally distributed returns found similar results.

In short, the analyses performed in this research found no evidence regarding the presence of the January barometer in any of the Mexican stock market indices examined. Furthermore, January returns of such stock indices turned out to be an ineffective indicator of their performance during the remaining months of the year.

Chapter 6: Discussion and Conclusions

6.1 Introduction

This final chapter presents the discussion regarding the main findings reported in chapter 5, as well as the conclusions of the research. Section 6.2 discusses which of the hypotheses of construct specified in chapter 4 were rejected and which of them were not, and briefly outlines some possible explanations for the corresponding outcomes. Part 6.3 reviews the theoretical and practical implications of the results of this research. Segment 6.4 examines the conclusions regarding the research problem. Finally, section 6.5 presents some points of view concerning the repercussions of this study for further research.

6.2 Results and Hypotheses of Construct

Table 22 presents a synopsis of the results corresponding to each of the hypotheses specified in section 4.3.1. The criterion applied to design Table 22 was the following: Whenever the presence of an anomaly was not significant in the corresponding full period for the index examined means that the analyses rejected the hypothesis regarding the existence of such an anomaly. Similarly, when the anomaly was not statistically significant in the corresponding last subperiod under examination for each of the indices, then the analyses failed to reject the premise regarding its disappearance. The following subsections review in detail the conclusions for each of the seasonal anomalies' hypotheses.

6.2.1 Conclusions About the Day-of-the-Week Effect

The results of the regression models failed to reject the hypothesis concerning the presence of the day-of-the-week effect in the returns of the IPC, the IPC LargeCap, and the IPC SmallCap in the corresponding full periods under analysis. This conclusion about the existence of the day-of-the-week effect in the Mexican stock market agrees with the findings reported by Cabello & Ortiz (2003), Kristjanpoller & Muñoz (2012), Seif et al. (2017), and Winkelried & Iberico (2018). Also, the econometric analyses identified significantly positive Monday returns in the IPC and the large-capitalization index, a finding that agrees with the

conclusions put forward by Philpot & Peterson (2011) regarding the reversal of the Monday effect.

Anomaly	IPC				IPC LargeCap			
	Returns		Volatility		Returns		Volatility	
	The anomaly exists (H_A)	The anomaly disappeared (H_0)	The anomaly exists (H_C)	The anomaly disappeared (H_0)	The anomaly exists (H_A)	The anomaly disappeared (H_0)	The anomaly exists (H_C)	The anomaly disappeared (H_0)
Day-of-the-Week Effect	Failed to reject	Rejected	Failed to reject	Failed to reject	Failed to reject	Rejected	Failed to reject	Rejected
Holiday Effect	Rejected*	---	Failed to reject	Rejected	Rejected*	---	Failed to reject	Rejected
Turn-of-the-Month Effect	Failed to reject*	Failed to reject	Rejected	Rejected (The anomaly appeared in 2013 - 2018)	Failed to reject	Rejected	Rejected	---
January Effect	Rejected*	--- (A March effect appeared in 2009 - 2018)	Rejected	---	Rejected * (March effect in 2006 - 2018)	--- (March and October effects appeared in 2009 - 2018)	Rejected	--- (A March effect appeared in 2009 - 2018)
Halloween Indicator	Rejected*	---	Rejected	---	Rejected*	---	Rejected	--- (Lower volatility during the Summer months in 2009 - 2018)
January Barometer	Rejected*	---	---	---	Rejected*	---	---	---

Anomaly	IPC MidCap				IPC SmallCap			
	Returns		Volatility		Returns		Volatility	
	The anomaly exists (H_A)	The anomaly disappeared (H_0)	The anomaly exists (H_C)	The anomaly disappeared (H_0)	The anomaly exists (H_A)	The anomaly disappeared (H_0)	The anomaly exists (H_C)	The anomaly disappeared (H_0)
Day-of-the-Week Effect	Rejected*	---	Failed to reject	Rejected	Failed to reject*	Rejected	Failed to reject	Failed to reject
Holiday Effect	Failed to reject	Failed to reject*	Failed to reject	Rejected	Rejected	---	Failed to reject	Rejected
Turn-of-the-Month Effect	Failed to reject	Rejected	Rejected	---	Failed to reject*	Rejected	Rejected	---
January Effect	Rejected*	--- (A March effect appeared in 2009 - 2018*)	Rejected	---	Rejected*	---	Failed to reject	Failed to reject
Halloween Indicator	Rejected*	---	Rejected	---	Failed to reject	Failed to reject*	Failed to reject	Failed to reject
January Barometer	Rejected*	---	---	---	Rejected*	---	---	---

* Robust according to ANOVA and/or Kruskal-Wallis tests

Table 22. Findings Overview

The results rejected the hypothesis that the day-of-the-week anomaly has recently vanished from the returns of these three stock indices. Moreover, it seems that the outcomes of the most recent subperiod considerably influenced the conclusion about the existence of that seasonal anomaly in the returns of the large- and small-capitalization indices during the full period since the analyses did not identify the day-of-the-week anomaly in earlier subperiods. These findings diverge with some reports in the literature regarding the disappearance of such a seasonal effect from the stock markets in other countries (Alt et al., 2011; Connolly, 1989; Steeley, 2001). On the other hand, the day-of-the-week effect seems to be very

persistent in Mexico, as has been the case in other international stock markets (Gregoriou et al., 2004).

In contrast, the econometric models consistently rejected the hypothesis concerning the existence of the day-of-the-week effect in the returns of the IPC MidCap. That is, the regression analyses did not find any significant evidence of the presence of that anomaly in the medium-capitalization index. This conclusion seems robust, considering that the results of the Kruskal-Wallis test supported that finding.

The results of the regression models failed to reject the hypothesis concerning the presence of the day-of-the-week effect in the volatility of the four indices under examination. Moreover, the regression results failed to reject the hypothesis that this anomaly has disappeared from the IPC and the IPC SmallCap volatility. However, the analyses rejected that premise for the IPC LargeCap and the IPC MidCap.

This study found mixed results on the presence of the day-of-the-week effect in the Mexican stock market, and so might be the reasons for its existence. More specifically, the outcomes identified such an anomaly in three of the indices analyzed, but on different days of the week. For example, the finding of higher average returns on Mondays for the IPC and IPC LargeCap might be an expected result, because such an outcome might be the consequence of three-day returns accumulation during the weekend, as the trading time hypothesis asserts (French, 1980). Under such circumstances, this result would not constitute a stock market anomaly, but evidence in favor of the efficiency of the Mexican stock market.

Another possibility is that there is a spillover effect caused by return patterns in other markets (Dicle & Levendis, 2014). Assuming this was the case for the Mexican Stock Exchange, such a spillover effect may come from the U.S. market return patterns, due to the close relationship between these two markets (Lagunes & Watkins, 2009). It is also likely that the close-to-close returns used in this study, instead of close-to-open returns, are responsible for the findings regarding the day-of-the-week anomaly described here. Therefore, explanations such as the trading time hypothesis, the spillover effect, the close-to-close returns, among

others, may exist for the day-of-the-week anomaly found in this study in the Mexican stock market, all of which could be subject to additional research.

6.2.2 Conclusions Regarding the Holiday Effect

The results of the regression models rejected the hypothesis that the holiday effect was present in the IPC, the IPC LargeCap, and the IPC MidCap, a conclusion that was further supported by the Kruskal-Wallis test. This outcome agrees with the findings of several studies that report the nonexistence of the holiday effect in the Mexican stock market (Duarte et al., 2013; Kristjanpoller, 2012b; Seif et al., 2017; Tennyson, 2009; Winkelried & Iberico, 2018).

On the contrary, the corresponding regression model for the IPC MidCap failed to reject the hypothesis regarding the existence of the holiday effect in that index. More precisely, the analyses identified a post-holiday anomaly in the medium-capitalization index, an outcome that agrees with the conclusions reported in the literature about the presence of such a calendar effect in the Mexican stock market (Duarte et al., 2013; Kristjanpoller, 2012b; Seif et al., 2017). Additionally, the analysis failed to reject the hypothesis regarding the disappearance of the holiday anomaly from the IPC MidCap. Thus, quite possibly, the presence of the holiday effect during the first subperiod influenced the statistical results failing to reject the existence of such an anomaly in the medium-capitalization index in the full period.

The regression models failed to reject the premise regarding the existence of the holiday effect in the volatility of the four indices under examination. Moreover, the statistical outcomes rejected the hypothesis that the pre-holiday and post-holiday volatility anomalies faded away from the Mexican stock market. There was an exception, however, since the regression results failed to reject the hypothesis about the recent vanishing of the volatility pre-holiday anomaly from the IPC.

The evidence regarding the existence of a low volatility pre-holiday and high volatility post-holiday pattern in the four indices across all time intervals examined was significant and

consistent. In particular, this was the case of the IPC size indices, where the econometric models found no indication that the significance of such a volatility pattern had decreased, much less disappeared. Such a low pre-holiday and high post-holiday volatility pattern might be the consequence of a market correction. Moreover, there was a similar relationship in the size indices' returns, although the corresponding coefficients turned out to be not significant (see Table 7). This relationship resembles a mirror image of the adjustment suggested by Tennyson (2009), about the statistically higher pre-holiday returns followed by lower post-holiday returns in the Mexican stock market.

Fabozzi, Ma, & Briley (1994) argue that behavioral factors, such as the change in the mood of investors before and after holidays, explain the holiday effect. Moreover, Chancharat, Maporn, Phuensane, & Chancharat (2018) claim that the source of the holiday effect is that investors are focused on short term returns and that they tend to overlook the long term.

A feasible explanation for the presence of the holiday anomaly is that, before holidays, investors tend to sell some stocks from their portfolios to increase their spending power during such holidays. Contrarily, after holidays investors buy stocks when they think that such assets are undervalued and represent a profitable opportunity. More research is needed, however, to explore these and other possible reasons for the outcomes presented here. Likewise, the issue regarding the permanence of the significantly lower pre-holiday and significantly higher post-holiday volatility pattern remains open.

6.2.3 Conclusions Concerning the Turn-of-the-Month Effect

The results of the two versions of the regression model used to examine the turn-of-the-month effect failed to reject the hypothesis of the existence of such anomaly in the returns of the four indices of the Mexican Stock Exchange considered in this study. The outcomes of the Kruskal-Wallis test supported this conclusion in the case of the IPC and the IPC SmallCap. The analyses' findings rejected the premise that the turn-of-the-month effect disappeared from the IPC size indices. In contrast, regression analyses for the IPC returns failed to reject the hypothesis that this calendar anomaly vanished after the Great Recession, a conclusion also supported by the Kruskal-Wallis test. Hence, it is reasonable to state that the highly

significant and considerable outcomes displayed by this anomaly during the first two subperiods examined, namely, the pre-crises and Great Recession intervals, considerably influenced the analyses failing to reject the hypothesis concerning the existence of the turn-of-the-month effect during the full period in the IPC.

The analyses consistently rejected the hypothesis of the existence of the turn-of-the-month effect in volatility in each of the four indices in the corresponding full periods. Remarkably, however, that anomaly emerged in the variance equations of the IPC and the IPC LargeCap in the last subperiod under examination. Thus, variance regression analyses rejected the hypothesis that the turn-of-the-month effect disappeared from the volatility of the IPC and the large-capitalization index.

So, econometric and statistical tests performed in this research found considerable evidence supporting the presence of the turn-of-the-month effect on the returns of the four indices examined, a result that agrees with the conclusions of several studies concerning this calendar anomaly in the stock market in Mexico (Kristjanpoller & Arenas, 2015; Kunkel et al., 2003; McConnell & Xu, 2008; Winkelried & Iberico, 2018). Nevertheless, evidence that such anomaly has vanished was also found, particularly in the case of the IPC.

The higher than average returns on the first trading day of each month found in the IPC and the IPC LargeCap, irrespective of the number of days involved in the turn of the month definition, might be a result of investors buying stocks from wages, as well as from principal and interest payments they receive at the end of the month, as has been suggested by the payday hypothesis (Arsad, Chuah, & Nordin, 2011). The window dressing hypothesis proposed by Lakonishok & Smidt (1988), on the other hand, could be related to the significantly lower than average returns in the medium- and small-capitalization indices four trading days before the end of the month. Possibly, institutional investors tried to improve the performance of their portfolios by selling low-performing, less liquid stocks of small- and medium-sized companies in advance of preparing the reports for their clients.

On the other hand, the evidence of the presence of the turn-of-the-month anomaly in volatility is less conclusive. A relatively small number of turn-of-the-month volatility coefficients were significant in the size indices and none in the IPC in the corresponding full intervals. Remarkably, this calendar effect surfaced in the volatility of the IPC and the IPC LargeCap during the respective most recent subperiods, where variance in the last trading day of the month was significantly higher. Possibly, this was because of investors reacting to bad company news released by the end of the month (Mills, Siriopoulos, Markellos, & Harizanis, 2000) and as supported by the highly significant negative leverage coefficients for both indices. This announcement hypothesis, as well as the demand for liquidity and the investment rebalancing hypotheses (Kristjanpoller & Arenas, 2015), might help to explain the presence of the turn-of-the-month effect in the Mexican Stock Exchange. This issue, though, remains open for further examination.

6.2.4 Conclusions Related to the January Effect

The results of the regression analyses and the Kruskal-Wallis test unambiguously rejected the hypothesis regarding the existence of the January effect in returns and volatility of the four indices of the Mexican stock market examined in this research. Nevertheless, the IPC LargeCap exhibited significantly higher average returns along with statistically lower volatility in March during the most recent subperiod from 2009 to 2018, a result that conflicts with the ideas proposed by the EMH. Average returns in March were also higher for the IPC in the same time interval, even though that index did not show evidence that volatility in March had been different from that on other months since the regression models found no indication of volatility clustering.

The conclusions about the existence of the month-of-the-year effect in the returns of the IPC LargeCap and the IPC agree with the findings reported by Cabello & Ortiz (2004), Rojas & Kristjanpoller (2014) and Seif et al. (2017) regarding the presence of that calendar anomaly in the stock market in Mexico. Furthermore, Darrat et al. (2011), López & Rodríguez (2010), and Rojo (2013) also reported the existence of the March effect in the returns of the IPC. The anomaly in March's average returns was also reported by Garay & Demmler (2019) for three of the sector indices of the Mexican stock market they examined in addition to the IPC.

Again, the emergence of that calendar effect in the most recent subperiod conflicts with the reports in the literature.

Several research papers have concluded that the month-of-the-year effect has moved from January to other months (Darrat et al., 2011; Dzhabarov & Ziemba, 2012; Spoor & Rodriguez, 2015). It is possible that, because of the same still unclear reasons, this phenomenon has also taken place in the Mexican stock market, and instead of higher than average returns in January the IPC and the IPC LargeCap had exhibited larger than expected returns in March, along with a lower volatility level in the case of the latter.

However, the usual reasons put forward to explain the January effect, such as the tax-loss selling or the window dressing hypotheses, do not make sense in clarifying the higher March average returns in the Mexican stock market. It is possible, though, that such an anomaly is the opposite of the September effect proposed by Siegel (2014), who claims that September average returns are the lowest of the year in the stock markets of several countries⁶³.

A feasible explanation for the September effect is the depressing influence of the shortening daylight hours in the forthcoming winter season in the northern hemisphere (Saunders, 1993). Inversely, thus, the approaching spring and the uplifting longer days may be the cause for higher returns in March. This behavioral-based explanation, though, is highly disputable. An obvious problem with this line of reasoning is why this phenomenon was detected in the IPC and the IPC LargeCap only, and not in the other two indices. Therefore, the causes for the presence of this anomaly in the Mexican stock market are an issue that requires additional analysis.

⁶³ The September effect was not found in this study. While September average returns were the lowest for the IPC during the full period and the first subperiod, the difference with January average returns was not statistically significant, as can be observed in Table 12 and the results of the Kruskal-Wallis test presented in section 5.6.

6.2.5 Conclusions About the Halloween Indicator

The results of the regression models rejected the hypothesis that the Halloween indicator existed in the IPC, the IPC LargeCap, and the IPC MidCap, a finding that seems robust considering that the results of the Kruskal-Wallis test supported this conclusion. Nonetheless, the outcomes concerning the Halloween effect in the small-capitalization index require a more detailed assessment. On the one hand, the regression analysis failed to reject the hypothesis regarding the presence of the Halloween effect in the IPC SmallCap during the full period when controlling for January returns. On the other hand, such an analysis failed to reject the hypothesis that the Halloween anomaly had vanished from the small-capitalization index after the Great Recession. Therefore, while the Halloween indicator was relevant only at the 10% significance level⁶⁴ in the subperiod following the global financial crisis, this result may have caused the finding of the anomaly in the full period examined.

The regression analyses, as well as the Kruskal-Wallis and ANOVA tests, carried out for the IPC, the IPC LargeCap, and the IPC MidCap found no significant presence of the Halloween effect in such indices in any of the time intervals considered, an outcome that largely agrees with the findings of previous research in this respect (Bouman & Jacobsen, 2002; Haggard & Witte, 2010; Jacobsen & Zhang, 2018; Lloyd et al., 2017; Takki, 2017). It is also worth reminding that, as opposed to the IPC and the IPC MidCap, the IPC LargeCap exhibited evidence of ARCH and GARCH effects, as well as volatility asymmetry.

The IPC SmallCap, on the other hand, displayed a significant presence of the Halloween effect in the full period from 2006 to 2018, when controlling for January returns, which agrees with the results reached by Takki (2017). The literature has reported that some calendar anomalies are more prevailing for small company stocks than for other stocks (Banz, 1981; Basu, 1977; McConnell & Xu, 2008). It is also possible that a narrow stock index, such as the IPC SmallCap, can more easily reveal some of the features of the individual stocks that comprise the index, where seasonal effects can still be distinguished, as opposed to

⁶⁴ The p -value of the corresponding coefficient was 0.07.

broader stock indices where calendar anomalies are no longer traceable (Dicle & Levendis, 2014). So, in the full period analyzed, the characteristics of the IPC SmallCap could contribute to reveal the presence of the Halloween indicator in such an index.

Lloyd et al. (2017) state that, according to the literature, the Halloween indicator is due to an increase in risk during the winter months. Previous research has suggested that such an anomaly is a consequence of the January effect, or that it is a self-fulfilling prediction. Nevertheless, for the small-capitalization index, the Halloween volatility coefficient was negative, implying lower volatility during the winter months in that index. One of the regression models also included the January effect to test for the Halloween indicator, but January's coefficient turned out to be negative and nonsignificant. Furthermore, the small-capitalization index did not show evidence of the month-of-the-year effect in the analyses carried out for such an anomaly. There are no sensible reasons why the self-fulfilling prophecy should be specific to the IPC SmallCap, the only index in this research that showed evidence of the Halloween indicator. Hence, these explanations for the presence of this calendar anomaly in the small-capitalization index are not very persuasive.

A reasonable explanation for the presence of the Halloween indicator in the IPC SmallCap might be related to liquidity. Small-company stocks are relatively less liquid than medium and large-company stocks. Therefore, it is reasonable to assume that liquidity factors, such as those associated with the summer vacations and the agricultural cycle suggested by Bouman & Jacobsen (2002), could more directly influence the returns of smaller-company stocks. Nevertheless, more analyses are needed to assess these and other factors as possible reasons for the existence of the Halloween anomaly in the IPC SmallCap.

Finally, between 2006 and 2009, the average returns of the IPC LargeCap and the IPC SmallCap in January were significantly lower than the summer months' average returns. This result possibly implies the presence of an inverse January effect in those indices. This anomaly, though, faded away after the Great Recession.

6.2.6 Conclusions Regarding the January Barometer

The regression models, as well as the corresponding Kruskal-Wallis tests, rejected the hypothesis concerning the presence of the January barometer in each of the four Mexican Stock Exchange indices examined in this research, so these outcomes seem robust. Moreover, the findings of this study agree with the results reported by Seif et al. (2017) who found that February to December average returns in the stock market in Mexico were higher following negative Januarys than those following positive Januarys, but who also concluded that such difference was not statistically significant and that the January barometer was absent from the stock market in Mexico.

The conclusion regarding the nonexistence of the January barometer in the stock market in Mexico endorses the results reported by Bohl & Salm (2010), who determined that such a calendar effect was not widespread in stock markets outside the United States. It is even possible that the finding of this seasonal anomaly in the U.S. stock market and the stock markets of some other countries is just spurious or the consequence of data mining biases, as argued by Marshall & Visaltanachoti (2008, 2010).

To sum up, this research examined a total of six seasonal anomalies in four stock indices of the Mexican Stock Exchange. Only the day-of-the-week and the turn-of-the-month effects were consistently present in the returns of those indices. The analyses carried out in the study found the remaining four anomalies only in some instances. Specifically, the holiday effect and the Halloween indicator emerged in the IPC MidCap and the IPC SmallCap, respectively. Also, while the January effect did not exist in the indices' returns, a March anomaly was found in the IPC, and the large- and medium-capitalization indices.

As for the presence in the volatility of the indices of the same calendar effects, except the January barometer, the four indices exhibited evidence of the day-of-the-week and holiday anomalies. The January effect was identified in the volatility of the small-capitalization index only, although a March effect also occurred in the large-capitalization index. The Halloween indicator was found only in the volatility of the IPC SmallCap. Finally, it is worth noticing

that the calendar anomalies found in the four indices involve daily returns. Therefore, market reaction in Mexico may be slower than suggested by the EMH.

6.3 Theoretical and Practical Implications

This section is concerned with the theoretical and practical implications of the conclusions discussed in part 6.2. Theoretical implications examine the results mainly from the Efficient Markets Hypothesis point of view. Practical implications focus not only on investors and practitioners but also on the role of the findings of this research for policymakers.

6.3.1 Implications for Theory

According to the results presented here, the Mexican Stock Exchange was reasonably efficient in the weak form sense from 2000 to 2018, a conclusion that agrees with the findings of several studies (Bonilla et al., 2011; Coronel-Brizio et al., 2007; Duarte & Mascareñas, 2014; Duarte et al., 2015).

However, the lasting presence of some of the seasonal anomalies remains a challenge to the propositions of the EMH. More specifically, investors seemingly have not arbitrated away the turn-of-the-month and the day-of-the-week effects in the Mexican Stock Exchange. The presence of five of the anomalies in the small-capitalization index's returns and volatility remains another challenge to the EMH ideas. Furthermore, the recent emergence of the month-of-the-year anomaly, particularly the March effect, identified in three of the indices, defies the ideas regarding market efficiency.

It is conceivable, though, that the presence and permanence of such calendar anomalies are the result of investors' adjustments in their decision-making process, a situation that could be better described by the ideas put forward by the Adaptive Markets Hypothesis than by the premises of the EMH. It is also possible that the discovery of seasonal effects in the Mexican stock market is the result of a joint test problem of the models used to perform the analyses (Dimson & Mussavian, 1998; Fama & French, 1988). Nevertheless, this issue also exists in

those cases where the results found no anomalies since the models applied in both instances were the same.

6.3.2 Implications for Practitioners and Policymakers

Spotting a market anomaly, seasonal or otherwise, is the first step to design a successful investment strategy based on that anomaly. For example, the presence of the turn-of-the-month effect in the IPC LargeCap means that average daily returns are around 0.23% higher on the first trading day of the month than on other days of the month, which translates into a possibly profitable strategy of investing in that index just before the beginning of the month. Similarly, the medium- and small-capitalization indices' average daily returns are lower around 0.23% and 0.20%, respectively, four trading days before the end of each month as compared to their average returns throughout the rest of the month. Perhaps a profitable strategy for investors might be shorting those indices five trading days before the end of the month. Then, they could invest the proceeds in CETES during the rest of the month, and subsequently buy the IPC LargeCap right before the market closes on the last trading day of the month or, alternately, invest their money in the IPC SmallCap during most of the following month, not forgetting to short the index again five trading days before the month ends.

However, the issue concerning the economic significance of these and other investment strategies based on calendar anomalies persists. That is, the question remains as to whether transaction costs would offset, or even surpass, the abnormal returns possibly earned by implementing seasonal-effects-based investment strategies. Another related matter is whether such investment schemes offer higher risk-adjusted returns than a simple buy-and-hold investment approach.

The degree of efficiency of a market is directly related to price stability. Therefore, policymakers should be concerned with the possible presence of anomalous stock returns, such as seasonal effects since mispricing might contribute to further volatility and to increase market participants' uncertainty.

An important implication of the results of this research relates to volatility. With only a few exceptions, the best fitting models for daily data involved volatility clustering and leverage. This outcome is evidence that those features are present in the high-frequency returns data in the Mexican stock market, characteristics that the literature has also reported for other markets (Cagli et al., 2011; Salisu, 2014). The IPC and the size indices exhibited volatility persistence, which implies that volatility declines slowly and, therefore, that high and low volatility intervals tend to stretch out for some time. Moreover, the results of this research imply that bad news has a further influence than good news on the indices' volatility. Accordingly, investors and policymakers should consider these characteristics of daily returns in the Mexican stock market in their corresponding decision-making process.

6.4 Conclusions About the Research Problem

The analyses carried out in this study only found the day-of-the-week and the turn-of-the-month effects in the returns of the IPC and the IPC LargeCap. Nonetheless, the turn-of-the-month effect disappeared from the IPC only. Also, a month-of-the-year anomaly in March appeared in those indices during the last subperiod, and a positive October effect (i.e., an inverse Mark Twain effect) emerged in the IPC LargeCap in the same subperiod. The day-of-the-week and holiday effects appeared in the volatility of the IPC and the IPC LargeCap, and only the day-of-the-week effect vanished from the volatility of the former. Additionally, a volatility anomaly in March appeared in the IPC LargeCap in the last subperiod examined.

The holiday anomaly emerged in the returns of the IPC MidCap, while the day-of-the-week effect and the Halloween indicator appeared in the IPC SmallCap returns. The analyses also found the turn-of-the-month anomaly those indices. The holiday vanished away from the IPC MidCap, while the Halloween indicator also faded away from the IPC SmallCap in the most recent subperiod. On the other hand, the day-of-the-week effect identified in the IPC SmallCap did not fade away, nor the turn-of-the-month anomaly found in both indices. The medium- and small-capitalization indices also exhibited day-of-the-week and holiday effects in volatility, and only the day-of-the-week effect vanished from the IPC SmallCap. This

index also showed January and Halloween effects in volatility, but both anomalies disappeared in the most recent subperiod.

In conclusion, the turn-of-the-month effect was consistently present in the returns of the four indices, while the day-of-the-week anomaly appeared in the IPC, the IPC LargeCap, and the IPC SmallCap. Except for the IPC, the turn-of-the-month effect did not disappear from the returns of any of the indices. Moreover, the day-of-the-week anomaly did not fade away either from any of the three indices where it emerged.

Likewise, the volatility of the four indices consistently exhibited day-of-the-week and holiday effects. The day-of-the-week anomaly faded away from the volatility of the IPC and the IPC SmallCap. However, the holiday effect did not disappear from the volatility of any of the four indices. The January effect was not present in any of the stock indices, nor the January barometer.

Thus, throughout the time interval included for this research, the Mexican Stock Exchange reasonably complied with the weak form of market efficiency from the seasonal anomalies' standpoint, since several of the six calendar effects examined were absent from the returns and volatility of the four stock indices considered. Nevertheless, the analyses found some persistent calendar effects in such indices, particularly several anomalies related to daily observations.

6.5 Implications for Further Research

Several possibilities for additional research arise from this study, some of which have been outlined already in this chapter. Such is the case, for example, of studying whether the propositions of the AMH are more appropriate than those of the EMH to clarify the existence of the seasonal anomalies reported here. Also, more analyses are needed to determine the economic significance of the calendar anomalies found here.

One of the delimitations set up for this research was that possible explanations for the existence of the anomalies would not be examined, even though some of them are mentioned here. This issue opens another possibility for additional research. An additional delimitation of this study was that only four indices of the Mexican Stock Exchange were to be analyzed. Therefore, another area for further research is the possible presence of calendar anomalies in other stock indices and individual company stocks in the Mexican stock market. Moreover, it is quite likely that the existence of calendar anomalies in the returns of assets such as oil, bonds, financial derivatives, and foreign currency has been examined even to a lesser extent than in the stock market in Mexico.

One additional issue that might be relevant for further examination relates to the data frequency. More specifically, the analyses of the January effect, the Halloween indicator, and the January barometer in Mexico could be carried out using daily or weekly returns instead of using monthly returns of the Mexican Stock Exchange indices. Such analyses may contribute to test the robustness of the results reported in this research. Further calendar anomalies, such as the week-44 effect and the school holidays effect, might be considered for examination in the context of the Mexican stock market, along with their interactions with other seasonal effects.

Besides the regression models used in this research, it might be desirable to consider other ARCH family parameterizations to examine seasonal anomalies in the Mexican stock market in other studies on that topic. That is the case, for instance, of the ARCH in mean (ARCH-M) group specifications. A feature of such models, like the EGARCH-M, is that, besides considering clustering and asymmetry in volatility, they also allow the mean equation to directly depend on the variance equation (Kang, 2011). Other models, such as the VAR-GARCH in mean with a BEKK representation (Caporale, Spagnolo, & Spagnolo, 2016), might also be worth exploring to test whether such specifications better fit the time series than the ones applied in this research, and also to verify whether the results reported here are robust.

Finally, it is feasible and desirable to apply the analyses carried out in this study to other emerging stock markets. In particular, it might be of special relevance to broaden this research to encompass other major Latin American stock markets, such as those of Argentina, Brazil, Chile, Colombia, and Peru.

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